The Foreign Exchange Risk Premium Over the Long Run

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Abstract

This paper analyses the behavior of the foreign exchange risk premium using long-horizon regressions. A long-horizon analysis may provide new evidence about three key issues concerning the foreign exchange risk premium. The first issue is the relationship between expected foreign exchange returns and expected returns on other assets. Long-horizon regressions are able to explain a large portion of the variation of foreign exchange returns using instruments that have been shown to predict domestic asset returns. I undertake a careful small-sample study to examine the size of the statistics and provide evidence of increased power. The second issue is the high variability of the foreign exchange risk premium. Using the long-horizon regression results, I show that Fama's (1984) finding that the variability of the risk premium is greater than that of the expected change in the spot rate holds even for horizons extending out to four years and is, therefore, not the result of market frictions which would bind only in the short run. The third issue is the economic model that can explain foreign exchange risk premia. I show that both the length of the holding period and the inclusion of global and local risk factors are important for tests of latent variable models.

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1 Introduction

The behavior of excess returns on foreign currency deposits remains one of the more puzzling issues of study in international finance. Under the assumption of rational expectations, the excess return can be decomposed into a time-varying risk premium plus an orthogonal forecast error. A large number of papers employing a wide variety of theoretical models and econometric techniques have tried to link the foreign currency risk premium to economic fundamentals.[1] These efforts have failed as empirical estimates of the risk premium reveal that it has a large variance while the economic variables used in theories of exchange rate determination are not as volatile. As a result, some authors have suggested either that the rational expectations hypothesis fails completely or that the expectations of market participants are rational but appear to have systematic errors (Lewis (1995)).

If the predictable component of the excess return is a risk premium and if international capital markets are not completely segmented, then the foreign exchange risk premium should be related to risk premia on assets in other markets.[2] A number of studies have addressed this question (e.g., Giovannini and Jorion (1987, 1989), Mark (1988), McCurdy and Morgan (1991), Harvey (1991), Campbell and Hamao (1992), Cumby and Huizinga (1992), Korajczyk and Viallet (1992), and Bekaert and Hodrick (1992)). Most of these studies concentrate on examining moments of foreign and domestic asset returns over the short run (i.e., a one week to three month horizon) and thus have ignored one of the striking empirical findings in the recent finance literature: the long-horizon (i.e., out to four or five years) predictability of domestic asset returns using certain instruments which are taken to be proxies for underlying risk factors (e.g., Fama and French (1988, 1989), Campbell and Shiller (1988)).[3] Importantly for this paper, this long-horizon return predictability seems to have a common pattern across countries. For example, Cutler, Poterba and Summers (1991) show that high current values of dividend yields predict higher future stock returns in a number of countries. Harvey (1991) shows that a common set of variables predicts equity returns in a large cross section of countries.

In this paper, I adapt the empirical techniques from the domestic asset return prediction literature to analyze long-run movements in foreign exchange excess returns. I maintain the rational expectations assumption and interpret time-varying expected returns as risk premia. A long-horizon analysis may provide new evidence about three key issues concerning the foreign exchange risk premium. The first issue is the relationship between expected foreign

[1]See Hodrick (1987), Dumas (1994), Lewis (1995) and Engle (1996) for surveys.

[2]If the international capital markets are *segmented*, then assets with the same exposures to risks that trade in different markets could have different expected returns. In contrast, if the capital markets are *integrated,* then the assets should have the same expected returns.

[3]The notable exception is Bekaert and Hodrick (1992) which I discuss below.

exchange returns and expected returns on other assets. If the foreign exchange market is integrated with domestic asset markets then instruments which predict returns in the domestic markets should help explain returns in the foreign exchange market. Some of the studies cited above have attempted to document such a relationship in the short-horizon data. However, as the short-run data are quite noisy, the reported parameter estimates are often imprecise and it is difficult to determine if common sources of predictability are present. In contrast, the long-horizon technique used here produces clear, consistent results for the selected instruments and countries examined. The degree of explanatory power is quite striking: in many of the countries that I examine, over 40 per cent of the variation in four-year excess foreign exchange returns is explainable using instruments that forecast stock and bond returns. I argue that the strong results are due to the time series nature of the foreign exchange risk premium. In particular, long-horizon regressions are a good method to model the behavior of expected returns that are persistent and heteroskedastic (Campbell (1994), Stambaugh (1993)).

The second issue is whether the large variability of the foreign exchange risk premium that is found in the short-horizon analyses extends to longer horizons. In an often cited paper, Fama (1984) shows that the risk premium is more volatile than the expected one-period change in the future spot exchange rate. This finding has been termed a "puzzle" as it is difficult for risk-based theories to explain. One possible explanation comes from the domestic asset pricing literature. In this literature, market frictions (e.g. solvency constraints or transaction costs) have been investigated as possible reasons for the failure of consumption-based asset pricing models to explain (short-horizon) equity returns (e.g., He and Modest (1995)). The frictions, while binding in the short run, may have less influence on returns in the long run as investors have greater flexibility to adjust their portfolios. Empirical support for this view comes from Daniel and Marshall (1997) who find that the consumption-based asset pricing model can explain equity returns with reasonable coefficients of risk aversion when the holding period of the investor is lengthened out to one year. Thus, the "equity premium puzzle" appears to be a problem for the short-run data.

Motivated by these results, I examine whether frictions that may be present only in the short run are responsible for Fama's (1984) finding. Using the long-horizon regressions, I am able to report a new finding: the foreign exchange risk premium remains more volatile than the expected change in the spot exchange rate even at quite long horizons, suggesting that frictions will not resolve this puzzle.

The third issue that I wish to address is the conflicting results in previous studies about the economic model that can explain foreign exchange returns. These studies perform latent variable tests of Merton's (1973) intertemporal capital asset pricing model (ICAPM) at relatively short horizons (i.e. one to three months). Huang (1989) and Lewis (1990) reject a single latent variable model for currency returns at a one-month horizon, but not at a three month horizon. In contrast, Cumby (1988) rejects a latent variable model at a three month horizon. In this paper, I use long-horizon regressions to increase the power of tests that classify the sources of risk premia. Testing the model using a system of long-horizon regressions, I show that Eurocurrency returns respond to both global and local risk factors and thus should not be modeled in a single latent variable framework.

The paper that is closest to mine is Bekaert and Hodrick (1992) who construct implied long-horizon statistics for equity and currency returns from short-horizon vector autoregressions (VAR). They show that currency returns are predictable over long horizons using the forward premium (i.e. the spot exchange rate less the one-period forward exchange rate) as the predictor. The forward premium has been shown to be able to predict currency returns over short horizons in numerous studies. As mentioned above, it is far less certain whether this predictability is related to time-varying risk premia in other markets. Thus, in this paper, I show that currency returns are predictable over long horizons using a number of domestic asset market variables (e.g. dividend yields) as predictors. This provides further evidence on the long-run linkages between markets. In addition, I examine several reasons why the long-horizon regression test may have better statistical power to detect time-varying expected returns than the VAR method of Bekaert and Hodrick (1992). This additional power is important due to the relatively short time span of floating exchange rates. Below, I present simulations to evaluate the additional power that results from increasing the forecast horizon.

Both the VAR results in Bekaert and Hodrick (1992) and the long-horizon results in this paper use asymptotic standard errors based on a Generalized Method of Moments (GMM) estimator. However, it is well known that these estimators may suffer from severe small-sample problems.[4] Thus, while the long-horizon regression tests may have good power properties, the size of the statistics may be suspect. I therefore undertake a careful small-sample study that accounts for a number of potential econometric problems. I show that the statistical significance of the asymptotic results presented here and in Bekaert and Hodrick (1992) are overstated in some cases. However, I am able to reject the null hypothesis of no predictability at standard significance levels for most returns.

The analysis presented here and in Bekaert and Hodrick (1992) is subject to two other possible biases. First, Richardson (1993) notes that test statistics in long-horizon analyses are not independent across forecast horizons. It is thus possible that a finding of return predictability at *some* long horizon is the result of "specification mining" through *many* horizons. To account for this possibility, I present tests that account for the correlation of the test statistics across the horizons examined. Second, I am careful to choose my

[4]See, for example, the July, 1996 issue of the *Journal of Business and Economic Statistics*.

forecasting variables from other studies on domestic asset return prediction and thus cannot be blamed for “data mining”. However, I could be accused of “data snooping” as the US dollar currency returns are not independent of US dollar returns on the domestic assets. To show that my results are robust to this bias, I present an analysis based on Foster et al. (1997).

The rest of this paper proceeds as follows. Section 2 starts by presenting the results of the long-horizon regressions for excess foreign exchange returns. However, long-horizon tests are subject to a number of potential econometric problems that may affect the size of the tests. Section 3 addresses these issues in a careful robustness evaluation. In Section 4, I detail how the strong results obtained are likely due to the good power properties of these regressions. I also examine the ability of the long-horizon regressions to shed light on the persistence and volatility puzzles in international finance. Section 5 reports the tests of the latent variable model. Section 6 concludes.

2 Long Horizon Regressions

2.1 Foreign exchange excess returns

In this section, I obtain a logarithmic version of the foreign exchange excess return from the perspective of a US investor. The US investor: (i) borrows one US dollar for one period at the risk-free interest rate $I_{t,t+1}^{US}$; (ii) converts the US dollar into units of foreign currency j at the prevailing spot exchange rate $S_t^{US/j}$, expressed in US dollars per unit of foreign currency j; and (iii) invests the proceeds in a foreign currency deposit at rate $I_{t,t+1}^{j}$. When the foreign deposit matures, the investor converts the proceeds back into US dollars at the prevailing spot rate of $S_{t+1}^{US/j}$. The one-period US dollar excess rate of return on the foreign currency deposit $ES_{t,t+1}^{j}$ is defined via:

$$\left(1 + I_{t,t+1}^{j}\right) \cdot S_{t+1}^{US/j} / S_t^{US/j} = \left(1 + I_{t,t+1}^{US}\right) \cdot \left(1 + ES_{t,t+1}^{j}\right). \tag{1}$$

I take logs and obtain:

$$es_{t,t+1}^{j} = s_{t+1}^{US/j} - s_t^{US/j} + i_{t,t+1}^{j} - i_{t,t+1}^{US}, \tag{2}$$

where small letters represent log values of the variables, $i = \ln(1 + I)$ and $es = \ln(1 + ES)$. The excess return is composed of the capital gain on the foreign currency plus the foreign interest income less the domestic interest cost. It has the convenient property that returns aggregated over the forecast horizon k are the k-period sum of the one-period returns which is denoted:

$$ses_{t,t+k}^{j} \equiv \sum\nolimits_{s=0}^{k-1} es_{t+s,t+s+1}^{j}. \tag{3}$$

Note that if covered interest parity (CIP) holds,[5] then:

$$es^{j}_{t,t+1} = s^{US/j}_{t+1} - f^{US/j}_{t,t+1}, \tag{4}$$

where $f^{US/j}_{t,t+1}$ is the (log) forward exchange rate in US dollars per unit of foreign currency j. This is the same return as that on a no-finance strategy of contracting to buy a unit of foreign currency of country j at time t for price $f^{US/j}_{t,t+1}$ to be paid next period and selling it at the prevailing spot price $s^{US/j}_{t+1}$.

The logarithmic version of the one-period foreign exchange excess return in (2) is the basic unit of interest in this study. I impose the rational expectations hypothesis so that the excess return can be decomposed into a time-varying risk premium plus an orthogonal forecast error. Under the joint null hypothesis of CIP (i.e., no arbitrage), UIP (i.e., no risk premium) and rational expectations, the forward exchange rate is an unbiased estimator of the future spot exchange rate (the "unbiasedness hypothesis"). This implies the expected value of (2) is zero. Tests of the null hypothesis can be conducted by regressing (2) on instruments which are linked to time-varying risk premia.

If the predictable component of the foreign exchange excess return is a risk premium and if international capital markets are not completely segmented from their domestic counterparts, then expected foreign exchange returns should be linked to expected domestic asset returns. Many studies have tested for common sources of risk in domestic and foreign asset markets (Giovannini and Jorion (1987,1989), Mark (1988), McCurdy and Morgan (1991), Harvey (1991), Campbell and Hamao (1992), Cumby and Huizinga (1992), and Korajczyk and Viallet (1992)). These studies examine the predictability of excess foreign exchange returns over short horizons (where k is one to three months in (3)) using instruments shown to have power for domestic asset return prediction. Often the parameter estimates are imprecise and may vary by the country examined. For example, Giovannini and Jorion (1987) show that predictable excess dollar returns on both the US stock market and foreign currencies are negatively related to US nominal interest rates and positively related to foreign interest rates. The volatility of the risk premia for both series are positively related to nominal rates. However, it is often not possible to reject the null of no relationship. One of the objectives of

[5] Covered interest parity is the relation: $f^{US/j}_{t,t+1} - s^{US/j}_{t} = r^{US}_{t,t+1} - r^{j}_{t,t+1}$ which is obtained when there are no arbitrage opportunities in international currency and money markets. This condition is very likely to hold in the Eurocurrency markets examined below as these markets contain few barriers to arbitrage. A separate concept used below is that of uncovered interest parity (UIP) where the known value of the forward exchange rate is replaced by the expected value of the future spot exchange rate. Uncovered interest parity fails in the presence of the foreign exchange risk premium. UIP in levels (rather than in log form) will also fail due to Jensen's inequality (Siegel's paradox). However, this effect is small empirically (Backus et al., 1993).

this paper is to see if the apparently fragmented results that are reported in the short-horizon studies can be improved upon in a long-horizon analysis.

2.2 Long-horizon regressions

There is a large body of literature which examines the degree of predictability of excess domestic asset returns over horizons extending out to four or five years.[6] The stylized fact has emerged that stock and bond market excess returns are predictable at long horizons using instruments which act as proxies for unobserved state variables. Several econometric methods have been used to detect these long-run relationships. A common approach, and the one adopted below, is to use a long-horizon regression where the aggregate excess return over future periods (typically out to four years) is regressed onto current period instruments that are believed to be related to risk premia. Overlapping observations are used and Hansen's (1982) Generalized Method of Moments methodology is employed to generate standard errors for the coefficients that are asymptotically robust to general forms of autocorrelation and heteroskedasticity. The typical result is that the regression coefficients increase in size and significance and that the goodness-of-fit measure (R^2) improves as the forecast horizon lengthens.

In this paper, I use this methodology to provide evidence on the linkages between foreign exchange returns and returns on domestic assets (stocks and bonds). My ability to model these linkages depends on the variables selected as forecasting instruments. Variable selection is an issue that remains contentious in any test of return predictability. In order to avoid charges of "data mining", my tests should use instrumental variables that are linked in a plausible manner to the unobservable state variables. I select these variables from work performed in other papers and am thus subject to a "data snooping" criticism. I show in Section 3 below how robust my results are to this critique.

Previous studies that have examined domestic asset pricing across a variety of countries suggest that the instrumental variables may be broken into two groups that represent either "local" or "world" economic factors (e.g., Harvey (1991), Ferson and Harvey (1993,1994), and Bekaert and Harvey (1997)). For example, Harvey (1991) examines the predictability of stock returns in several countries and finds that "world" variables have more forecasting power at one-month horizons. The world variables that can forecast local returns include the lagged world excess stock return, the S&P 500 dividend yield, the slope of the US term structure and a junk bond spread. The lagged own country stock return and the dividend yield are the two local variables that have good forecasting power. Ferson and Harvey (1993) find that the "global risk premium" appears to be the primary source of predictability in

[6] See Campbell, Lo and MacKinlay (1997, Chapter 2) for a survey.

stock returns from 18 countries. In contrast, Ferson and Harvey (1994) find that a set of variables related to the "fundamental attributes" of the equities in the various countries largely subsume the influence of the global variables. None of these studies have examined the impact of global and local variables at different forecast horizons.

Other studies that do not adopt the "local" versus "world" dichotomy nevertheless use similar instruments to predict returns. For example, Dumas and Solnik (1995) examine a version of Harvey's (1991) model to determine the influence of foreign exchange risk on equity returns. They use the rate of return on a global portfolio of equities and US asset yields as instruments to find that exchange rate risk is priced in an international setting. Campbell and Clarida (1987) demonstrate the predictability of short-term foreign currency deposits using the spread between three and one-month Eurocurrency interest rate differentials and the interest differential between Eurodollar and other Eurocurrency deposits.

In addition to using instruments which can predict domestic asset returns, it may be important to include instruments which are specific to the foreign exchange market. For example, Korajczyk and Viallet (1992) extract the latent factors which are capable of explaining movements in equity returns. While these factors help forecast foreign exchange risk premia, the forward returns have components unrelated to the factors. In the extensive literature on international asset pricing, the variable which appears to give the most power to reject the null of a constant risk premium over a short horizon (one to three months) is the forward premium.[7]

From these studies I have selected two groups of variables to use as instruments to predict foreign exchange excess returns. To compare my results to earlier work, I also divide the instruments into "local" variables and common or "world" variables. The local group of instruments includes the foreign (country j) dividend yield (dy_t^j), the term structure slope in country j (sp_t^j), and the forward premium on the foreign currency ($fp_t^{US/j}$). The local variable long-horizon regressions performed below are thus of the form:

$$ses_{t,t+k}^j = \theta_0 + \theta_1 \cdot sp_t^j + \theta_2 \cdot dy_t^j + \theta_3 \cdot fp_t^{US/j} + \nu_{t,t+k}. \tag{5}$$

The second group of world variables are the same across all countries. These variables are the US dividend yield (dy_t^{US}) and slope of the US term structure of interest rates (sp_t^{US}) leading to long-horizon regressions of the form:

$$ses_{t,t+k}^j = \theta_0 + \theta_1 \cdot sp_t^{US} + \theta_2 \cdot dy_t^{US} + \nu_{t,t+k}. \tag{6}$$

The use of US variables as proxies for world risk premia seems intuitive given the relative size of the US capital markets and the influence of the US economy.

[7] The forward premium is defined as the difference between the current spot exchange rate and the forward rate: $fp_t^{US/j} = f_{t,t+1}^{US/j} - s_t^{US/j}$. Under CIP, this is equal to the difference in short-term interest rates.

I estimate (5) and (6) using OLS and compute the standard errors using the Newey-West (1987) estimator of the residual variance-covariance matrix that is robust to general forms of heteroskedasticity and autocorrelation.[8] I examine forecast horizons ranging from one month to four years ($k = 1$ to $k = 48$). The null hypothesis is that the expected foreign exchange excess return is constant and thus not related to the instruments (i.e., the unbiasedness hypothesis holds up to a constant). If the null is true, then the selected instruments should be statistically (and economically) insignificant and increasing the forecast horizon should have little effect on the results. If the null is rejected in favor of the (unspecified) alternative, then the ability of the regressions to model risk premia depend on the variables included. Given that the instruments display a common pattern in predicting long-horizon domestic asset returns, it is hoped that they display a common pattern in predicting long-horizon foreign exchange returns. If foreign exchange risk premia are primarily related to "own country" effects, then the local variables – which are related to local asset returns – will have explanatory power. If foreign exchange risk premia share common sources of risk, then they will be related to world (US) variables. Of course, some combination of these two effects is likely.

2.3 Data

All data used in this paper are from Datastream. The exchange rates are supplied at a daily interval in British pounds per foreign currency which I translate into US dollar equivalents. I use the mid-market (average of bid and offer) observation on the last business day of each month. The one-month mid-market Eurocurrency rate is used as the short-term risk-free rate for all countries. Daily observation are supplied and I again select the last observation in each month. The exact number of days between the last business day in each month is used to translate the annual rates of return to monthly rates.[9] The one-month forward exchange rate is generated by assuming that covered interest parity holds. The forward premium is in logs. The excess returns on the foreign currency positions and the forecasting instruments are quoted in continuously compounded monthly per cent rates.

The yield on the long government bond at the end of the month is supplied by the OECD.

[8] I use the Newey-West (1987) form of the estimated covariance matrix to ensure positive definiteness in both the original OLS regressions and in their Monte Carlo counterparts. The autocorrelation correction is of degree $k-1$ which implicitly assumes that the explanatory variables capture all of the expected returns. The Newey-West procedure may not be a good choice in a long-horizon regression as it gives little weight to correlations at long horizons which may be particularly important in this framework. However, the small sample analysis will provide exact standard errors.

[9] In Eurocurrency markets the compounding convention is actual number of days divided by 360 for all currencies except the British Pound which uses a 365 day year.

The term structure slopes are estimated by subtracting the one-month Euro rates from these yields. For dividend yields, I use the measure provided with the Datastream Global Stock Market Indices. These indices are a market-value weighting of the largest stocks in each country. As dividend payments can display a seasonal pattern, I construct a new dividend yield series by calculating the sum of the actual dividends paid over the last 12 months divided by the current price.

I have chosen six foreign countries with "well traded" currencies for the analysis. Germany and Japan are chosen as they represent the major world economies besides that of the US. The UK and France are also large economies with exchange rates that are likely more related to European economic conditions. Canada is chosen as a small open economy with close financial and economic ties to the US. In contrast, Switzerland is a small economy with close ties to European economies.

Table 1 provides summary statistics of the data. While the average excess returns on the foreign currencies are close to zero over a one-month forecast horizon, they are quite variable. As mentioned above, it is this variability that may have confounded earlier searches for the risk premium. The mean slopes of the term structures of interest rates are close to zero over the period examined. Both the slope variables and the forward premia are quite variable compared to the dividend yield measures. All of the instruments are persistent, but appear stationary.

2.4 Long-horizon regression results

I start by examining the ability of the "local" variables to predict the foreign exchange excess returns. The results of the long-horizon OLS regressions (5) are shown in Table 2. I report the OLS estimate of the coefficient, the Newey-West standard error and the corresponding asymptotic marginal significance level (p value). The local variables have significant explanatory power that generally increases with the forecast horizon. The regressions have relatively small R^2 statistics (adjusted for degrees of freedom) at the shortest (one month) forecast horizon for all of the countries except Switzerland ($R^2 = 0.256$). The best fit (maximum adjusted R^2 statistic) is obtained at the four-year horizon for the German Mark and Canadian dollar excess returns and at the three-year horizon for the UK Pound, French Franc and Swiss Franc excess returns. At the four-year horizon, the degree of linear predictability ranges from 0.202 for the Yen to 0.578 for the Mark, with an average near 0.4.

The coefficients on the slopes of the foreign countries' term structure generally increase with the forecast horizon out to three years, though the increase is not monotonic for the Japanese Yen and Canadian dollar regressions. At the shortest horizon of one month, the coefficient on the slope variable is statistically significant at the 10 per cent level in the

Canadian dollar regression only. At long horizons, the slope variables are significant at the 5 per cent level for all countries except Canada and Japan. The coefficients on the local dividend price ratios become more negative as the forecast horizon lengthens. At the longest horizon, the local dividend yield is significant at the 5 per cent level for all countries except for Switzerland (p value of 0.092) and Japan (p value of 0.118).

The coefficients on the forward premia are statistically significant at short horizons for all currencies except the German Mark. The coefficients on the forward premia are statistically significant at the four-year horizon for all currencies except the Canadian dollar. As with the dividend yield, the coefficients on the forward premia are negative and decrease with the forecast horizon, with the Canadian dollar regressions again being the exception. The negative sign on the forward premia at long horizons matches the short-horizon result found in numerous other studies. It also matches the implied long-horizon coefficients from the VARs estimated by Bekaert and Hodrick (1992).

To the best of my knowledge, this is the first study to document such a consistent pattern of foreign exchange return predictability based on *domestic* instruments at long horizons. In previous tests, the short-horizon results were much more fragmented. For example, the coefficient on the foreign country dividend yield is negative for UK Pound and German Mark returns, but positive for Japanese Yen returns in Cumby and Huizinga (1992). A similar difference is recorded in the monthly VAR estimates provided by Bekaert and Hodrick (1992). The consistent results here suggest a pervasive relationship between long-horizon foreign exchange and equity returns in different countries. The last column in each panel shows the Wald test statistics of the null hypothesis that the coefficients on the three forecasting variables are jointly equal to zero. The p-values associated with the statistics show a statistically significant relationship for most of the countries and horizons examined. Below, I argue that the strong findings are a result of the good power properties of the long-horizon regressions.

Directly estimating expected long-horizon returns may have additional benefits over the VAR approach. Neely and Weller (2000) have criticized the results of Bekaert and Hodrick (1992) by showing that the parameters associated with the short-run VAR are not stable, leading to poor long-horizon results. The instability appears to be associated with the equity market parameters in the VAR while the currency return equations appear to be well specified. In contrast, in this paper, the long-horizon currency return forecasts are obtained directly from the regressions and the long-horizon coefficients are more stable than their short-horizon counterparts. Karolyi and Stulz (1996) argue that the degree of international market integration may be time varying, further complicating long-horizon tests. However, the Eurocurrency markets examined here are largely beyond the control of the national governments thus reducing the impact of changing national regulations that affect the degree of integration.

The results of tests of the predictability by the world variables (6) are displayed in Table 3. As with the local variables, the adjusted R^2 statistics improve with the forecast horizon reaching their maximum vales at 4 years for the Mark, Pound, and Swiss Franc excess returns. Excluding the Canadian dollar returns, the degree of predictability at the four-year horizon is relatively large with adjusted R^2 statistics ranging from 0.240 for the Japanese Yen to 0.488 for the Mark. The slope of the US term structure is generally insignificant at the shortest horizon while it is significant at the four-year horizon for all countries except Canada. As with the foreign country's term structure, the coefficients on the US term structure are positive and increasing. While the US dividend yield is generally not significant, the point estimates of the coefficients generally decrease with forecast horizon out to three years, excluding the Yen return regressions. The Wald (χ^2) test statistics of the null are significant at the one per cent level at long horizons for the foreign exchange returns from all countries except Canada.

3 Robustness Issues

The strong results presented in Tables 2 and 3 could be a consequence of the good power properties of the long-horizon regressions. However, the results could also arise due to size distortions of the test statistics. The results could also be from several possible specification biases. In this section, I show how my results are robust to these concerns.

There are several econometric issues that must be addressed when performing long-horizon regressions. I start by examining a potential small-sample bias in the coefficients. I then examine how well the estimated asymptotic standard errors match their small-sample counterparts. Both of these problems may be addressed by Monte Carlo simulations which are presented below. Previous work on testing equilibrium relationships in the foreign exchange market has revealed that conditional heteroskedasticity is likely to be present. In order to give the tests more power, I parameterize the time-varying heteroskedasticity in the Monte Carlo simulations. As the assumption of Normally distributed errors is suspect, I perform non-parametric bootstrap simulations where the distribution of the standardized errors is determined by the data at hand. I also point out the importance of using "pivotal" statistics in assessing the results of bootstrap simulations.

3.1 Sample size and coefficient bias

Previous work has uncovered a possible bias in the OLS coefficients in regressions such as (5) and (6). As noted by Stambaugh (1999), Hodrick (1992) and Nelson and Kim (1993), there is a potential for small-sample bias in the regression coefficient in the presence of an autoregressive, endogenous variable. Stambaugh (1999) considers the following system:

$$
\begin{aligned}
y_t &= \gamma + \delta x_{t-1} + u_t; \qquad u \sim iid\left(0, \sigma_u^2\right) \\
x_t &= \mu + \phi x_{t-1} + v_t; \qquad v \sim iid\left(0, \sigma_v^2\right) \\
\sigma_{u,v} &\neq 0,
\end{aligned}
\tag{7}
$$

where y_t is the asset return being forecast and x_t is the instrumental variable. Ordinary least squares will product an asymptotically consistent estimate of δ, but in small samples the OLS estimator is biased, where the bias is proportional to that on the estimator of the autoregressive coefficient of x:

$$
E\left(\widehat{\delta} - \delta\right) = \left(\sigma_{u,v}/\sigma_v^2\right) \cdot E(\widehat{\phi} - \phi). \tag{8}
$$

The result is that "the lagged value of x may appear to be a predictor of y even though it has no predictive power" (Nelson and Kim, 1993).

In the regressions in this paper, many of the explanatory variables are persistent and it is likely that all of them are endogenous. It is also likely that the error terms are contemporaneously correlated across asset markets. To account for the potential bias in the coefficient estimates, I perform Monte Carlo simulations under the null hypothesis of no return predictability.

3.2 Asymptotic versus small-sample standard errors

The second major problem with the long-horizon methodology is the possibility of poor estimates of the standard errors. The GMM procedure is useful in regressions such as (5) where the sampling interval of the data (monthly) is finer than that of the forecast interval (one month to four years). Under the maintained hypothesis, the error term in a k period forecast regression is serially correlated of degree $k-1$. To account for this effect, I calculate asymptotic standard errors following Newey and West (1987) where the autocorrelation correction is of degree $k-1$.

While the Newey-West procedure provides standard errors that are asymptotically consistent, many authors have noted that there may be small-sample problems here as well; i.e., the small-sample distribution of the coefficient's standard error may not be well approximated by the asymptotic GMM distribution (e.g., Hodrick (1992) and Nelson and Kim (1993)). The Monte Carlo procedure adopted below will provide an estimate of the small-sample distribution of the coefficients in (5). I can then make small-sample inferences based on these distributions.

3.3 Monte Carlo simulations

3.3.1 Expected returns under the null

In order to account for the small-sample bias in both the coefficient and standard errors, I follow the procedure of Hodrick (1992), Nelson and Kim (1993) and Mark (1995) and estimate the small-sample distribution of the regression coefficients via Monte Carlo simulations. I generate the small-sample distributions of the coefficients and test statistics in the "local" variable regressions (5). The small-sample behavior of the forward discount variable at long horizons is of particular interest as it provides a natural analogue to the short-horizon tests of the unbiasedness hypothesis that are usually conducted.

I assume that the multivariate data generating process can be represented by a two-country VAR:

$$Z_t^j = \delta_0 + \sum\nolimits_{l=1}^{L} \delta_l \cdot Z_{t-l}^j + \varepsilon_t, \tag{9}$$

where $Z_t^j = (es_{t-1,t}^j,\, sp_t^j,\, dy_t^j,\, fp_t^{US/j})'$. The first row of the VAR contains the dependent variable (the one-month foreign exchange excess return). Under the null hypothesis, the foreign exchange excess return is a constant. I estimate (9) under the null by restricting the first row of the δ_l matrices to be zeros. The next three rows of the VAR contain the explanatory variables from (5) for country j which are regressed onto L lags of the variables. The lag length L of the VAR is set to two for each country as this removes the autocorrelation effects in the residuals.

3.3.2 Conditional heteroskedasticity

The multivariate distribution of the error terms ε_t in (9) needs to be estimated. Tests performed on the errors of (9) reveal that they display conditional heteroskedasticity.[10] In order to parameterize the heteroskedasticity, I make the simplifying assumptions that the diagonal elements of the time-varying variance matrix H_t can be modeled as a GARCH(1,1) processes and that the time-varying covariances may be modeled in the constant correlation framework of Bollerslev (1990):

$$\begin{aligned} h_{i,i;t} &= \alpha_{0i} + \alpha_{1i} \cdot h_{i,i;t-1} + \alpha_{2i} \cdot \varepsilon_{i,t-1}^2,\ i = es, sp, dy, fp \\ h_{i,j;t} &= \rho_{i,j} \cdot (h_{i,i;t} \cdot h_{j,j;t})^{0.5},\ i \neq j \end{aligned} \tag{10}$$

where $h_{i,j;t}$ is the i, j^{th} element of H_t. These assumptions allow a small number of parameters to model the conditional heteroskedasticity and have been used in previous empirical tests

[10] I conducted Engle's (1982) test for autoregressive conditional heteroskedasticity (ARCH) and found that ARCH effects are present in many of the series. These results are not reported here to save space and are available from the author upon request.

in the foreign exchange market (Bollerslev (1990), Baillie and Bollerslev (1990), Giovannini and Jorion (1989)). I estimate the parameters of the GARCH(1,1) process by maximum likelihood from the OLS errors of the two-country VAR systems.[11] I perform Pagan-Sabau specification tests for the GARCH(1,1) process and find that this parsimonious specification fits the data well. The empirical distributions of the test statistics are then conditional on this parameterization and the null hypothesis of no return predictability.

3.3.3 Non-normality

There is a large literature which shows that financial time series violate the Normality assumption in both unconditional and conditional forms (e.g., Engle and Gonzalez-Rivera (1991)). I perform Jarque-Bera tests for Normality on the residuals from the VAR regressions (9) standardized by their GARCH(1,1) variances (10) ($\widehat{\varepsilon}_t \widehat{H}_t^{-1/2}$) and can reject the null hypothesis of Normal innovations for almost all of the residuals.[12] Thus, I assume that the multivariate distribution of the errors is $\varepsilon_t \sim F(0, H)$ where F is an unknown distribution. I follow Lamoureux and Lastrapes (1990) and perform bootstrap simulations where the errors are drawn with replacement from the set of estimated standardized residuals ($\widehat{\varepsilon}_t \widehat{H}_t^{-1/2}$).

3.3.4 The small-sample algorithm

Each equation in the VAR is estimated by OLS using monthly data over the period 1975:6 to 1997:6 (a total of 269 observations). The parameters of the GARCH(1,1) process (10) are estimated numerically from the OLS errors. With the resulting estimates $(\widehat{\delta}, \widehat{H}_t)$, the non-parametric bootstrap simulations can be conducted as follows:

(i) For each bootstrap simulation i, draw 1000 (an arbitrary large number) observations with replacement from the estimated standardized error term vector $\widehat{\varepsilon}_t \widehat{H_t}^{-1/2}$.

(ii) Using initial estimates of $\widehat{H}_0$ and $\widehat{\varepsilon}_0$,[13] obtain $\widehat{H}_1$ and $\widehat{\varepsilon}_1$. Iterate until 1000 error terms have been obtained.

(iii) Simulate the VAR equations (9) using the hypothetical error terms over 1000 periods. Drop the first 731 observations (to avoid any "start-up" problems) leaving 269 observations of pseudo-data.

(iv) Aggregate the pseudo monthly excess returns to obtain their long horizon values (the dependent variables for different horizons k in regressions (5)).

[11] The variables in the GARCH model are constrained to be positive.

[12] Again, these results are available upon request.

[13] I set $\widehat{H}_0$ equal to the unconditional estimator $\widehat{H}$ and $\widehat{\varepsilon}_0$ equal to zero.

(v) Regressions as in (5) are performed on $T-k$ observations of the pseudo-data, generating estimates of the coefficients and the test statistics for each simulation.

(vi) From the $i = 1, ...10,000$ simulations, the small-sample distributions of the coefficients and test statistics can be obtained.

3.3.5 Pivotal statistics

One issue that has not received enough attention in the empirical asset pricing literature is the importance of using pivotal statistics when conducting Monte Carlo and bootstrap simulations. A statistic that is a function of both the data and unknown parameters is "pivotal" if it has the same distribution for all values of the unknown parameters. The statistic is "asymptotically pivotal" if it has a limiting distribution that does not depend on the unknown parameters (Hall (1992)). A number of studies have shown that it is vital to use pivotal statistics in conducting small-sample tests in time series data (Li and Maddala (1996)). If pivotal statistics are not used, the small-sample inference can be very misleading.

The importance of using pivotal statistics in the current bootstrap simulation can be seen by the following. Consider comparing the asymptotic significance of the regression coefficients θ in (5) to their small-sample significance obtained from the bootstrap distribution. Using the original data, the distribution of the estimated θ coefficients depends on the true volatility process for the data which we do not observe. Similarly, in each of the bootstrap simulations using generated data, the distribution of the estimated θ coefficients depends on the estimated volatility process. The latter is a function of the heteroskedasticity coefficients in (10), a set of "nuisance parameters" which differ from their true values. Aggregating across all bootstrap simulations results in a small-sample distribution of the simulated θ statistics which depends on the nuisance parameters in an unknown manner. Thus, for example, it would not be correct to compare the estimated θ coefficient obtained from the data directly to its "ranking" in the small-sample distribution. The estimated coefficient is a function of the true volatility parameters while the small-sample distribution is a function of the estimated heteroskedasticity coefficients.

The solution is to use statistics that do not depend on unknown parameters. In the asymptotic significance tests, the influence of the (unknown) volatility process is minimized by constructing the standard t statistic where the estimated value of the coefficient is divided by its estimated standard deviation. In the bootstrap simulations, the t statistic associated with each of the coefficients standardizes the distributions for the estimated variances. Thus, the t statistic is (asymptotically) pivotal and in the results below, I report their small-sample distributions.[14] The Wald statistic that tests the joint significance of the three forecasting

[14] In general, statistics that are asymptotically Normal or χ^2 are pivotal.

variables is also pivotal.

3.4 Non-parametric bootstrap results

The results of the 10,000 nonparametric bootstrap simulations of regression (5) are presented in Table 4. The first number in each cell in Table 4 repeats the OLS point estimate from Table 2 for convenience. The second number is the average value of the estimates from the 10,000 simulated regressions. Under the null hypothesis, this number should be zero; it may differ from zero due to the small-sample bias problem. The third number is the small-sample marginal significance level (a two-sided p value) of the t statistic associated with the parameter estimate.

In general, the pattern of statistical significance of the estimated coefficients from the small-sample distributions matches that of the asymptotic distributions in Table 2. The match is particularly close at the one-month horizon where the number of effective data points is the largest. As the forecast horizon lengthens, the statistical significance of some the coefficients appears to be overstated. For example, the statistical significance of the foreign term structure slope variable appears to be significantly lower than that of its asymptotic representation at long horizons for the Swiss Franc returns. The foreign country's dividend yield significance may be overstated for the German Mark excess return. According to the small-sample distributions, the forward premia are significant at the shortest horizon for all of the countries except Germany which matches the asymptotic results. However, the forward premium is significant at the four-year horizon for French France returns only. This suggests that the long-horizon asymptotic results presented in Table 2 and in Bekaert and Hodrick (1992) may be overstated for this variable.[15] The bias in the estimated coefficients does not appear to be a major problem as the average values of the coefficients generated under the null in the bootstrap distributions are usually much smaller than the original coefficients generated from the data. The bias does appear to increase with the forecast horizon as the effective number of data points is reduced.

Under the null hypothesis of no return predictability, the average adjusted R^2 statistics from the bootstrap distributions are small at short horizons. The average values of the statistics rise as the forecast period lengthens to about 25 per cent at the four-year horizon. As a result, the marginal significance levels of the statistics initially deteriorate then improve.

[15] Meredith and Chinn (1998) test for long-horizon UIP where the change in the exchange rate over a forecast horizon of k periods is regressed on the difference between domestic and foreign interest rates on assets of the *same* horizon (e.g. 5 and 10 year bond yields). Interestingly, they find that UIP holds; i.e. there does not appear to be a foreign exchange risk premium. Given the limited time span of available data and the even greater degree of overlap implicit in their tests, it would be interesting to subject their tests to the robustness procedures presented here.

The marginal significance level of the χ^2 statistic test of the null generally decreases with the forecast horizon. At the three-year horizon the test statistic is significant at the 10 per cent level for German Mark, Japanese Yen, and French Franc returns. The marginal significance level on the UK Pound return regression is 12.6 per cent while the Swiss Franc and Canadian Dollar return regressions have poor long horizon results (31.8 and 57.2 per cent at the three-year forecast horizon, respectively).

There are two issues to keep in mind while deciding upon the overall significance of these results. The first is that a standard significance level (e.g., a 5 per cent test) may not be an appropriate criterion given the large degree of overlap of the data. Mark (1995) makes this point in his analysis of long-horizon exchange rate movements over the floating exchange rate period. The common pattern of the coefficients across all of the countries examined suggests that some economic relationship is present; however, the ability of the selected instruments to capture this phenomenon may be limited by the relatively short span of the data. As the forecast horizon lengthens, the excess return (3) will be persistent. Differentiating among the effects of the individual instruments is problematic as the instruments are also persistent.

The second issue is that there can be a large difference between "statistical" and "economic" significance. For example, Bauer (2001) shows that the relatively "weak" statistical results translate into strong implications for international portfolio allocations. A US investor is able to choose currency hedged portfolios of foreign and US stocks according to the current value of the US dividend yield, the foreign dividend yield, or the forward premium. The portfolios are chosen to maximize expected utility and an indication of the economic significance of the instrumental variables may be obtained from the portfolio's certainty equivalent return. As the current values of the forecasting instruments change, the certainty equivalent return can vary a lot. These results, which show a large degree of economic significance, can be compared to those small-sample p values in Table 4 that indicate statistical insignificance at traditional levels.

3.5 "Snooping" biases

3.5.1 Snooping across forecast horizons

There are two potential biases in the above analysis that involve "snooping" of the data. The first bias is that a correct test of the null hypothesis involves testing the regression coefficients to determine if they are jointly equal to zero across all of the forecast horizons. Richardson (1993) notes that the finding of improved forecastability at certain long horizons (e.g., three or four years) may simply be due to a search over all possible horizons (i.e., "specification mining"). Mark (1995) performs a test that accounts for the relatively low power of short-horizon return regressions and the relatively large power of long-horizon return regressions to detect the persistent alternative. The test statistic is the maximum value of the t statistic across all of the forecast horizons for each of the variables examined. In this paper, the distribution of this statistic can be determined by the bootstrap simulations.

Table 5 gives the marginal significance levels obtained. Although a few of the statistics appear to have relatively large marginal significance levels, overall this test suggests rejecting the null. The last column of Table 5 is the marginal significance level of the maximum Wald (χ^2) statistic. The null can be rejected at approximately 10 to 20 per cent levels for the German Mark, Japanese Yen, British Pound and French Franc. The Swiss Franc and Canadian dollar return regressions reject the null at approximately the 42 per cent level, reflecting the poor results found in the single predictive regressions.

3.5.2 Variable selection snooping

The second potential snooping bias comes from choosing instrumental variables that have been shown to predict US stock and bond returns in numerous other studies. As the excess currency returns used in (5) and (6) are also denominated in US dollars and thus correlated with US stock and bond returns, the tests performed here are not independent of previous tests.

To examine how robust my results are to this criticism, I compare my long-horizon foreign exchange return regression results to those from a long-horizon regression to predict excess returns on US stocks.[16] I use the US equity return as my "original data set" as these returns have been data mined more than most data sets. Also, I focus on the predictability using the global instruments (the US term structure slope (sp_t^{US}) and US dividend yield (dy_t^{US})) which have been shown to predict excess returns on US stocks in numerous other studies. Following Foster et al. (1997), I determine the amount of variable snooping bias that is present in my analysis by examining the ratio of the (adjusted) R^2 test statistic on the foreign exchange excess return regression (6) to the (adjusted) R^2 test statistic from a similar regression predicting US equity returns. If the original data had been snooped so that the global variables predicted US equity returns well only by chance, then the R^2 test statistic on the foreign exchange excess return regression should be smaller. Thus, the R^2 ratio should be less than one. The extent to which the ratio is less than one depends on the correlations between the foreign exchange returns and the US equity returns.

To estimate this correlation as well as accounting for the other statistical problems present in long-horizon regressions, I undertake a small-sample study based on a modified version of the non-parametric bootstrap procedure given above. I estimate a new VAR which includes the excess return on the foreign currency (es^j), the excess return on the US stock market

[16] I use the Datastream US stock market index and subtract the US dollar Eurodeposit rate.

(er^{US}), the US term structure slope (sp_t^{US}) and US dividend yield (dy_t^{US}). I impose the null hypothesis that neither es^j nor er^{US} can be predicted by the two instruments. I then simulate the data using the same non-parametric bootstrap procedure as outlined above. Using the 10,000 iterations of the simulated data, I can determine the small-sample distribution of the R^2 ratios under the joint null hypothesis that neither excess foreign exchange nor excess equity returns are predictable using the given instruments.

Table 6 presents the results. The first number in each cell is the ratio of the R^2 statistic from the foreign exchange return regression at horizon k to the R^2 statistic from a similar regression predicting US equity returns. For most forecast horizons and currencies, the ratios are above 1.00 indicating that the foreign exchange returns are *more* predictable than the US equity returns. The second number in each cell is the ratio of the average R^2 statistic from the 10,000 simulated foreign exchange return regressions to the average R^2 statistic from the 10,000 simulated stock return regressions. Under the null hypothesis, both statistics should be zero, but the potential biases outlined above inflate these values. The average values of the R^2 ratio statistics generated under the null increase at the 12 month forecast horizon then remain relatively flat. In most cases, the estimated values of the ratios obtained from the data are well above their average values generated under the null hypothesis. The notable exception is the Canadian dollar returns. Thus, according to this metric, the amount of variable selection bias in my regressions appears to be very small.

The third number in each cell is the marginal significance level (p value) of the R^2 ratio statistics according to the bootstrap simulations. At long horizons, the marginal significance level of the statistic is often below 10 percent. The indicates that foreign exchange returns are predictable using domestic instruments even after accounting for the degree of predictability exhibited by domestic asset returns. There appears to be long-run linkages between domestic and international asset markets.

4 Implications of Long-Horizon Tests for the Persistence and Volatility Puzzles

The results presented above suggest that the long-horizon regression test has good statistical power to detect time-varying foreign exchange risk premia. In this section, some potential explanations for the results are explored. I also examine the implications of these tests for two well known puzzles in the literature.

4.1 Power at long horizons and the "persistence puzzle"

Campbell (1994) and Stambaugh (1993) have shown that lengthening the forecast horizon may increase the power to detect time-varying expected returns. Both authors measure the asymptotic power of a test statistic by its "approximate slope".[17] To calculate the approximate slope of a test statistic, an alternative hypothesis is fixed and assumed to be true. The power of the test statistic against the alternative is also fixed. As the sample size (T) increases, the significance level (s) of the test falls and it becomes easier to reject the null in favor of the alternative. The approximate slope is defined as the limit of $-2\log(s)/T$ as $T \to \infty$.

Campbell (1994) compares the approximate slope of long-horizon tests to those of other tests that have been proposed to detect predictable returns. He gives two criteria for the long-horizon regression to have greater approximate slope than other methods. The first criterion is that the expected portion of the return (the risk premium given rational expectations) be persistent (i.e. positively autocorrelated but stationary). The second is that the return innovations must be negatively correlated with expected returns.

Both of these criteria are satisfied in foreign exchange returns. The persistence of the risk premium has been noted before (e.g., Fama (1984), Macklem (1991), Eichenbaum and Evans (1995), Bekaert (1996)). To see this, observe that the forward premium ($f_{t,t+1}^{US/j} - s_t^{US/j}$), which is positively serially correlated as shown in Table 1, may be decomposed as:

$$f_{t,t+1}^{US/j} - s_t^{US/j} = \left(f_{t,t+1}^{US/j} - E_t s_{t+1}^{US/j}\right) + \left(E_t s_{t+1}^{US/j} - s_t^{US/j}\right). \tag{11}$$

The persistence of the forward premium implies that either the foreign exchange risk premium or the expected change in the spot rate (or both) is persistent.[18] However, both the realized return on foreign deposits ($f_{t,t+1}^{US/j} - s_{t+1}^{US/j}$) and the actual change in the spot exchange rate $\left(s_{t+1}^{US/j} - s_t^{US/j}\right)$ display small first order autocorrelations. Bekaert (1996) labels this finding as the "persistence puzzle". This apparent contradiction implies that noise may be obscuring the autocorrelation of either the risk premium or the expected change in the exchange rate (or both).

A large number of studies have examined the time series property of nominal exchange rates and found that the random walk model fits the data well at short-horizons (e.g., Meese and Rogoff (1983)). Under this model, the last term in (11) is a white noise error term, and the risk premium is the persistent component which would be detected by long-horizon regressions, as shown by the results in Tables 2 and 3. However, Mark (1995) demonstrates

[17] This concept was developed by Bahadur (1960) and extended by Geweke (1981).

[18] Taking autocorrelations of both sides of (11) yields a cross product term. However, if the risk premium and/or the expected depreciation are persistent, then the cross product term is likely to be negative in line with Fama's (1984) finding for the contemporaneous covariance term.

that a long-horizon regression model can provide better forecasts of the change in the nominal exchange rate than those from the random walk model as the forecast horizon lengthens using a combination of domestic and foreign money supplies and real incomes as forecasting variables.[19]

A test for a persistent component in the foreign exchange rate can be performed by regressing the change in the spot exchange rate on the set of local instruments:

$$ds_{t,t+k}^{US/j} = \theta_0 + \theta_1 \cdot sp_t^j + \theta_2 \cdot dy_t^j + \theta_3 \cdot fp_t^{US/j} + \nu_{t,t+k} \tag{12}$$

where $ds_{t,t+k}^{US/j} = s_{t+k}^{US/j} - s_t^{US/j}$. To preserve space only the long-horizon ($k = 48$ month) results are shown in Table 7; the rest of the results are available on request. In general, the instruments explain movements in the total foreign exchange excess return slightly better than they do long-run changes in the exchange rate according to the R^2 test statistics. However, the common pattern of the coefficients remains the same. The slope of the foreign country term structure is positive and increasing as with the excess return equation results. The coefficient is larger at the long horizon for all countries except Japan. The coefficients on the dividend yield and forward premia are negative. Thus it appears that both the foreign exchange risk premium and the expected change in the spot exchange rate contain persistent components.

The second statistical requirement given by Campbell (1994) for the superior asymptotic power of long horizon regressions is a negative correlation between expected return innovations and future returns. A recent study provides empirical evidence that this is found in the foreign return data. Cheung (1993) estimates a state-space model of the realized and expected excess foreign exchange return processes:

$$\begin{aligned} f_{t,t+1}^{US/j} - s_{t+1}^{US/j} &= (f_{t,t+1}^{US/j} - E_t s_{t+1}^{US/j}) + \nu_{t+1} && \text{(13a)} \\ (f_{t,t+1}^{US/j} - E_t s_{t+1}^{US/j}) &= \phi \cdot (f_{t-1,t}^{US/j} - E_{t-1} s_t^{US/j}) + a_t. && \text{(13b)} \end{aligned}$$

The realized return is the observed variable in the measurement equation (13a) while the dynamics of the unobserved expected excess return (the foreign exchange risk premium) compose the transition equation (13b). The advantage of this state-space model framework is that it is able to provide estimates of the time series properties of the (unobserved) risk premium using only the return data themselves. Thus, this finding does not result from

[19] Mark's results have been criticized due to potential problems with non-stationary variables. Both the exchange rate and his fundamental variable contain unit roots (i.e. the time series are integrated of order 1) which implies that a long run relationship will only exist if the variables are cointegrated. Several authors have suggested that these variables are not cointegrated and thus Mark's results are spurious. These problems do not affect my results as all of the variables that I use (foreign exchange excess returns, dividend yields, term structure slopes, etc.) will be stationary according to economic theory.

a search for appropriate instrumental variables. Cheung estimates this system using the Kalman filter on the excess returns to the British pound, German Mark and Japanese Yen over the 1973 to 1987 period. He finds that the risk premium is persistent (though stationary) and that the covariance of the unexpected change in the spot rate and the unexpected change in the risk premium are negative (i.e., $cov(a_t, \nu_t) < 0$) for all three currencies examined. Both of these empirical facts meet Campbell's requirements for superior asymptotic power in long-horizon regressions.

Campbell's (1994) analysis assumes that the actual and expected return processes have homoskedastic innovations. Stambaugh (1993) analyses the approximate slope advantages of long-horizon regressions under heteroskedasticity. Imposing a GARCH(1,1) model of innovation variance, he shows that long-horizon regressions have large asymptotic power in the presence of conditional heteroskedasticity and persistence in expected returns. The problem of time-varying heteroskedasticity is pervasive in studies of foreign exchange parity relations (e.g., Cumby and Obstfeld (1984), Hodrick (1987)). As well, Stambaugh compares the precision of the regression coefficient estimators obtained from long-horizon (OLS) regressions and those obtained from the VAR approach. The former are more precise when the data are leptokurtotic and the variance is persistent. Both of these effects are found in international asset returns (e.g. Bollerslev, Chou and Kroner (1992)).

Both Campbell and Stambaugh note that their results are asymptotic and that the small-sample power properties of a given data set should be evaluated via simulations. The small-sample power of the foreign exchange regressions used in this paper may be assessed by undertaking simulations similar to the ones performed above to evaluate the size of the statistics. In those non-parametric bootstrap simulations, the parameters in the first (foreign exchange return) equation in the VAR (9) were constrained to be zero. Thus the simulations generated data under the null hypothesis. To evaluate power, the same parameters are set equal to their OLS values. These new simulations generate data under the alternative hypothesis that is evaluated as being most likely.

For any statistic that has a χ^2 distribution under the null, Geweke (1981) shows that the approximate slope of the statistic is equal to the probability limit of the statistic under the alternative hypothesis divided by the sample size. For the long-horizon regressions performed here, the Wald test of no joint predictability of the three forecasting variables has a χ^2 null distribution. Thus the measure of power evaluated here is

$$c(k) = \chi^2_A(k)/T \tag{14}$$

where $\chi^2_A(k)$ is the value of the Wald statistic under the alternative at forecast horizon k. The ratios $c(k)/c(1)$ then measure the increase in power as the forecast horizon is lengthened from one month out to k months.

Table 8 presents the median and the 5th and 95th percentiles of the simulated ratios. The median values of the ratios are above 1.00 for a forecast horizon of $k = 12$ months for five of the six currencies examined (the Canadian dollar is again the exception) suggesting that increasing the forecast horizon improves the power of the tests. Beyond 12 months, the results are less conclusive with the German Mark regression having increased power at 24 months while the Japanese Yen, French Franc and Swiss Franc regressions appear to have increased power at even longer horizons. It should be noted, however, that many of the ratios show a high degree of variability as they are not pivotal, making strong conclusions problematic.

4.2 The "excess volatility" puzzle at long horizons

Another interesting issue of study is the variance of the foreign exchange risk premium. Fama (1984) uses a decomposition of the results obtained from return prediction regressions to show that the expected excess forward exchange rate return (the risk premium given rational expectations) must be more variable than the expected change in the spot rate:

$$var\left(E_t es^j_{t,t+1}\right) \geq var\left(E_t s^{US/j}_{t+1} - s^{US/j}_t\right). \tag{15}$$

He also shows that the covariance between the risk premium and the expected rate of depreciation is negative. This finding is termed the "excess volatility" puzzle as it is difficult for standard complete markets models to generate risk premia that are sufficiently volatile. However, all of the analyses that have corroborated Fama's initial findings have been conducted on short-horizon data.

As noted by He and Modest (1995), there are many market frictions which may affect asset prices in equilibrium. These include borrowing and solvency constraints as well as transactions costs. One hypothesis is that the frictions are likely to be binding in the short run but less so in the long run. To test this Daniel and Marshall (1997) extend the holding period of an investor out to one year in a consumption based asset pricing model. They find that a version of the model is able to explain equity returns much better with long-run holding periods that short ones. Thus, the "equity premium puzzle" appears to be a problem for the short-run data.

In the Eurocurrency markets examined in this paper, transactions costs are very small and are unlikely to be responsible for the excess volatility.[20] However, other constraints on investors' portfolios may be preventing sufficient trading in foreign exchange markets leading to the high degree of short-run volatility. It is possible that the frictions will be less

[20]Cornell (1989) and Bekaert and Hodrick (1993) find that transactions costs do not account for the finding of foreign exchange return predictability.

binding over longer holding periods as investors have more flexibility in their portfolio choice. Thus, the relatively high volatility of the foreign exchange risk premium may diminish as the forecast horizon is lengthened.

To test this, a long-run counterpart to (15) can be estimated using the results of the long-horizon regressions. The regressions performed in (5) yield the expected value of the excess foreign exchange returns over a k-period horizon while the regressions performed in (12) yield the expected value of the long-run change in the exchange rate. The long-horizon variance ratio can thus be calculated as:

$$vr_{t,t+k}^{j} = \frac{var(E_t\{es_{t+1}^{j} + es_{t+2}^{j} + \cdots + es_{t+k}^{j}\})}{var(E_t\{s_{t+k}^{US/j} - s_t^{US/j}\})}, \tag{16}$$

conditional on the parametrization of the regressions.

Table 9 shows the values of these ratios. In addition to the point estimates, the table provides the 75th and 95th percentiles of the empirical distribution of the ratio as determined by the small-sample simulations that generated data under the null hypothesis.[21] The ratios appear to decline slightly with the forecast horizon out to three years. At the four-year horizon there is a jump in the statistics due to the relatively weaker results of the four-year regression on the change in the exchange rate. With the exception of the ratio on the French Franc returns, the Fama (1984) finding that the variance of the expected excess return exceeds the variance of the change in the exchange rate appears to remain even over quite long horizons. Thus, unlike the domestic asset pricing literature, the "excess volatility puzzle" does not disappear in the long-horizon data.

5 Testing Latent Variable Models at Long Horizons

The results presented above suggest that the selected forecasting variables are able to forecast foreign exchange risk premia at long horizons. In this section, I examine whether these results are consistent with a version of the intertemporal capital asset pricing model (ICAPM).

5.1 Latent variable model and tests

In Merton's (1973) ICAPM, the expected return on an asset is driven by the covariances of the asset's return with the returns on a number of factors. The return on the market

[21] The VARs used in the next section provide forecasts of both the excess return (under the null that it is a constant) and the forward premium. I use both to generate a forecast of the change in the spot exchange rate. The regressions in (5) and (12) are performed which give forecast values. I report fractiles of the small-sample distributions as this is not a statistical test per se and thus marginal significance levels do not seem appropriate.

portfolio is assumed to be the first factor. The other factors arise from investors' demands to hedge shifts in the investment opportunity set. The total number of factors is assumed to be small relative to the number of assets being examined. In empirical tests of the model, the factors can either be observable (i.e., based on pre-specified variables) or unobservable (i.e., latent). In the latter case, a number of instrumental variables are used to forecast returns. As the number of latent variables is smaller than the number of instruments, cross-equation restrictions are imposed on the parameter space of the equations used to forecast returns. The latent variable test methodology is applied to international asset returns in Huang (1989), Lewis (1990), Bekaert and Hodrick (1992) and Campbell and Hamao (1992).

Latent variable tests using international asset returns differ from their counterparts that use domestic asset returns as the former require the additional hypothesis that international capital markets are integrated. If international asset markets are integrated, then assets with identical risk characteristics will have the same expected returns regardless of where they are traded (Campbell and Hamao (1992)). If the latent variable model is rejected by the data, then either the markets are not integrated or the model does not fit the data. This joint hypothesis problem suggests applying the model to Eurocurrency returns. The Eurocurrency market has small transaction costs and is generally free from government regulations that prevent trading.[22] Thus, Eurocurrency returns are likely to be integrated with each other (Jorion (1992)) and this integration will not change over time. Also, recall that the long-horizon variance ratios (16) in Table 9 support the view that frictions are not likely to be responsible for the existing puzzles with the moments of the risk premia. Thus, in the tests undertaken below, if the joint null hypothesis is rejected, the specification of the model is more likely to be the cause of the rejection rather than segmented markets.

There have been a number of latent factor models proposed for their ability to model Eurocurrency returns; Engle (1996) has a summary. These studies provide contradictory evidence on the relationship between the investor's holding period and the number of latent variables required to explain returns. Huang (1989) estimates a single latent variable model for returns on nine currencies across four forecast horizons ranging from one month to one year. Using instruments specific to the foreign exchange market (i.e. forward discounts), he finds that the single factor model is rejected at the one-month horizon but not at any of the other horizons. Lewis (1990) also finds that statistical tests of a single latent variable model on Eurocurrency returns are sensitive to the holding period examined. She shows that the single latent variable model is rejected at the one-month horizon, but not at the three month horizon. Her instrument list includes forward premia and differences between one and three month interest rates in the countries examined. In contrast, Cumby (1988) rejects a latent

[22]Marston (1995) provides a survey of issues involved in the integration of Eurocurrency markets and some new tests.

variable model using three month returns and a wider variety of instruments.

The long-horizon analyses performed above suggest three modifications to the existing latent variable tests which may help explain the contradictory results found in the earlier studies. The first modification is that is that the forecasting variables for returns should include instruments related to risk premia in other markets. Given the strong explanatory power of these instruments in the tests performed above, it is likely that factors which influence bond and stock returns are also likely to influence currency returns.

The second modification is that the tests may be more powerful if they distinguish between global and local sources of risk. If the local instruments used above represent local risk factors, then Eurocurrency returns are not driven solely by global risk factors. Thus, previous tests of the ICAPM that posited only global risks (i.e. risks that affect all returns) may be misspecified. In the long-horizon regressions performed above, as the holding period lengthens, the foreign exchange risk premium appears to be captured better by both the world and local instruments. The correlation among the variables in the two sets of instruments would make it difficult to differentiate between global and local risk factors in an unrestricted forecasting regression. However, imposing the additional structure from an economic model may help separate the effects of the two sources of risk.

The third modification is that the tests should be conducted over both short and long forecast horizons. The effect of different forecast horizons on the tests has been noted before. Lewis (1991) suggests that, at short horizons, the covariance of the return on the latent factor with that on the Eurocurrency may move idiosyncratically due to several possible sources of heteroskedasticity. Over longer holding periods, heteroskedasticity in asset returns is less strong so that the latent variable null would be not be rejected.

The long-horizon analysis above gives another perspective on these tests. At short horizons, the coefficients in the forecasting regressions are not estimated very precisely and may even have different signs across different returns. As the forecast horizon lengthens, the estimated coefficients are estimated more precisely as shown in Tables 2 and 3. Thus, contrary to Lewis (1991), the covariance between the returns could be proportional at all horizons and yet a long-horizon regression may be able to reveal a finding in favor of the latent variable model and international asset market integration.

In this section, I undertake tests of the latent variable model of Eurocurrency returns that account for these three additional effects.[23] I assume that the returns are driven by both local and world risk factors and that these factors can be captured by the instruments used above. In particular, there is a mean-variance efficient global "benchmark" portfolio that captures

[23] A more formal derivation of a latent variable tests can be found in Hodrick (1987), Lewis (1991), and Jorion (1992) and is not repeated here in the interest of brevity.

the influence of the world factor.[24] As I do not wish to specify a particular market portfolio as being mean-variance efficient, I assume that the expected excess return on the benchmark can be modeled as a linear projection on the world variables used above (the US term structure slope and dividend yield). I also assume that the coefficients linking Eurocurrency returns to the global benchmark return are proportional across different currency returns at each forecast horizon. The local risk factors are priced internationally but are assumed to influence only the own currency returns.[25] I assume that the influence of the local factors can be captured by the forward premium for each currency.[26]

Under these assumptions, the effects of both global and local risk factor can be incorporated into a model of expected Eurocurrency returns by estimating a system of long-horizon regressions:

$$\begin{aligned} ses^1_{t,t+k} &= \beta^1 \cdot \Theta \cdot W_t + \lambda^1 \cdot fp_t^{US/1} + v^1_{t,t+k} \\ &\vdots \\ ses^5_{t,t+k} &= \beta^5 \cdot \Theta \cdot W_t + \lambda^5 \cdot fp_t^{US/5} + v^5_{t,t+k}, \end{aligned} \tag{17}$$

where W_t is the vector of world variables (US dividend yield, US term structure slope and a constant) at time t and Θ is the vector of common coefficients. Thus the linear combination of $\Theta \cdot W_t$ represents the return on the (unobservable) global benchmark portfolio. The β^j parameters capture the different effects of the benchmark portfolio across the Eurocurrency returns. The (unrestricted) λ^j parameters capture the influence of the local risk factor (the forward premium for each country). I test the system (17) on Deutsche Mark, Japanese Yen, UK Pound, French Franc and Swiss Franc returns ($ses^j_{t,t+k}$ where $j = 1, ...5$ respectively). The Canadian dollar returns are excluded because of their poor long-horizon performance. The system is estimated separately for each forecast horizon k, using the same values of k as in the long-horizon regressions above. The system (17) is not identified in its present form and I follow the standard procedure in identifying $\beta^1 = 1.00$.

The system is estimated using GMM. The same form of the Newey-West (1987) corrections undertaken in the unrestricted long-horizon regressions are used to calculate the

[24] A setting such as this could arise from the intertemporal capital asset pricing model where the benchmark portfolio is the mean-variance efficient portfolio which has the maximum correlation with the intertemporal marginal rate of substitution (Lewis (1991)). An alternative could be to use the classic CAPM in an international setting which assumes that the price of exchange risk is zero (Dumas and Solnik (1995)). It should thus be stressed that the latent variable test is not a test of a particular economic model, but rather should be regarded as a parsimonious way of describing the data.

[25] The local factors will be priced internationally if their influence cannot be diversified away. The model presented tests this proposition by including the local factor returns along with the global benchmark portfolio returns.

[26] Robustness checks on these assumptions are undertaken below.

optimal weighting matrix for the system of equations at each k.[27] The model's null hypothesis of a single global benchmark portfolio imposes over-identifying restrictions on the parameters in the separate equations. Hansen's (1982) J statistic is used to reject or not reject the null. It is distributed chi-squared with degrees of freedom equal to the total number of orthogonality conditions (20) less the number of parameters (12).

5.2 Latent variable test results

Table 10 provides estimates of the beta coefficients from (17) and the test statistics of the model for each of the forecast horizons examined. The estimated beta coefficients do not change a lot as the forecast horizon lengthens except for those on the Japanese Yen returns. The asymptotic standard errors of the coefficients decline due to the increased power of the long-horizon regressions. However, the J statistics of the over-identifying restrictions indicate that the model is rejected at standard significance levels at all of the forecast horizons. Thus it appears that a single latent variable model augmented with a local risk factor is not capable of explaining currency returns at all horizons.

However, an examination of the impact of the model's restrictions on the instruments' ability to explain returns reveals another story. Table 11 shows three variance ratio statistics. The first (VR-Mod.) is the ratio of the forecast variance from the restricted model (17) to the forecast variance from an unrestricted OLS regression using the same variables. If the ratio is far below 1.00, then the restrictions imposed by the latent variable model are causing a large drop in forecast power.[28] The second (VR-Res.) is the ratio of the variance of the restricted model's residuals to the forecast variance of the same OLS regression. If VR-Res. is large compared to VR-Mod., then the forecasting ability of the instruments is not being captured by the model.

At the shortest horizon, the VR-Mod. ratios are large both in absolute magnitude and in relationship to the VR-Res. ratios for all currencies except the UK pound. This suggests that the model is capturing most of the predictable variation well. As the forecast horizon lengthens, the story becomes more complicated. The long-horizon (four year) VR-Mod. statistics are similar for the German Mark and Swiss Franc returns (0.627 and 0.791, respectively). Also, the portion of the predictability captured by the residual is small. These results indicate that the two currencies share similar risk factors. This is not too surprising

[27] Occasionally, this leads to convergence difficulties in the algorithm and a longer lag structure must be chosen. While it would be interesting to calculate the small-sample distribution of the test statistics, this would be very difficult given the large number of variables in each system. Also, the rejections of the model given below are so extreme (i.e. the p-values are so small) that small-sample results would not likely change the inference too much given the unrestricted regression results presented above.

[28] This statistic is widely used in tests of latent variable models (e.g. Campbell and Hamao (1992)).

given the closeness of the two economies. The VR-Mod. statistics for the UK Pound and French Franc returns are closer in value to the VR-Res. statistics indicating that the model explains less of the long-horizon movements in these currencies' returns.

The large values of the VR-Mod. and VR-Res. statistics for the Japanese Yen returns indicate that the combination of the (restricted) global and (unrestricted) local variables are not explaining Yen returns well. An examination of the global factor regressions in Table 3 reveals the reason. The coefficients on the US dividend yield in the Japanese Yen regressions are large and positive while they are large and negative in the regressions for the other currencies. The latent variable restrictions impose a common coefficient on this variable in all of the equations, leading to the poor results for the Yen.

The third statistic presented in Table 11 (VR-Loc.) is the portion of the variance of estimated currency returns that is due to the local risk factor:

$$\frac{var(\widehat{\lambda}^j \cdot fp_t^{US/j})}{var(\hat{\beta}^j \cdot \hat{\Theta} \cdot W_t + \widehat{\lambda}^j \cdot fp_t^{US/j})},$$

where the estimated coefficient values are from (17). As can be seen, the variance ratios indicate that the local risk factor can have a large influence on returns. At the shortest horizon, only the UK Pound is strongly influenced by its local factor. However, at long horizons the local risk factor can exert a large influence. Movements in long-horizon Japanese Yen returns are almost completely driven by the local risk factor, explaining the poor results detailed above. The local risk factors are also important for the Pound and French Franc returns.

While the model is formally rejected according to the statistical test, it is interesting to see if the rejections are economically significant. Cumby and Huizinga (1992) suggest an alternative test statistic to capture this. They show that the (non-centered) correlation coefficient (ρ) of the fitted values from any two returns in (17) will go to plus one or minus one in large samples if and only if the null hypothesis of a single (global) risk factor is true. This approach to testing the null allows much more economic information to be revealed. For example, the correlation coefficient could be quite high ($\rho \approx 0.9$) and yet be estimated very precisely so that the null would be rejected. However, the data would be showing a large degree of integration. Conversely, the degree of correlation between the excess returns could be much lower and yet a single latent variable test may not reject the null if the standard error were large enough. Cumby and Huizinga stress that this is not a formal test of the null as the distribution of the test statistic under the null is not known. It should be noted that the correlation will only be perfect in the model used here if the single global risk factor is present and if the local risk factors are not priced.

Table 12 presents the estimated correlation coefficients between each pair of currencies at all horizons. The correlations are high (i.e. > 0.80) for many of the currencies and horizons examined. The correlations tend to fall as the horizon lengthens for any pair involving Yen or French Franc returns. Thus even though the model is being formally rejected, it appears that the influence of a single (global) source of risk in Eurocurrency returns is large.

Additional analysis reveals the cause of the differences between the statistical and economic significance of the model. The results do not arise from either the instrument sets used or the currencies examined. Additional estimations (not shown) using a variety of instruments for the global and local factors reveal the same results. The model is still rejected if the Yen returns are excluded; other results indicate that the p values of the J statistics are still very small. Thus the statistical results presented above are not simply the result of the model not describing Yen returns. What appears to be driving the statistical rejection of the model is the inclusion of the local risk factors, represented by the forward premia. Table 13 provides estimates of (17) where the coefficients on the local risk factors have been set to zero. The model of a single global source of risk is not rejected at any of the forecast horizons. However, the VR-Loc. ratios of Table 11 show that the model is missing a significant source of return predictability.

Thus it appears that the combination of global and local sources of risk is important economically. While a basic version of the model that includes only the global risk factor cannot be rejected statistically, the model does not have the large degree of explanatory power of the unconstrained long-horizon regressions. When local risk premia are included, the degree of explanatory power is large and this power increases at long horizons. When both global and local risk factors are included, the power of the statistical tests rise leading to a rejection of the over-identifying restrictions. However, the rejections do not appear to be economically significant, according to the correlation coefficient metric used here.

6 Conclusions

Previous studies of the deviation from uncovered interest parity have concentrated on the short-run movement of the excess currency return and its relationship to excess returns in the stock and bond markets. In these short-horizon analyses, it is difficult to extract common patterns of return prediction from noisy data. In this study, I have adopted a long-horizon approach which has greater asymptotic power to reject the null of a constant risk premium in favor of a persistent alternative specification. As a result, while the relationship between the foreign exchange returns and the instruments that are associated with domestic asset risk premia are not very strong in the short-horizon (monthly) regressions performed here (as elsewhere), when I extend the forecast horizon I obtain a consistent pattern of coefficients across countries. Long-horizon regressions thus reveal a persistent component of expected returns on foreign currency deposits that is related to expected returns on domestic assets. I interpret this expected component as a time-varying rational risk premium, though I realize other interpretations are possible. In addition, I extend Fama's (1984) finding and reveal that the foreign exchange risk premium remains more volatile than the expected change in the spot exchange rate even at quite long horizons. This suggests that various market frictions – which would likely influence portfolio and consumption decisions in the short but not long run – will not be responsible for Fama's excess volatility puzzle.

Both the power and size of my tests are examined. Other authors have suggested that long-horizon regressions have good asymptotic power properties provided that the return data display certain time series characteristics. I show that the foreign exchange return data do indeed display these characteristics. Using a detailed, small-sample study, I demonstrate that the pattern of return prediction is robust to a variety of potential size distortions, though not all of the tests statistics are significant at standard levels.

I examine whether the a version of the ICAPM can provide the economic causes of the long-horizon regression results. A latent variable model augmented with a local risk factor is able to explain long-horizon returns on the European currencies examined. However, the model is not able to capture Japanese Yen returns simultaneously with the European ones. These results suggest that both local and global risk factors need to be used in subsequent modeling efforts. However, it remains an open question as to the underlying economic forces that give rise to global and local risk premia with high degrees of volatility even at long horizons.

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Table 1

Summary Statistics

The table shows summary statistics of the excess foreign exchange return series (*es*), slope of the term structure (*sp*), dividend yields (*dy*) and forward premia (*fp*) for the six foreign countries (Germany, Japan, UK, France, Switzerland and Canada) and the US. All of the series are expressed in monthly per cent continuously compounded form. The sample period is June, 1975 to June, 1997. The three estimated autocorrelations of the series are for a one, six and twelve month lag, respectively.

Variable	Mean	Standard Deviation	Autocorrelation ρ_1	ρ_6	ρ_{12}
$es^{Germany}$	-0.051	3.413	-0.005	-0.061	0.016
es^{Japan}	0.114	3.490	0.091	-0.117	0.096
es^{UK}	0.091	3.339	0.100	-0.080	-0.008
es^{France}	0.045	3.263	0.001	-0.057	0.013
$es^{Switzerland}$	-0.101	3.832	0.047	-0.090	0.025
es^{Canada}	-0.004	1.339	-0.028	-0.032	-0.070
sp^{US}	0.065	0.188	0.934	0.734	0.604
$sp^{Germany}$	0.116	0.150	0.945	0.786	0.537
sp^{Japan}	0.087	0.151	0.829	0.556	0.313
sp^{UK}	0.022	0.202	0.924	0.659	0.380
sp^{France}	0.028	0.239	0.592	0.216	0.046
$sp^{Switzerland}$	0.029	0.160	0.923	0.733	0.491
sp^{Canada}	0.076	0.170	0.931	0.642	0.392
dy^{US}	0.309	0.088	0.980	0.881	0.773
$dy^{Germany}$	0.215	0.067	0.980	0.879	0.772
dy^{Japan}	0.099	0.050	0.988	0.916	0.837
dy^{UK}	0.367	0.063	0.943	0.722	0.607
dy^{France}	0.332	0.128	0.983	0.886	0.744
$dy^{Switzerland}$	0.200	0.044	0.968	0.800	0.636
dy^{Canada}	0.276	0.081	0.951	0.658	0.471
$fp^{US/Germany}$	0.164	0.275	0.951	0.810	0.717
$fp^{US/Japan}$	0.241	0.269	0.920	0.578	0.371
$fp^{US/UK}$	-0.214	0.256	0.908	0.530	0.255
$fp^{US/France}$	-0.185	0.310	0.709	0.401	0.262
$fp^{US/Switzerland}$	0.306	0.329	0.961	0.820	0.737
$fp^{US/Canada}$	-0.107	0.153	0.843	0.509	0.258

Table 2
Long-Horizon Regressions of Excess Foreign Exchange Returns on Local Instruments

The table shows results of a long-horizon regression of the excess exchange rate return in country j over forecast horizon k ($ses^j_{t,t+k}$) on the set of local instruments associated with that country (the term structure slope (sp_t^j), the dividend yield (dy_t^j), and the forward premium ($fp_t^{US/j}$)). Newey-West standard errors (s.e.) are calculated assuming an overlap of k-1 terms in the error process. The asymptotic marginal significance levels (p values) are shown below the estimates. The R^2 statistics are adjusted for degrees of freedom. The value of the chi-squared test statistic associated with the Wald test of the null hypothesis that the coefficients on the explanatory variables are jointly equal to zero is shown in the column ($\chi^2(3)$) along with its p-value.

	German Mark						Japanese Yen					
	Coefficients						Coefficients					
Forecast Horizon (k)	constant (s.e.) p-value	sp_t^j (s.e.) p-value	dy_t^j (s.e.) p-value	$fp_t^{US/j}$ (s.e.) p-value	R^2	$\chi^2(3)$ p-value	constant (s.e.) p-value	sp_t^j (s.e.) p-value	dy_t^j (s.e.) p-value	$fp_t^{US/j}$ (s.e.) p-value	R^2	$\chi^2(3)$ p-value
1	0.010	1.243	-4.258	-1.447	0.015	5.860	0.007	-0.004	1.260	-3.160	0.048	16.885
	(0.007)	(1.429)	(3.073)	(1.066)		0.119	(0.005)	(1.659)	(4.105)	(0.879)		0.001
	0.167	0.385	0.166	0.175			0.130	0.998	0.759	0.000		
12	0.121	19.079	-54.482	-12.350	0.173	19.998	0.072	3.426	16.011	-32.506	0.306	44.101
	(0.085)	(11.380)	(38.312)	(6.764)		0.000	(0.041)	(13.018)	(38.452)	(5.135)		0.000
	0.154	0.094	0.155	0.068			0.756	0.792	0.677	0.000		
24	0.239	50.200	-107.742	-25.538	0.325	34.786	0.135	12.684	-6.279	-44.546	0.258	48.586
	(0.140)	(18.419)	(62.515)	(11.258)		0.000	(0.083)	(30.246)	(70.310)	(7.031)		0.000
	0.088	0.006	0.085	0.023			0.101	0.675	0.929	0.000		
36	0.392	85.456	-178.304	-36.569	0.514	71.271	0.200	-2.522	-33.035	-45.343	0.241	45.953
	(0.131)	(17.319)	(56.815)	(13.329)		0.000	(0.112)	(33.252)	(100.337)	(9.307)		0.000
	0.003	0.000	0.002	0.006			0.074	0.940	0.742	0.000		
48	0.585	90.330	-264.566	-34.522	0.578	94.841	0.313	-1.302	-143.964	-35.193	0.202	8.385
	(0.081)	(15.565)	(39.651)	(13.404)		0.000	(0.100)	(29.955)	(92.096)	(13.844)		0.039
	0.000	0.000	0.000	0.010			0.002	0.965	0.118	0.011		

Table 2, continued
Long-Horizon Regressions of Excess Foreign Exchange Returns on Local Instruments

The table shows results of a long-horizon regression of the excess exchange rate return in country j over forecast horizon k ($ses^j_{t,t+k}$) on the set of local instruments associated with that country (the term structure slope (sp^j_t), the dividend yield (dy^j_t), and the forward premium ($fp_t^{US/j}$)). Newey-West standard errors (s.e.) are calculated assuming an overlap of k-1 terms in the error process. The asymptotic marginal significance levels (p values) are shown below the estimates. The R^2 statistics are adjusted for degrees of freedom. The value of the chi-squared test statistic associated with the Wald test of the null hypothesis that the coefficients on the explanatory variables are jointly equal to zero is shown in the column ($\chi^2(3)$) along with its p-value.

	UK Pound						French Franc					
	Coefficients						Coefficients					
Forecast Horizon (k)	Constant (s.e.) p-value	sp^j_t (s.e.) p-value	dy^j_t (s.e.) p-value	$fp_t^{US/j}$ (s.e.) p-value	R^2	$\chi^2(3)$ p-value	Constant (s.e.) p-value	sp^j_t (s.e.) p-value	dy^j_t (s.e.) p-value	$fp_t^{US/j}$ (s.e.) p-value	R^2	$\chi^2(3)$ p-value
1	0.023	-1.521	-7.186	-2.371	0.056	18.037	0.011	0.761	-4.478	-2.395	0.033	10.885
	(0.012)	(1.162)	(3.105)	(0.894)		0.000	(0.006)	(1.675)	(1.464)	(1.264)		(0.012)
	0.051	0.191	0.021	0.008			0.058	0.649	0.002	0.058		
12	0.329	-0.465	-94.986	-17.429	0.281	32.146	0.120	11.391	-42.041	-16.695	0.166	19.691
	(0.081)	(10.246)	(21.992)	(6.858)		0.000	(0.051)	(9.323)	(13.173)	(7.788)		0.000
	0.000	0.964	0.000	0.011			0.020	0.222	0.001	0.032		
24	0.557	21.346	-160.695	-33.733	0.407	39.502	0.178	42.742	-71.303	-45.020	0.321	31.586
	(0.172)	(16.321)	(44.077)	(8.793)		0.000	(0.079)	(16.328)	(18.661)	(14.135)		0.000
	0.001	0.191	0.000	0.000			0.024	0.009	0.000	0.001		
36	0.838	44.312	-236.120	-43.416	0.518	41.475	0.189	76.768	-88.812	-76.526	0.459	66.235
	(0.240)	(19.127)	(59.232)	(14.239)		0.000	(0.082)	(19.813)	(18.129)	(15.621)		0.000
	0.000	0.021	0.000	0.002			0.021	0.000	0.000	0.000		
48	0.995	57.077	-275.359	-50.219	0.512	54.083	0.229	70.274	-99.224	-81.593	0.394	38.165
	(0.268)	(12.561)	(62.300)	(19.711)		0.000	(0.125)	(20.245)	(37.139)	(21.906)		0.000
	0.000	0.000	0.000	0.011			0.067	0.001	0.008	0.000		

Table 2, continued
Long-Horizon Regressions of Excess Foreign Exchange Returns on Local Instruments

The table shows results of a long-horizon regression of the excess exchange rate return in country j over forecast horizon k ($ses^j_{t,t+k}$) on the set of local instruments associated with that country (the term structure slope (sp^j_t), the dividend yield (dy^j_t), and the forward premium ($fp_t^{US/j}$)). Newey-West standard errors (s.e.) are calculated assuming an overlap of k-1 terms in the error process. The asymptotic marginal significance levels (p values) are shown below the estimates. The R^2 statistics are adjusted for degrees of freedom. The value of the chi-squared test statistic associated with the Wald test of the null hypothesis that the coefficients on the explanatory variables are jointly equal to zero is shown in the column ($\chi^2(3)$) along with its p-value.

	Swiss Franc						Canadian Dollar					
	Coefficients						Coefficients					
Forecast Horizon (k)	constant (s.e.) p-value	sp^j_t (s.e.) p-value	dy^j_t (s.e.) p-value	$fp_t^{US/j}$ (s.e.) p-value	R^2	$\chi^2(3)$ p-value	Constant (s.e.) p-value	sp^j_t (s.e.) p-value	dy^j_t (s.e.) p-value	$fp_t^{US/j}$ (s.e.) p-value	R^2	$\chi^2(3)$ p-value
1	0.008	-0.880	-1.542	-1.961	0.256	7.876	0.002	-1.071	-1.206	-1.837	0.067	23.044
	(0.010)	(1.477)	(5.525)	(0.998)		0.486	(0.003)	(0.562)	(1.113)	(0.595)		0.000
	0.415	0.551	0.780	0.050			0.535	0.057	0.278	0.002		
12	0.141	8.363	-47.780	-16.590	0.160	23.309	0.035	-9.015	-11.891	-3.147	0.104	6.368
	(0.123)	(11.629)	(62.598)	(5.967)		0.000	(0.038)	(4.321)	(12.463)	(4.032)		0.095
	0.251	0.472	0.445	0.005			0.369	0.037	0.340	0.435		
24	0.225	31.236	-62.957	-33.890	0.270	28.340	0.135	-15.159	-43.252	4.145	0.170	7.510
	(0.191)	(19.013)	(96.957)	(10.376)		0.000	(0.072)	(7.377)	(19.520)	(8.888)		0.057
	0.238	0.100	0.516	0.001			0.062	0.040	0.027	0.641		
36	0.293	49.133	-72.750	-49.345	0.376	21.739	0.224	-10.364	-71.143	11.173	0.229	8.302
	(0.234)	(21.316)	(111.594)	(12.967)		0.000	(0.107)	(9.158)	(27.729)	(11.786)		0.040
	0.211	0.021	0.514	0.000			0.037	0.258	0.010	0.343		
48	0.370	32.887	-107.559	-52.381	0.364	26.843	0.274	4.351	-86.322	14.733	0.279	6.670
	(0.147)	(17.299)	(63.812)	(18.133)		0.000	(0.134)	(10.918)	(34.765)	(15.714)		0.083
	0.012	0.057	0.092	0.004			0.041	0.690	0.013	0.348		

Table 3
Long-Horizon Regressions of Excess Foreign Exchange Returns on World Instruments

The table shows results of a long-horizon regression of the excess exchange rate return in country j over forecast horizon k ($ses^{j}_{t,t+k}$) on the set of world instruments (the term structure slope in the US (sp_t^{US}) and the US dividend yield (dy_t^{US})). Newey-West standard errors (s.e.) are calculated assuming an overlap of k-1 terms in the error process. The asymptotic marginal significance levels (p values) are shown below the estimates. The R^2 statistics are adjusted for degrees of freedom. The value of the chi-squared test statistic associated with the Wald test of the null hypothesis that the coefficients on the explanatory variables are jointly equal to zero is shown in the column ($\chi^2(2)$) along with its p-value.

	German Mark					Japanese Yen				
	Coefficients					Coefficients				
Forecast Horizon (k)	constant (s.e.) p-value	sp_t^{US} (s.e.) p-value	dy_t^{US} (s.e.) p-value	R^2	$\chi^2(2)$ p-value	constant (s.e.) p-value	sp_t^{US} (s.e.) p-value	dy_t^{US} (s.e.) p-value	R^2	$\chi^2(2)$ p-value
1	-0.004	2.509	0.587	0.009	2.804	-0.010	3.795	2.798	0.023	5.951
	(0.009)	(1.627)	(2.561)		0.246	(0.011)	(1.614)	(3.304)		0.051
	0.656	0.123	0.819			0.367	0.019	0.397		
12	0.033	23.327	-14.249	0.138	13.820	-0.157	45.358	45.840	0.210	9.519
	(0.112)	(13.001)	(34.728)		0.001	(0.121)	(15.615)	(36.177)		0.009
	0.766	0.073	0.682			0.192	0.004	0.205		
24	0.052	55.550	-23.628	0.317	33.125	-0.186	66.698	57.166	0.229	20.300
	(0.227)	(24.979)	(71.440)		0.000	(0.242)	(21.228)	(71.457)		0.000
	0.818	0.026	0.741			0.443	0.002	0.424		
36	0.199	74.370	-69.137	0.477	30.305	-0.161	79.936	55.162	0.258	15.019
	(0.310)	(30.364)	(95.503)		0.000	(0.338)	(29.693)	(101.487)		0.001
	0.522	0.014	0.469			0.633	0.007	0.587		
48	0.178	92.586	-64.345	0.488	26.278	-0.182	84.768	66.604	0.240	13.528
	(0.301)	(28.022)	(95.554)		0.000	(0.389)	(33.978)	(121.125)		0.001
	0.554	0.001	0.501			0.640	0.013	0.582		

Table 3, continued
Long-Horizon Regressions of Excess Foreign Exchange Returns on World Instruments

The table shows results of a long-horizon regression of the excess exchange rate return in country j over forecast horizon k ($ses^j_{t,t+k}$) on the set of world instruments (the term structure slope in the US (sp_t^{US}) and the US dividend yield (dy_t^{US})). Newey-West standard errors (s.e.) are calculated assuming an overlap of k-1 terms in the error process. The asymptotic marginal significance levels (p values) are shown below the estimates. The R^2 statistics are adjusted for degrees of freedom. The value of the chi-squared test statistic associated with the Wald test of the null hypothesis that the coefficients on the explanatory variables are jointly equal to zero is shown in the column ($\chi^2(2)$) along with its p-value.

	UK Pound					French Franc				
	Coefficients					Coefficients				
Forecast Horizon (k)	Constant (s.e.) p-value	sp_t^{US} (s.e.) p-value	dy_t^{US} (s.e.) p-value	R^2	$\chi^2(2)$ p-value	Constant (s.e.) p-value	Sp_t^{US} (s.e.) p-value	dy_t^{US} (s.e.) p-value	R^2	$\chi^2(2)$ p-value
1	0.006	0.629	-1.930	-0.002	1.662	-0.004	2.507	0.842	0.010	3.154
	(0.008)	(1.496)	(2.441)		0.436	(0.009)	(1.501)	(2.638)		0.207
	0.433	0.674	0.429			0.670	0.095	0.750		
12	0.118	2.313	-32.799	0.042	2.098	0.031	24.511	-10.249	0.141	12.665
	(0.097)	(16.430)	(30.117)		0.350	(0.110)	(13.145)	(34.120)		0.002
	0.223	0.888	0.276			0.775	0.062	0.764		
24	0.111	31.694	-29.517	0.154	4.194	0.030	60.645	-9.005	0.347	34.282
	(0.203)	(22.550)	(65.911)		0.123	(0.219)	(23.768)	(69.186)		0.000
	0.586	0.160	0.654			0.892	0.011	0.896		
36	0.097	68.913	-25.694	0.347	11.529	0.149	82.581	-41.763	0.485	28.125
	(0.275)	(24.121)	(85.746)		0.003	(0.305)	(30.279)	(94.139)		0.000
	0.724	0.004	0.764			0.626	0.006	0.657		
48	0.076	96.922	-17.634	0.466	19.779	0.135	98.488	-33.882	0.467	24.542
	(0.235)	(21.796)	(67.254)		0.000	(0.314)	(28.760)	(100.720)		0.000
	0.747	0.000	0.793			0.666	0.001	0.737		

Table 3, continued
Long-Horizon Regressions of Excess Foreign Exchange Returns on World Instruments

The table shows results of a long-horizon regression of the excess exchange rate return in country j over forecast horizon k ($ses^{j}_{t,t+k}$) on the set of world instruments (the term structure slope in the US (sp_t^{US}) and the US dividend yield (dy_t^{US})). Newey-West standard errors (s.e.) are calculated assuming an overlap of k-1 terms in the error process. The asymptotic marginal significance levels (p values) are shown below the estimates. The R^2 statistics are adjusted for degrees of freedom. The value of the chi-squared test statistic associated with the Wald test of the null hypothesis that the coefficients on the explanatory variables are jointly equal to zero is shown in the column ($\chi^2(2)$) along with its p-value.

	Swiss Franc					Canadian Dollar				
	Coefficients					Coefficients				
Forecast Horizon (k)	constant (s.e.) p-value	sp_t^{US} (s.e.) p-value	dy_t^{US} (s.e.) p-value	R^2	$X^2(2)$ p-value	Constant (s.e.) p-value	sp_t^{US} (s.e.) p-value	dy_t^{US} (s.e.) p-value	R^2	$\chi^2(2)$ p-value
1	-0.004	2.570	0.291	0.007	2.353	0.003	-0.260	-0.794	-0.006	0.528
	(0.010)	(1.839)	(3.029)		0.308	(0.004)	(0.559)	(1.114)		0.768
	0.727	0.162	0.923			0.481	0.642	0.476		
12	0.034	22.872	-16.922	0.107	14.778	0.063	-7.623	-18.859	0.070	5.670
	(0.136)	(15.257)	(41.492)		0.001	(0.034)	(3.664)	(9.411)		0.059
	0.805	0.134	0.683			0.059	0.038	0.045		
24	0.071	54.876	-33.688	0.283	36.515	0.141	-12.892	-42.050	0.098	6.011
	(0.243)	(26.815)	(75.996)		0.000	(0.073)	(7.528)	(18.313)		0.050
	0.769	0.041	0.656			0.054	0.087	0.022		
36	0.199	76.456	-76.189	0.459	41.099	0.127	-5.000	-38.677	0.044	1.757
	(0.322)	(31.586)	(99.626)		0.000	(0.118)	(9.211)	(29.592)		0.415
	0.538	0.015	0.444			0.279	0.587	0.191		
48	0.164	93.421	-70.893	0.503	35.274	0.070	9.054	-21.573	0.045	0.966
	(0.290)	(26.091)	(93.245)		0.000	(0.154)	(11.609)	(38.458)		0.617
	0.573	0.000	0.447			0.648	0.435	0.575		

Table 4

Small Sample Distributions of Estimators from Long-Horizon Regressions of Excess Foreign Exchange Returns on Local Instruments

The table shows the small sample distributions of the coefficients on the regressors in a long-horizon regression of the excess exchange rate return in country j over forecast horizon k ($ses^j_{t,t+k}$) on the set of local instruments associated with that country (the term structure slope (sp^j_t), the dividend yield (dy^j_t), and the forward premium ($fp_t^{US/j}$)). The first number in each cell is the OLS value from Table 2. The second number is the average value of the coefficient in the 10,000 non-parametric bootstrap simulations. The (p-values) are the small-sample marginal significance levels of the t statistics using the Newey-West standard errors assuming an overlap of k-1 terms in the error process. The R^2 statistics are adjusted for degrees of freedom. The value of the chi-squared test statistic associated with the Wald test of the null hypothesis that the coefficients on the explanatory variables are jointly equal to zero is shown in the column ($\chi^2(3)$) . For both of these latter statistics the average values and marginal significance levels (p-values) from the small sample distributions are also shown.

	German Mark						Japanese Yen					
	Coefficients						Coefficients					
Forecast	constant	sp^j_t	div^j_t	$fp_t^{US/j}$	R^2	$\chi^2(3)$	constant	sp^j_t	div^j_t	$fp_t^{US/j}$	R^2	$\chi^2(3)$
Horizon	avg.	avg.	avg.	avg.	avg.	avg.	Avg.	avg.	avg.	avg.	avg.	avg.
(k)	p-value	p-value	p-value	p-value	p-value	p-value	p-value	p-value	p-value	p-value	p-value	p-value
1	0.010	1.243	-4.258	-1.447	0.015	5.860	0.007	-0.004	1.260	-3.160	0.048	16.885
	0.002	-0.156	-1.692	-0.207	0.000	3.342	0.001	0.513	1.983	-0.186	0.000	3.291
	0.268	0.377	0.286	0.232	0.080	0.155	0.189	0.869	0.861	0.001	0.002	0.002
12	0.121	19.079	-54.482	-12.350	0.173	19.999	0.072	3.426	16.011	-32.506	0.306	44.101
	0.023	-1.426	-17.065	-2.036	0.104	8.897	0.013	4.769	20.911	-1.955	0.093	8.352
	0.446	0.245	0.496	0.272	0.190	0.094	0.328	0.984	0.880	0.001	0.019	0.008
24	0.239	50.200	-107.742	-25.538	0.325	34.786	0.135	12.684	-6.279	-44.546	0.258	48.586
	0.037	-1.808	-28.687	-3.924	0.185	14.953	0.028	8.235	37.463	-3.422	0.161	13.143
	0.428	0.129	0.462	0.238	0.151	0.089	0.469	0.962	0.859	0.005	0.196	0.034
36	0.392	85.456	-178.304	-36.569	0.514	71.271	0.200	-2.522	-33.035	-45.343	0.241	45.953
	0.047	-2.196	-36.994	-5.724	0.245	23.236	0.044	10.511	51.987	-4.457	0.210	19.952
	0.215	0.033	0.211	0.213	0.069	0.060	0.507	0.801	0.766	0.038	0.361	0.096
48	0.585	90.330	-264.566	-34.522	0.578	94.841	0.313	-1.302	-143.964	-35.193	0.202	8.385
	0.058	-2.687	-44.290	-7.014	0.291	37.684	0.062	12.667	64.092	-5.548	0.247	29.459
	0.030	0.029	0.038	0.294	0.078	0.090	0.294	0.796	0.422	0.292	0.543	0.690

Table 4, continued

Small Sample Distributions of Estimators from Long-Horizon Regressions of Excess Foreign Exchange Returns on Local Instruments

The table shows the small sample distributions of the coefficients on the regressors in a long-horizon regression of the excess exchange rate return in country *j* over forecast horizon *k* ($ses^j_{t,t+k}$) on the set of local instruments associated with that country (the term structure slope (sp_t^j), the dividend yield (dy_t^j), and the forward premium ($fp_t^{US/j}$)). The first number in each cell is the OLS value from Table 2. The second number is the average value of the coefficient in the 10,000 non-parametric bootstrap simulations. The (*p*-values) are the small-sample marginal significance levels of the *t* statistics using the Newey-West standard errors assuming an overlap of *k-1* terms in the error process. The R^2 statistics are adjusted for degrees of freedom. The value of the chi-squared test statistic associated with the Wald test of the null hypothesis that the coefficients on the explanatory variables are jointly equal to zero is shown in the column ($\chi^2(3)$) . For both of these latter statistics the average values and marginal significance levels (*p*-values) from the small sample distributions are also shown.

	UK Pound						French Franc					
	Coefficients						Coefficients					
Forecast Horizon (k)	constant avg. *p*-value	sp_t^j avg. *p*-value	div_t^j avg. *p*-value	$fp_t^{US/j}$ avg. *p*-value	R^2 avg. *p*-value	$X^2(3)$ avg. *p*-value	Constant Avg. *p*-value	sp_t^j avg. *p*-value	div_t^j avg. *p*-value	$fp_t^{US/j}$ avg. *p*-value	R^2 avg. *p*-value	$\chi^2(3)$ avg. *p*-value
1	0.023	-1.521	-7.186	-2.371	0.056	18.037	0.011	0.761	-4.478	-2.395	0.033	10.885
	0.002	-0.039	-0.231	-0.016	0.000	3.243	0.001	-0.014	-0.016	0.032	0.000	3.287
	0.104	0.210	0.030	0.011	0.001	0.002	0.085	0.648	0.003	0.062	0.010	0.021
12	0.329	-0.465	-94.986	-17.429	0.281	32.146	0.120	11.391	-42.041	-16.695	0.166	19.691
	0.026	-0.403	-2.309	-0.113	0.092	8.812	0.011	-0.142	-0.258	0.311	0.074	7.717
	0.022	0.989	0.011	0.102	0.028	0.030	0.153	0.380	0.044	0.149	0.106	0.072
24	0.557	21.346	-160.695	-33.733	0.407	39.502	0.178	42.742	-71.303	-45.020	0.321	31.586
	0.050	-0.535	-3.814	-0.189	0.157	14.065	0.021	-0.060	-0.355	0.290	0.127	11.464
	0.130	0.411	0.062	0.046	0.045	0.067	0.239	0.101	0.046	0.072	0.066	0.063
36	0.838	44.312	-236.120	-43.416	0.518	41.475	0.189	76.768	-88.812	-76.526	0.459	66.235
	0.073	-0.528	-5.286	-0.287	0.204	21.474	0.030	0.261	-0.236	0.027	0.165	16.409
	0.163	0.219	0.080	0.130	0.038	0.126	0.293	0.039	0.036	0.024	0.038	0.035
48	0.995	57.077	-275.359	-50.219	0.512	54.083	0.229	70.274	-99.224	-81.593	0.394	38.165
	0.094	-0.244	-6.212	-0.596	0.239	30.528	0.039	0.422	-0.328	0.080	0.194	23.876
	0.191	0.062	0.087	0.238	0.078	0.145	0.477	0.078	0.237	0.084	0.116	0.161

Table 4, continued

Small Sample Distributions of Estimators from Long-Horizon Regressions of Excess Foreign Exchange Returns on Local Instruments

The table shows the small sample distributions of the coefficients on the regressors in a long-horizon regression of the excess exchange rate return in country *j* over forecast horizon *k* ($ses^j_{t,t+k}$) on the set of local instruments associated with that country (the term structure slope (sp^j_t), the dividend yield (dy^j_t), and the forward premium ($fp_t^{US/j}$)). The first number in each cell is the OLS value from Table 2. The second number is the average value of the coefficient in the 10,000 non-parametric bootstrap simulations. The (*p*-values) are the small-sample marginal significance levels of the *t* statistics using the Newey-West standard errors assuming an overlap of *k-1* terms in the error process. The R^2 statistics are adjusted for degrees of freedom. The value of the chi-squared test statistic associated with the Wald test of the null hypothesis that the coefficients on the explanatory variables are jointly equal to zero is shown in the column ($\chi^2(3)$) . For both of these latter statistics the average values and marginal significance levels (*p*-values) from the small sample distributions are also shown.

	Swiss Franc						Canadian Dollar					
	Coefficients						Coefficients					
Forecast Horizon (*k*)	constant avg. *p*-value	sp^j_t avg. *p*-value	div^j_t avg. *p*-value	$fp_t^{US/j}$ avg. *p*-value	R^2 avg. *p*-value	$\chi^2(3)$ avg. *p*-value	constant avg. *p*-value	sp^j_t avg. *p*-value	div^j_t avg. *p*-value	$fp_t^{US/j}$ Avg. *p*-value	R^2 avg. *p*-value	$\chi^2(3)$ Avg. *p*-value
1	0.008	-0.880	-1.542	-1.961	0.026	7.876	0.002	-1.071	-1.206	-1.837	0.067	23.044
	0.003	-0.459	-1.906	-0.160	0.001	3.349	-0.001	0.068	0.166	-0.147	0.000	3.314
	0.520	0.681	0.954	0.076	0.024	0.070	0.403	0.049	0.255	0.006	0.000	0.000
12	0.141	8.363	-47.780	-16.590	0.160	23.309	0.035	-9.015	-11.891	-3.147	0.104	6.368
	0.023	-3.948	-18.355	-1.614	0.104	8.830	-0.006	0.593	1.048	-1.226	0.090	8.960
	0.519	0.528	0.748	0.098	0.222	0.065	0.427	0.136	0.490	0.740	0.346	0.486
24	0.225	31.236	-62.957	-33.890	0.270	28.340	0.135	-15.159	-43.252	4.145	0.170	7.510
	0.036	-5.786	-30.609	-3.130	0.181	14.789	-0.010	1.014	1.423	-1.880	0.143	13.472
	0.568	0.283	0.860	0.104	0.226	0.130	0.209	0.172	0.207	0.612	0.341	0.525
36	0.293	49.133	-72.750	-49.345	0.376	21.739	0.224	-10.364	-71.143	11.173	0.229	8.302
	0.044	-6.940	-40.218	-4.527	0.234	22.664	-0.014	1.512	1.767	-2.532	0.172	17.949
	0.600	0.192	0.897	0.102	0.186	0.318	0.199	0.407	0.192	0.418	0.283	0.562
48	0.370	32.887	-107.559	-52.381	0.364	26.843	0.274	4.351	-86.322	14.733	0.279	6.670
	0.048	-7.737	-48.365	-5.482	0.273	34.675	-0.019	1.920	2.364	-3.206	0.192	24.453
	0.332	0.297	0.571	0.255	0.292	0.355	0.249	0.920	0.240	0.417	0.241	0.688

Table 5
Joint tests of null ("unbiasedness") hypothesis across all forecast horizons

Entries are marginal significance levels (p values) from the non-parametric bootstrap simulations of the largest t-statistic for the coefficients on the explanatory variables shown in Table 2. The variables are the slope of the foreign country's term structure (sp_t^j), dividend yield (div_t^j) and forward premium ($fp_t^{US/j}$). Also shown is the chi-squared statistic of the test of the joint significance of the variables. The marginal significance level is determined by the small-sample bootstrap simulations used in Table 4.

Currency	sp_t^j	div_t^j	$fp_t^{US/j}$	$\chi^2(3)$
German Mark	0.019	0.031	0.199	0.105
Japanese Yen	0.769	0.283	0.020	0.204
UK Pound	0.045	0.061	0.078	0.184
French Franc	0.048	0.038	0.028	0.091
Swiss Franc	0.175	0.411	0.105	0.427
Canadian Dollar	0.736	0.176	0.160	0.424

Table 6
Variable Selection Bias in Long-Horizon Foreign Exchange Return Regressions

The table shows the R^2 ratio test statistics of the variable selection bias associated with the long-horizon regressions using world variables (7). Each R^2 ratio test statistic is the ratio of the R^2 statistic from the long-horizon foreign exchange return regression to the R^2 statistic from a long-horizon US equity return regression. The small sample distribution of this statistic is derived using a non-parametric bootstrap procedure that is similar to the one used in Table 4. The avg. is the ratio of the average R^2 statistic from the long-horizon foreign exchange return regressions in the simulations to the average R^2 statistic from the long-horizon US equity regressions in the simulations. The small-sample marginal significance level (*p*-value) is the percent of the small sample distribution that is larger than the statistic calculated using the original data.

		Forecast horizon *k*				
		1	12	24	36	48
German Mark	R^2 ratio	1.115	1.145	2.395	2.475	3.581
	avg.	0.024	0.661	0.689	0.704	0.710
	p-value	0.110	0.137	0.062	0.039	0.070
Japanese Yen	R^2 ratio	2.714	1.743	1.734	1.337	1.764
	avg.	-0.008	0.650	0.679	0.690	0.692
	p-value	0.019	0.043	0.147	0.204	0.309
UK Pound	R^2 ratio	-0.236	0.348	1.166	1.797	3.419
	avg.	0.034	0.673	0.698	0.711	0.712
	p-value	0.480	0.526	0.294	0.116	0.082
French Franc	R^2 ratio	1.198	1.171	2.624	2.513	3.429
	avg.	0.002	0.625	0.637	0.645	0.648
	p-value	0.095	0.148	0.060	0.051	0.113
Swiss Franc	R^2 ratio	0.880	0.886	2.138	2.379	3.696
	avg.	0.084	0.663	0.688	0.701	0.711
	p-value	0.146	0.220	0.091	0.043	0.059
Canadian Dollar	R^2 ratio	-0.685	0.584	0.739	0.227	0.333
	avg.	0.044	0.672	0.697	0.701	0.704
	p-value	0.782	0.364	0.455	0.760	0.800

Table 7
Long-horizon (48 month) regressions of change in spot exchange rate on local instruments

The table shows results of a long-horizon regression of the change in the spot exchange rate in country *j* over a 48 month forecast horizon ($ds^j_{t,t+48}$) on the set of local instruments associated with that country (the term structure slope (sp^j_t), the dividend yield (dy^j_t), and the forward premium ($fp_t^{US/j}$)). Newey-West standard errors (s.e.) are calculated assuming an overlap of 47 terms in the error process. The asymptotic marginal significance levels (*p* values) are shown below the estimates. The R^2 statistics are adjusted for degrees of freedom. The value of the chi-squared test statistic associated with the Wald test of the null hypothesis that the coefficients on the explanatory variables are jointly equal to zero is shown in the column ($\chi^2(3)$) along with its asymptotic marginal significance level (*p*-value).

	Coefficients					
Currency	constant (s.e.) *p*-value	sp^j_t (s.e.) *p*-value	div^j_t (s.e.) *p*-value	$fp_t^{US/j}$ (s.e.) *p*-value	R^2	$\chi^2(3)$ *p*-value
German Mark	0.404 (0.111) 0.000	103.045 (12.879) 0.000	-169.221 (45.537) 0.000	-20.252 (13.697) 0.139	0.480	69.957 0.000
Japanese Yen	0.300 (0.090) 0.001	-0.259 (24.880) 0.992	-37.195 (78.168) 0.634	-27.251 (11.939) 0.022	0.105	8.004 0.046
UK Pound	0.653 (0.252) 0.009	61.608 (9.046) 0.000	-206.945 (55.219) 0.000	-41.825 (16.888) 0.013	0.485	57.944 0.000
French Franc	0.112 (0.110) 0.305	86.325 (18.248) 0.000	-100.634 (31.013) 0.001	-92.465 (21.598) 0.000	0.452	49.596 0.000
Swiss Franc	0.187 (0.153) 0.222	59.642 (12.396) 0.000	17.177 (69.025) 0.803	-34.489 (16.808) 0.040	0.238	45.811 0.000
Canadian Dollar	0.146 (0.107) 0.175	8.763 (8.290) 0.290	-60.126 (27.523) 0.029	19.299 (13.652) 0.157	0.253	7.278 0.064

Table 8

Simulated Approximate Slope Ratios from the Long-Horizon Regressions

The table shows the ratio of the measure of approximate slope at forecast horizon *k*, *c(k),* to the measure at a one-month forecast horizon *c(1)*. The approximate slope measure *c(k)* is equal to the χ^2 statistic of the Wald test -- that the three "local variables" as shown in Table 2 have no explanatory power in a long-horizon regression at forecast horizon *k* -- divided by the sample size *T*. When the ratio is above 1.00 it indicates that the long-horizon regression has better explanatory power at forecast horizon *k* than at the one-month forecast horizon, according to the approximate slope measure of power. The distribution of the ratio is calculated using the same non-parametric bootstrap procedure as in Table 4 except that the VAR is simulated under the alternative hypothesis. The median, 5th and 95th percentiles (5 pc and 95 pc, respectively) of the ratios are shown.

		Forecast horizon *k*			
		12	24	36	48
German Mark	*c(k)/c(1)*	9.078	1.487	0.875	0.382
	5 pc.	4.295	0.521	0.240	0.075
	95 pc.	20.033	4.488	3.346	1.837
Japanese Yen	*c(k)/c(1)*	1.387	0.976	2.470	1.552
	5 pc.	0.242	0.062	0.261	0.092
	95 pc.	7.544	8.985	27.464	20.852
UK Pound	*c(k)/c(1)*	2.017	0.674	0.881	0.366
	5 pc.	0.631	0.089	0.160	0.021
	95 pc.	5.823	4.030	5.869	3.924
French Franc	*c(k)/c(1)*	1.446	1.044	1.811	1.195
	5 pc.	0.252	0.092	0.208	0.072
	95 pc.	6.619	7.642	16.019	13.904
Swiss Franc	*c(k)/c(1)*	1.641	1.380	2.823	1.794
	5 pc.	0.352	0.138	0.331	0.139
	95 pc.	6.407	9.081	21.140	17.576
Canadian	*c(k)/c(1)*	0.116	0.033	0.045	0.024
Dollar	5 pc.	0.008	0.002	0.002	0.001
	95 pc.	0.899	0.422	0.596	0.425

Table 9

Implied Fama (1984) Variance Ratios from the Long-Horizon Regressions

The table shows the ratio of the variance of the expected foreign exchange excess return (the risk premium given rational expectations) to the variance of the expected change in the exchange rate (*vr*). Expectations are calculated using a long-horizon regression model where the return or change in the exchange rate is regressed on the set of local instruments associated with that country (the term structure slope (sp_t^j), the dividend yield (dy_t^j), and the forward premium ($fp_t^{US/j}$)). The 75th and 95th percentiles (75 pc and 95 pc, respectively) of the ratio are also shown as generated by the non-parametric bootstrap simulations.

		Forecast horizon k				
		1	12	24	36	48
German Mark	*vr*	2.197	1.737	1.568	1.464	1.593
	75 pc.	1.054	1.045	1.039	1.036	1.034
	95 pc.	1.184	1.148	1.132	1.129	1.126
Japanese Yen	*vr*	2.135	1.731	1.683	1.687	2.612
	75 pc.	1.045	1.035	1.028	1.024	1.021
	95 pc.	1.135	1.107	1.094	1.086	1.081
UK Pound	*vr*	1.639	1.415	1.402	1.354	1.454
	75 pc.	1.079	1.072	1.076	1.077	1.076
	95 pc.	2.009	1.805	1.794	1.792	1.847
French Franc	*vr*	1.467	0.879	0.914	0.885	0.828
	75 pc.	1.059	1.051	1.049	1.047	1.045
	95 pc.	1.196	1.161	1.157	1.159	1.160
Swiss Franc	*vr*	3.107	3.382	2.392	1.943	2.370
	75 pc.	1.060	1.051	1.043	1.038	1.034
	95 pc.	1.186	1.158	1.142	1.131	1.126
Canadian	*vr*	2.326	1.838	1.400	1.473	1.480
Dollar	75 pc.	1.107	1.060	1.035	1.023	1.018
	95 pc.	1.305	1.198	1.149	1.125	1.117

Table 10

Parameter Estimates and Tests of a Single Latent Variable Model for Eurocurrency Returns With One Local Risk Factor

The table shows the estimated beta parameters of the latent variable model augmented by a local risk factor (17). The betas are the coefficients on the global risk factor which is a linear combination of the US dividend yield, US term structure slope and a constant. The coefficients on these variable are the same for each country so the linear combination represents a global risk factor. The beta for Germany is normalised to unity for identification. The local risk factor is the forward premium on the currency of the associated country. The asymptotic standard errors are reported below the parameter estimates. The system is estimated using GMM as in Tables 2 and 3. The test statistic for the over-identifying restrictions of the model is presented at the bottom and is distributed as chi-squared with 8 degrees of freedom. The asymptotic marginal significance level (*p*-value) is presented below the test statistic.

		Forecast horizon *k*				
		1	12	24	36	48
German Mark	β	1.00	1.00	1.00	1.00	1.00
Japanese Yen	β	1.606	2.637	2.343	0.510	1.651
	(s.e.)	(0.175)	(0.129)	(0.043)	(0.018)	(0.024)
UK Pound	β	0.648	0.811	0.847	0.480	0.450
	(s.e.)	(0.143)	(0.039)	(0.022)	(0.008)	(0.010)
French Franc	β	1.088	0.860	3.140	0.525	0.356
	(s.e.)	(0.095)	(0.031)	(0.076)	(0.007)	(0.006)
Swiss Franc	β	1.128	0.580	1.520	0.701	0.871
	(s.e.)	(0.083)	(0.039)	(0.015)	(0.007)	(0.004)
Test of model	$\chi^2(8)$	45.448	567.984	2479.451	7465.968	3965.815
	p-value	<0.001	<0.001	<0.001	<0.001	<0.001

Table 11

Variance Ratio Statistics of a Single Latent Variable Model for Eurocurrency Returns With One Local Risk Factor

The table shows variance ratio statistics of the latent variable model augmented by a local risk factor (17). The estimated parameters of the model are presented in Table 9. The first (VR-Mod.) is the ratio of the forecast variance from the restricted latent variable model to the forecast variance from an unrestricted OLS regression using the same variables. The second (VR-Res.) is the ratio of the variance of the restricted model's residuals to the forecast variance from the same OLS regression. The third (VR-Loc.) is the ratio of the variance of the local risk factor to the forecast variance from the restricted latent variable model .

		Forecast horizon *k*				
		1	12	24	36	48
German Mark	*VR-Mod.*	2.474	0.912	0.841	0.400	0.627
	VR-Res.	0.545	0.208	0.263	0.189	0.069
	VR-Loc.	0.030	0.000	0.161	0.145	0.143
Japanese Yen	*VR-Mod.*	1.691	1.494	2.560	0.137	3.060
	VR-Res.	0.846	2.402	0.672	0.769	2.061
	VR-Loc.	0.000	0.120	0.020	0.536	0.978
UK Pound	*VR-Mod.*	0.337	0.977	0.677	1.553	0.659
	VR-Res.	1.541	0.430	0.282	0.606	0.254
	VR-Loc.	0.170	0.028	0.016	0.573	0.262
French Franc	*VR-Mod.*	2.289	0.739	2.971	0.383	0.434
	VR-Res.	0.735	0.259	0.825	0.339	0.357
	VR-Loc.	0.000	0.048	0.213	0.221	0.337
Swiss Franc	*VR-Mod.*	1.251	0.656	1.552	0.400	0.791
	VR-Res.	0.774	0.186	0.147	0.153	0.016
	VR-Loc.	0.040	0.189	0.106	0.022	0.002

Table 12

Correlation Coefficients of Fitted Values from Single Latent Variable Model for Eurocurrency Returns With One Local Risk Factor

The table shows the correlation coefficients between the fitted values for two Eurocurrency returns. The fitted values come from the latent variable model augmented by a local risk factor (17). The coefficients are one way of estimating the economic content of the model. Cumby and Huizinga (1992) show that the correlation coefficients should be plus or minus one when a single risk factor is the only source of risk. Here the coefficients will deviate from one due to the inclusion of a local risk factor.

	Forecast horizon *k*	German Mark	Japanese Yen	UK Pound	French Franc
Japanese Yen	1	0.991			
	12	0.940			
	24	0.949			
	36	0.856			
	48	0.794			
UK Pound	1	0.892	0.920		
	12	0.985	0.889		
	24	0.944	0.995		
	36	0.667	0.394		
	48	0.824	0.509		
French Franc	1	0.990	1.000	0.923	
	12	0.970	0.889	0.961	
	24	0.779	0.870	0.868	
	36	0.849	0.750	0.668	
	48	0.766	0.631	0.736	
Swiss Franc	1	0.997	0.988	0.885	0.987
	12	0.968	0.862	0.972	0.961
	24	0.985	0.972	0.969	0.833
	36	0.945	0.806	0.772	0.901
	48	0.966	0.754	0.900	0.831

Table 13

Parameter Estimates and Tests of a Single Latent Variable Model for Eurocurrency Returns With No Local Risk Factor

The table shows the estimated beta parameters of the latent variable model (17) with the coefficients on the local risk factor set to zero. The betas are the coefficients on the global risk factor which is a linear combination of the US dividend yield, US term structure slope and a constant. The coefficients on these variables are the same for each country so the linear combination represents a global risk factor. The beta for Germany is normalised to unity for identification. The asymptotic standard errors are reported below the parameter estimates. The system is estimated using GMM as in Tables 2 and 3. The test statistic for the over-identifying restrictions of the model is presented at the bottom and is distributed as chi-squared with 8 degrees of freedom. The asymptotic marginal significance level (*p*-value) is presented below the test statistic.

		Forecast horizon *k*				
		1	12	24	36	48
German Mark	β	1.000	1.000	1.000	1.000	1.000
Japanese Yen	β	1.537	1.670	1.348	0.486	0.410
	(s.e.)	(0.710)	(0.372)	(0.142)	(0.089)	(0.070)
UK Pound	β	0.612	0.567	0.712	0.722	0.914
	(s.e.)	(0.412)	(0.203)	(0.094)	(0.128)	(0.070)
French Franc	β	0.980	1.047	1.106	0.945	0.841
	(s.e.)	(0.116)	(0.045)	(0.055)	(0.024)	(0.022)
Swiss Franc	β	0.986	0.957	1.044	1.041	1.076
	(s.e.)	(0.207)	(0.100)	(0.033)	(0.021)	(0.016)
Test of model	$\chi^2(8)$	4.619	4.424	4.129	5.964	4.166
	p-value	0.797	0.817	0.845	0.651	0.842