Alternative Long-horizon Exchange-rate Predictors

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This paper employs quarterly observations on US dollar prices of the pound, Deutschmark, Swiss franc, and yen from 1973,2 to 1994,4 to sort out three broad issues raised by recent work showing that economic fundamentals have predictive power for exchange rates at long horizons. Three alternative fundamentals have been proposed in the literature: those implied by purchasing-power parity, uncovered interest parity, and the flexible-price monetary model. We first ask which of these three alternative fundamentals has the most predictive power. Secondly, we ask if pooling across currencies or if using multivariate statistical techniques improves prediction accuracy over standard regression techniques. Thirdly, we examine whether the conclusions drawn from statistical analyses of in-sample econometric estimates concerning long-horizon convergence of exchange rates and their fundamentals coincide with those implied by analyses of out-of-sample forecasts. The short answers to these questions are; the monetary-model fundamentals, yes, and a qualified no.

Keywords: exchange rates; prediction; fundamentals

SUMMARY

Recent research has found statistical evidence that nominal exchange rates converge towards their theoretically implied fundamental determinants over the long run. This paper examines the forecasting power of alternative empirical specifications for quarterly US dollar prices of the British pound, the Deutschmark, the Swiss franc, and the yen over horizons up to four years to address three broad issues raised by this recent work.

The first issue concerns the empirical specification of the fundamentals. The literature has employed monetary-model fundamentals, consisting of linear combinations of relative money supplies and relative real income, and those implied by two of the monetary model's building blocks: the forward rate as suggested by uncovered interest parity, and relative price levels as implied by purchasing power parity. Accordingly, we first ask, 'Which of the alternative fundamentals proposed in the literature has the highest predictive ability?' Of the three fundamentals that we examined, we find that the monetary-model fundamentals appear to be the most robust predictors of long-run changes in nominal exchange rates, while at shorter horizons, none of the fundamentals were found to have significant predictive power.

Secondly, we attempt to sort out various practical issues involved in obtaining accurate forecasts. Since a major impediment towards establishing that exchange-rate deviations from their fundamentals are transient and forecastable is that insufficient information is contained in the relatively short time series available since the float, we explore ways to use the data efficiently by incorporating cross-sectional information. We do this by pooling the data and estimating systems of

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seemingly-unrelated regressions and fixed-effects regressions with the generalized method of moments. In this vein, we also examine the performance of the multivariate vector error-correction model (VECM). By simultaneously modelling both the short-run and long-run behaviour of a vector time series, the VECM incorporates auxiliary and potentially important non-exchange rate information. Here, we find that the mean-square prediction errors from the pooled regressions are systematically smaller than those from the OLS regression forecasts and are marginally better than the VECM forecasts. The relative success of these pooled regressions suggests that the various markets may be characterized by common speeds of adjustment towards a common set of fundamental values.

Thirdly, we ask 'Do we draw the same conclusions regarding long-run convergence of exchange rates and their fundamentals from standard analysis of econometric estimates as we do from evaluating out-of-sample predictions?' This is a question concerning the appropriate methodology since regressions that fit well in a particular period are sometimes not robust to changes in the sample, and we want to determine whether that is the case here. We find that the inferences drawn from in-sample and out-of-sample analyses generally coincide.

INTRODUCTION

The empirical exchange-rate literature of the last decade is fraught with the failure of theoretically sound econometric specifications to beat the random walk in out-of-sample prediction. The genesis of the literature is Meese and Rogoff (1983a), who studied regressions of US dollar prices of the Deutschmark, pound and yen on macroeconomic fundamentals implied by theories of exchange-rate determination popularized in the 1970s. At forecast horizons of 1 year or less from 1976,11 to 1981,6, they found that the random walk model generated lower mean-square prediction errors than the out-of-sample fit of their regressions. Similarly, Meese and Rogoff (1988) showed that the random walk regularly beat exchange-rate regressions on real interest rate differentials in predicting log real exchange rates for these currencies as well as their implied cross rates from 1980,11 to 1986,3. Indeed, the inability to show that exchange rates are systematically related to their fundamentals led Meese (1986) and Woo (1987) to conclude that actual exchange rate behaviour may have been driven by rational speculative bubbles.

Countering these nihilistic findings is a recent but growing body of evidence that macroeconomic fundamentals may, in fact, have predictive power for exchange rates. At forecast horizons up to 1 year, MacDonald and Taylor's (1993) monthly vector error-correction model (VECM) of the flexible-price monetary model outperforms the random walk for the US dollar–Deutschmark rate during 1989,1–1990,12, and Clarida and Taylor's (1993) weekly forward and spot exchange-rate VECM beats the random walk at horizons for the dollar–pound and dollar–Deutschmark rate during 1989,27–1990,26.[1]

More dramatic, however, is the evidence that predictive ability relative to the random walk improves as the forecast horizon is lengthened beyond one year.[2] Mark (1995) employs long-horizon regressions of US dollar prices of the Canadian dollar, Deutschmark, Swiss franc, and yen on deviations of the log spot rate from the long-run value implied by the flexible-price monetary model to produce one-quarter to 4-year-ahead forecasts over the period 1981–1991. He finds that the mean square prediction errors of the long-horizon regressions generally improves relative to the random walk as the forecast horizon is lengthened. At the 4-year horizon, his regression point predictions achieved reductions in root-mean-square prediction error (RMSPE) relative to the random walk of 48% for the Deutschmark, 59% for the Swiss franc, and 43% for the yen and concludes that the weight of the statistical evidence rejects the hypothesis that the log exchange rate follows a random walk. Similarly, Chinn and Meese (1995) employ monetary-model fundamentals in long-horizon regressions of the log exchange rate on the deviation of its implied long-run value, and find some measure of improvement over the random walk for the Deutschmark, Canadian dollar, and yen at the 3-year horizon from 1985,12 to 1990,12. Using long historical time series, Lothian and Taylor (1995) fit an AR(1) to the annual real dollar–pound rate from 1791 to 1973 and the annual real pound–franc rate from 1803 to

1973. They then use the fitted models to form dynamic forecasts for the post-float period, 1973–1990. At the 5-year horizon, their forecasts achieve striking reductions in RMSPEs, relative to the random walk, of 22% for the dollar–pound rate and 30% for the pound–franc rate.

Further evidence of exchange-rate forecastability and the eventual convergence of currency prices to their fundamentals is found in Bekaert and Hodrick (1992) and Cumby (1988), who emphasize the predictive content of the forward premium in their studies of foreign currency excess returns; Cumby and Huizinga (1991), who study decompositions of the exchange rate into permanent and transitory components; and the resurgent confirmations of long-run purchasing-power parity as in Edison (1987), Edison *et al.* (1994), Frankel and Rose (1995), and Wu (1994).[3]

This paper addresses three broad issues raised by the recent findings of long-run convergence of exchange rates and their fundamentals. First, we ask, 'Which of the alternative fundamentals proposed in the literature has the highest predictive ability?' The literature has employed monetary-model fundamentals, consisting of linear combinations of relative money supplies and relative real income, and those implied by two of the monetary model's building blocks: the forward rate as suggested by uncovered interest parity (UIP), and relative price levels as implied by purchasing power parity (PPP).[4]

Secondly, we ask questions like 'How important is the empirical modelling strategy?' 'Can more efficient estimates and predictions be obtained from pooling across currencies?' and 'How well do multivariate techniques such as vector error correction methods perform?' As emphasized by Lothian and Taylor (1995) and Frankel and Rose (1995), the difficulty in establishing that exchange-rate deviations from their fundamentals are transient and forecastable is that insufficient information is contained in the relatively short time series available since the float. One strategy that has been taken has been to lengthen the time series by extending them backwards, as in Lothian and Taylor, or Edison (1987). Since our examination focuses on the nominal exchange rate, the earliest that we can start our sample is with the move to generalized floating in 1973 so this option is not available to us. Instead, we explore ways to improve efficiency and forecast precision by incorporating cross-sectional information. One way that we do this is by pooling the data and estimating systems of seemingly-unrelated regressions systems and fixed-effects regressions using the generalized method of moments. Alternatively, we examine the performance of the multivariate VECM as suggested by Bekaert and Hodrick (1982), MacDonald and Taylor (1993) and Clarida and Taylor (1993). By simultaneously modelling both the short-run and long-run behaviour of a vector time series, the VECM incorporates auxiliary and potentially important non-exchange-rate information. The potential problem with the VECM is that it is heavily parameterized. The trade-off then, is whether the contribution of the short-run dynamics to prediction accuracy is sufficient to offset the added parameter uncertainty.

Thirdly, we ask 'Do we draw the same conclusions regarding long-run convergence of exchange rates and their fundamentals from standard analysis of econometric estimates as we do from evaluating out-of-sample predictions?' Regressions that fit well in a particular period are sometimes not robust to changes in the sample, and we want to determine whether that is the case here.

To answer these questions, we study quarterly US dollar prices of the British pound (BP), the Deutschmark (DM), the Swiss franc (SF), and the yen. We examine alternative methods for characterizing and testing for exchange-rate predictability using the full sample which extends from 1973,2 to 1994,4. Out-of-sample prediction exercises are performed beginning in 1982,1.

The paper is organized as follows. The next section discusses the empirical formulations and construction of the fundamentals. Econometric considerations and estimation strategies are discussed in the section after. Empirical results are then given, followed by concluding remarks.

ALTERNATIVE FORMULATIONS OF THE FUNDAMENTALS

This section describes three formulations of the fundamentals that have been stressed in recent work on exchange rates. These are long-run values of the exchange rate implied by PPP, UIP, and a particular version of the flexible-price monetary model.

Let ϕ denote the fundamental (or long-run) exchange-rate value. We are interested in determining the predictive content of the current deviation, z_t, of the log spot rate, s_t, from its fundamental value,

$$z_t = \phi_t - s_t. \tag{1}$$

We take as a maintained hypothesis that $\{s_t\}$ and $\{\phi_t\}$ are cointegrated so that $\{z_t\}$ is covariance stationary but we do not formally test whether $\{z_t\}$ contains a unit root. Blough (1992) and Cochrane (1991) have argued that in any finite sample, such tests have arbitrarily low power and may therefore be pointless.[5]

Purchasing-Power Parity Fundamentals

Let p_t be the log US price level and p_t^* be the log 'foreign' price level. Under PPP, the fundamentals are

$$\phi_t^{PPP} = p_t - p_t^*. \tag{2}$$

We use CPIs to measure national price levels. Different base years in the domestic and foreign CPIs simply have the effect of adding a constant value to z_t, which gets impounded into the regression's constant term.

Drawing on the extraneous evidence reported in recent PPP research confirming that $s_t = p_t - p_t^*$ in the long run, we fix the coefficients on the relative price levels to unity. The aim is to improve prediction accuracy by imposing (as opposed to estimating) theoretical restrictions that have found empirical support elsewhere.[6]

Uncovered Interest Parity Fundamentals

Here, we consider a second building block of the monetary approach to model the fundamentals. Using UIP, the expected k-period percentage change in the exchange rate is given by the k-period nominal interest rate differential, which by covered interest parity is equal to the k-period forward premium. Although UIP has long been convincingly rejected by the data (Cumby, 1988; Cumby and Obstfeld, 1984; Fama, 1984), the forward premium has been found to have predictive power (Bekaert and Hodrick, 1992; Clarida and Taylor, 1993). Under UIP, the fundamental value is

$$\phi_t^{UIP} = f_t \tag{3}$$

where f_t is the log forward exchange rate.

Monetary-Model Fundamentals

PPP and UIP combined with certain parametric forms of money demand functions imply that the log spot rate can be represented as the expected present value of future values of $(m_t - m_t^*) - \lambda(y_t - y_t^*)$, where λ is the income elasticity of money demand, m_t is the log home country money supply, y_t is log home country real income, and '*' denotes foreign country variables. We follow Chinn and Meese (1995), MacDonald and Taylor (1993), and Mark (1995) who find that modelling the fundamental value as

$$\phi_t^{MM} = (m_t - m_t^*) - \lambda(y_t - y_t^*) \tag{4}$$

is useful in predicting future values of the nominal exchange rate. We impose the long-run neutrality of money by setting the coefficient on the log money supplies to 1. Since there is no widespread agreement on the size of the income elasticity of money demand, we consider two variants of the monetary model where we alternately impose a fixed value of 1 for the coefficient λ and where we estimate λ.

We apply two techniques for estimating λ. First, we use Stock and Watson's (1993) dynamic OLS (DOLS) cointegration vector estimator. Secondly, we pool the data, constrain λ to be equal across currencies, and estimate the system of Stock and Watson regression equations jointly. Details are given in the appendix.

ECONOMETRIC SPECIFICATIONS

We discuss the formulation and estimation of three econometric models that have been employed in the literature and the uses to which we put them. They are: long-horizon regressions, backward-averaged regressions, and the VECM.

Long-Horizon Regressions

In the long-horizon regression, we regress the k-period future change in the log exchange rate on its current deviation from its fundamental value,

$$s_{t+k} - s_t = \alpha_k + \beta_k z_t + \varepsilon_{t,k}. \quad (5)$$

If there is long-run convergence of the exchange rate to its fundamentals, s_t will tend to increase (decrease) over time when it is currently below (above) its fundamental value, implying a positive value for the slope coefficient, β_k.[7] These regressions have been employed by Fama and French (1988) and Campbell and Shiller (1988) to study long-horizon predictability of equity returns, and by Mark (1995) and Chinn and Meese (1995) in examining long-horizon exchange-rate changes. Typically, these researchers have discovered that point estimates of the slope coefficient, its asymptotic t-ratio, and regression R^2 display a 'hump' shape initially increasing with horizon.[8]

We employ the long-horizon regression as a tool for out-of-sample prediction, but due to poor small sample properties of the OLS asymptotic t-ratio we do not test restrictions on the slope coefficient in examining whether the exchange rate is predictable. Hodrick (1992), Nelson and Kim (1993) and Mark (1995) find, for sample sizes normally encountered with macro time series, that asymptotic tests based on serial correlation robust asymptotic standard errors formed by summing a large number of autocovariance matrices are subject to considerable size distortion and are virtually meaningless unless appropriate adjustments are made.

This being the case, however, using the long-horizon regression for out-of-sample prediction is not an obviously silly thing to do. Biasedness in small samples does not necessarily imply low accuracy. In addition, the parsimonious representation of the long-horizon regression reduces the effects of parameter uncertainty that are encountered in the more heavily parameterized VECM.

Backward-Averaged Regressions

To test the hypothesis that z_t enters significantly into Equation (5), we employ the backward-averaged regression suggested by Jegadeesh (1991). In this formulation, we regress k times the one-period change in s_t on the k-period moving average of current and past values of z_t:

$$k(s_{t+1} - s_t) = \delta_k + \gamma_k \left(\frac{1}{k} \sum_{j=0}^{k-1} z_{t-j} \right) + v_{t,k} \quad (6)$$

Why this is useful can be seen by recognizing that if $\{\Delta s_t\}$ and $\{z_t\}$ are both covariance stationary, the population value of the numerator of the long-horizon slope coefficient β_k, $\mathrm{Cov}(s_{t+k} - s_t, z_t)$ is equal to $\mathrm{Cov}(\Delta s_{t+1}, \sum_{j=0}^{k} z_{t-j})$, which is the population value of the numerator of γ_k in Equation (6). Thus, testing the hypothesis that $\gamma_k = 0$ is equivalent to testing $\beta_k = 0$.

The advantage of the backward-averaged regression is that it does not induce artificial serial correlation in the error since the dependent variable in Equation (6) is the one-period change in s_t. Because we are not required to sum up a large number of autocovariance matrices to calculate asymptotic standard errors, the asymptotic t-ratios have better small-sample properties. To justify doing asymptotic inference, we rely on Hodrick's (1992) Monte Carlo study of the small sample properties of the backward averaged regression, where he show that the empirical distribution of the asymptotic t-ratios for the backward-averaged regression are reasonably close to the asymptotic distribution.[9]

We do not employ the backward-averaged regression in the out-of-sample prediction analysis since it is obviously not useful for generating predictions beyond a one-period forecast horizon.

Joint Estimation of Long-Horizon and Backward Averaged Regressions

In addition to OLS, we estimate Equations (5) or (6) jointly as a system of seemingly-unrelated regressions (SUR) and as a fixed-effects regression (FE) using generalized methods of moments (GMM) to investigate the usefulness of exploiting cross-sectional information from pooling across currencies.

The GMM objective function is,

$$\left(\frac{1}{T} \sum_{t=1}^{T} h_t \right)' S_T^{-1} \left(\frac{1}{T} \sum_{t=1}^{T} h_t \right) \quad (7)$$

where h_t is the vector of orthogonality conditions and S_T is a consistent estimator of the spectral density matrix of h_t at frequency zero.

Let η be the parameter vector from the system. We estimate the asymptotic covariance matrix of the GMM estimator, η_T, by

$$\mathrm{Var}(\eta_T) = \frac{1}{T}(D_T' S_T^{-1} D_T)^{-1} \quad (8)$$

where $D_T = \frac{1}{T}\sum_{t=1}^{T} (\partial h_t(\eta_T)/\partial\eta)$ and, following Newey and West (1987), $S_T = \Omega_{T,0} + \sum_{j=1}^{m} (1 - \frac{j}{(m+1)})(\Omega_{T,j} + \Omega_{T,j}')$, $\Omega_{T,j} = \frac{1}{T}\sum_{t=1}^{T} h_t h_{t-j}'$.

To describe the orthogonality conditions, let us index the n currencies under consideration by $j = 1, \ldots, n$. For the long-horizon regression, stack the k-period regression errors for each currency into the vector, $\underline{\varepsilon}_{t,k} = (\varepsilon_{t,k}^1, \ldots, \varepsilon_{t,k}^n)'$. For horizon k under SUR, we estimate the $2n$ parameters, $(\alpha_k^j, \beta_k^j), j = 1, \ldots, n$. Let z_t^j be the deviation of currency j's (log) spot rate from its fundamental value, and let the instrument vector be $Z_t = (1, z_t^1, \ldots, z_t^n)'$. Then for the regression (5) of horizon k, we set $h_t = (\underline{\varepsilon}_{t,k} \otimes Z_t)$. The GMM estimator of the parameter vector η_T from this seemingly-unrelated system has a particular convenient closed form solution which we describe in the appendix.

Under the FE regression, the slope coefficients are constrained to be equal across currencies and we only estimate the $n+1$ coefficients $(\alpha_k^j, \beta_k), j = 1, \ldots, n$. Here, we set $h_t = (\varepsilon_{t,k}^1(1, z_t^1), \ldots, \varepsilon_{t,k}^n(1, z_t^n))'$.

Similarly, we perform joint estimation of the backward-averaged regressions Equations (6), by letting $\bar{z}_{t,k}^j = (1/k)\sum_{i=0}^{k-1} z_{t-i}^j$ be country j's k-period moving average of current and past values of z_t^j. Under SUR, the instrument vector is, $\tilde{Z}_{t,k} = (1, \bar{z}_{t,k}^1, \ldots, \bar{z}_{t,k}^n)'$ and upon stacking the error terms from each equation into the vector $\underline{v}_{t,k} = (v_{t,k}^1, \ldots, v_{t,k}^n)'$, the orthogonality conditions used in estimating the backward-averaged regressions are $h_t = (\underline{v}_{t,k} \otimes \tilde{Z}_{t,k})$. For the FE regression, we set $h_t = (v_{t,k}^1(1, \bar{z}_{t,k}^1), \ldots, v_{t,k}^n(1, \bar{z}_{t,k}^n))'$.

The Vector Error-Correction Model

The multivariate VECM was employed by MacDonald and Taylor (1993) in their study of the monetary model and Clarida and Taylor (1993) in their study of uncovered interest parity. The VECM, if correctly specified, offers an attractive alternative because it contains a complete record of the autocovariance structure of the observations. As emphasized by Bekaert and Hodrick (1992) and Campbell and Shiller (1988) in their parallel VAR analyses, covariances of observations separated at long horizons can be deduced from the VECM without actually having to estimate the long-horizon covariances, thus lessening the effects of small-sample bias and the size distortion in asymptotic tests that have accompanied standard long-horizon regressions.[10] Furthermore, out-of-sample predictions may benefit by accounting for the short-run dynamics of the system. The potential disadvantages are first, that the VECM is heavily parameterized so that the additional parameter uncertainty may spoil the out-of-sample forecasts, and secondly, that the prediction performance may not be robust to misspecification in seemingly innocuous dimensions such as the number of lags to employ.

For clarity of exposition, we present a first-order VECM. Schwarz's (1978) BIC criteria determined that there is an optimal lag length of 1 in each of the VECMs that we fitted.[11] To proceed, let x_t denote the vector of observations represented by the VECM with the first element being the log spot rate. Under the PPP fundamentals, $x_t = (s_t, p_t - p_t)'$. Under UIP, $x_t = (s_t, f_t)'$, and under the monetary model, $x_t = (s_t, [m_t - m_t^*], [y_t - y_t^*])'$. Next, we represent the deviation of the exchange rate from its fundamental value, or the equilibrium error of the system, as $z_t = \alpha' x_t$ where α is the cointegration vector. In terms of our earlier notation, $\alpha' = (-1, 1)$ under PPP and UIP, and $\alpha' = (-1, 1, -\lambda)$ under the monetary model. The first-order VECM representation of the $l \times 1$ vector x_t for a particular exchange rate is,

$$\Delta x_{t+1} = \underline{c} + A\Delta x_t + \underline{\gamma} z_t + u_t, \quad (9)$$

with $E(u_t u_t') = \sum$. Given the equilibrium-error sequence, $\{z_t\}$, we estimate each equation of the VECM by OLS.

The multiperiod forecasting formulae and implied long-horizon statistics are obtained by first premultiplying Equation (9) by α' to get the time-series representation for the equilibrium error sequence, $\{z_t\}$,

$$\alpha' x_{t+1} = \alpha' x_t + \alpha' \underline{c} + \alpha' A\Delta x_t + \alpha' \gamma z_t + \alpha' u_t, \quad (10)$$

or equivalently,

$$z_{t+1} = \alpha' A \Delta x_t + (1 + \alpha'\gamma) z_t + \alpha' u_t. \tag{11}$$

Next, stack Δx_{t+1} and z_{t+1} together as the system,

$$\begin{pmatrix} \Delta x_{t+1} \\ z_{t+1} \end{pmatrix} = \begin{pmatrix} A & \gamma \\ \alpha' A & 1 + \alpha'\gamma \end{pmatrix} \begin{pmatrix} \Delta x_t \\ z_t \end{pmatrix} + \begin{pmatrix} u_{t+1} \\ \alpha' u_{t+1} \end{pmatrix}. \tag{12}$$

Now let $y_t = (\Delta x_t', z_t)'$, $\tilde{y}_t = y_t - E(y_t)$, $\varepsilon_t = (u_t', \alpha' u_t)'$, and

$$B = \begin{pmatrix} A & \gamma \\ \alpha' A & 1 + \alpha'\gamma \end{pmatrix}.$$

Equation (12) can now be more compactly written as the first-order vector autoregression,

$$\tilde{y}_{t+1} = B\tilde{y}_t + \varepsilon_t. \tag{13}$$

Define e_j to be row selector vectors consisting of 0s and 1s such that $s_t = e_1 y_t$ and $z_t = e_2 y_t$. Then, by mimicking the VAR analysis of Campbell and Shiller (1988), Hodrick (1992), or Bekaert and Hodrick (1992), it is straightforward to show that the covariance matrix of y_t is,

$$\begin{aligned} C_0 &= E(\tilde{y}_t \tilde{y}_t') \\ &= E\left(\sum_{i=0}^{\infty} B^i \varepsilon_{t-1}\right)\left(\sum_{i=0}^{\infty} B^i \varepsilon_{t-1}\right)' \\ &= \sum_{i=0}^{\infty} (B^i) V (B^i)' \end{aligned} \tag{14}$$

where $V = E(\varepsilon_t \varepsilon_t')$.[12] The kth ordered autocovariance matrix of y_t is then,

$$C_k = E(\tilde{y}_t \tilde{y}_{t-k}') = B^k C_0. \tag{15}$$

It follows that the implied long-horizon slope coefficient of the k-period change in s_t on z_t is,

$$\begin{aligned} \beta_k &= \frac{\mathrm{Cov}(s_{t+k} - s_t, z_t)}{\mathrm{Var}(z_t)} \\ &= \frac{\mathrm{Cov}(\sum_{i=1}^{k} \Delta s_{t+i}, z_t)}{\mathrm{Var}(z_t)} \\ &= \frac{E[e_1(\sum_{i=1}^{k} \tilde{y}_{t+i})\tilde{y}_t' e_2']}{e_2 E(\tilde{y}_t \tilde{y}_t') e_2'} \\ &= \frac{e_1[\sum_{i=1}^{k} C_i] e_2'}{e_2 C_0 e_2'}. \end{aligned} \tag{16}$$

Similarly, the implied R^2 from a regression of the k-period change in s_t on z_t is,

$$\begin{aligned} R_k^2 &= \frac{\mathrm{Var}(\beta_k z_t)}{\mathrm{Var}(s_{t+k} - s_t)} \\ &= \beta_k^2 \frac{\mathrm{Var}(z_t)}{\mathrm{Var}(\sum_{i=1}^{k} \Delta s_{t+i})} \\ &= \beta_k^2 \frac{e_2 E(\tilde{y}_t \tilde{y}_t') e_2'}{e_1 E(\sum_{i=1}^{k} \tilde{y}_{t+1})(\sum_{i=1}^{k} \tilde{y}_{t+i})' e_1'} \\ &= \beta_k^2 \frac{e_2 C_0 e_2'}{e_1[kC_0 + \sum_{i=1}^{k-1} (C_i + C_i')] e_1'}. \end{aligned} \tag{17}$$

To do asymptotic inference, let $\eta_T = (\eta_{T,1}, \eta_{T,2})' = [\mathrm{vec}(A_T), \mathrm{vech}(\Sigma_T)]'$ be the vector of *all* of the coefficients of the VECM. We get consistent estimates of the covariance matrix of $\mathrm{vec}(A_T) = \eta_{T,1}$ with

$$\Theta_{T,1} = \sum_{t=1}^{T} \left(\frac{\partial u_t}{\partial \eta_1}\right) \Sigma_T^{-1} \left(\frac{\partial u_t}{\partial \eta_1}\right)$$

and of the covariance matrix of $\mathrm{vech}(\Sigma_T) = \eta_{T,2}$ with

$$\Theta_{T,2} = -\left(\frac{\partial^2 L(\eta_{T,1}, \eta_{T,2})}{\partial \eta_2 \partial \eta_2'}\right),$$

where $L(\eta_{T,1}, \eta_{T,2})$ is the log-likelihood function of the system (9). By the block diagonality of the covariance matrix of η_T, we set

$$\Theta_T = \begin{pmatrix} \Theta_{T,1} & 0 \\ 0 & \Theta_{T,2} \end{pmatrix}.$$

Since $\sqrt{T}(\eta_T - \eta_0) \stackrel{A}{\sim} N(0, \Theta)$ and the implied long-horizon regression slope coefficient is a function of these parameters, a mean-value expansion implies that

$$\sqrt{T}[\beta_k(\eta_T) - \beta_k(\eta_0)] \stackrel{A}{\sim} N\left[0, \left(\frac{\partial \beta_k(\eta_T)}{\partial \eta}\right) \Theta \left(\frac{\partial \beta_k(\eta_T)}{\partial \eta}\right)'\right].$$

EMPIRICAL RESULTS

The following subsection discusses our estimates of the backward-averaged regression and implied long-horizon statistics from the VECM. The subsection after reports results from the out-of-sample prediction exercise.

Characterizing Long-Horizon Predictability

Panel A of Tables 1 through 4 displays the OLS, SUR and FE estimates of the backward-averaged regressions. As mentioned above, the backward-averaged regression does not induce serial correlation into the error term, but without additional restrictions we have no guarantee that the error is serially uncorrelated. Following Hodrick (1992), we check robustness by computing Newey and West asymptotic t-ratios with four lags and alternatively, by setting the truncation lag to zero. We denote these asymptotic ts as $t(4)$ and $t(0)$ respectively. Panel B of these tables displays the long-horizon

Table 1. Characterizing long-horizon predictability with fixed coefficient PPP fundamentals.

A. Backward-averaged regression

Estimation technique	Horizon	Pound			Deutschmark			Swiss franc			Yen		
		$\hat{\gamma}_k$	$t(0)$	$t(4)$	$\hat{\gamma}_k$	$t(0)$	$t(4)$	$\hat{\gamma}_k$	$t(0)$	$t(4)$	$\hat{\gamma}_k$	$t(0)$	$t(4)$
	1	0.057	1.382	1.204	0.056	1.444	1.351	0.071	1.593	1.520	0.006	0.201	0.178
	4	0.310	1.758	1.578	0.230	1.402	1.362	0.327	1.682	1.699	0.083	0.686	0.614
OLS	8	0.761	1.959	1.816	0.652	1.874	1.840	0.750	1.740	1.794	0.318	1.171	1.073
	12	1.696	2.690	2.870	1.088	1.932	1.918	1.372	1.887	1.958	0.718	1.541	1.441
	16	2.963	3.060	3.444	1.668	2.000	2.019	2.127	1.898	1.965	1.132	1.560	1.452
	1	0.032	1.009	0.980	0.077	2.916	3.398	0.094	3.336	3.662	0.027	1.267	1.025
	4	0.175	1.217	1.241	0.344	2.980	3.602	0.391	3.033	3.634	0.172	1.870	1.502
SUR	8	0.392	1.211	1.258	0.662	2.557	3.042	0.686	2.278	2.713	0.473	2.164	1.920
	12	1.094	1.887	2.360	0.941	2.144	2.545	0.870	1.539	1.935	0.775	1.877	1.841
	16	2.213	2.673	3.529	1.717	2.672	3.535	1.575	1.856	2.401	1.205	1.719	1.821

	Statistics	Horizon				
		1	4	8	12	16
FE	$\hat{\gamma}_k$	0.019	0.114	0.401	0.874	1.447
	$t(0)$	0.650	1.069	1.842	2.347	2.531
	$t(4)$	0.731	1.040	1.764	2.498	2.829

B. Vector error-correction model

	Horizon	Pound			Deutschmark			Swiss franc			Yen		
		$\hat{\beta}_k$	asy.t	R^2	$\hat{\beta}_k$	asy.t	R^2	$\hat{\beta}_k$	asy.t	R^2	$\hat{\beta}_k$	asy.t	R^2
Implied long horizon statistics	1	0.056	1.199	0.021	0.056	1.466	0.022	0.073	1.694	0.032	0.010	0.369	0.002
	4	0.266	1.340	0.098	0.228	1.566	0.091	0.284	1.826	0.124	0.058	0.482	0.015
	8	0.415	1.291	0.134	0.388	1.684	0.152	0.477	2.087	0.204	0.115	0.507	0.030
	12	0.472	1.191	0.130	0.491	1.793	0.187	0.598	2.357	0.249	0.162	0.520	0.041
	16	0.486	1.080	0.114	0.555	1.882	0.205	0.672	2.578	0.271	0.200	0.530	0.049

	variable	coef.	asy.t	χ^2_3 (m.s.l.)	coef.	asy.t	χ^2_3 (m.s.l.)	coef.	asy.t	χ^2_3 (m.s.l.)	coef.	asy.t	χ^2_3 (m.s.l.)
Exchange rate equation	constant	0.003	0.353	8.102	0.003	0.288	2.582	0.007	0.705	2.904	0.009	1.355	1.649
	Δs_t	0.209	1.938	(0.044)	0.083	0.754	(0.461)	0.073	0.653	(0.407)	0.144	1.269	(0.684)
	$\Delta \tilde{p}_t$	1.038	1.482		0.279	0.209		0.321	0.271		0.108	0.144	
	z_t	0.093	2.140		0.067	1.504		0.083	1.659		0.017	0.515	

Table 2. Characterizing long-horizon predictability with fixed coefficient UIP fundamentals.

A. Backward-averaged regression

Estimation technique	Horizon	Pound $\hat{\gamma}_k$	Pound $t(0)$	Pound $t(4)$	Deutschmark $\hat{\gamma}_k$	Deutschmark $t(0)$	Deutschmark $t(4)$	Swiss franc $\hat{\gamma}_k$	Swiss franc $t(0)$	Swiss franc $t(4)$	Yen $\hat{\gamma}_k$	Yen $t(0)$	Yen $t(4)$
OLS	1	−1.080	−1.322	−1.228	−0.353	−0.434	−0.425	−1.009	−1.302	−1.322	−0.378	−0.901	−0.841
	4	−3.569	−0.898	−0.820	−1.367	−0.390	−0.378	−3.347	−0.999	−1.021	−1.417	−0.606	−0.558
	8	−5.893	−0.629	−0.562	−2.656	−0.352	−0.333	−5.549	−0.774	−0.779	−5.895	−0.919	−0.859
	12	−11.805	−0.766	−0.723	−6.980	−0.556	−0.525	−10.479	−0.890	−0.889	−17.558	−1.499	−1.434
	16	−22.645	−0.986	−0.933	−10.066	−0.511	−0.481	−16.396	−0.922	−0.910	−29.319	−1.565	−1.489
SUR	1	−0.542	−0.974	−0.833	−0.621	−0.912	−1.175	−0.684	−1.016	−1.364	−0.148	−0.416	−0.419
	4	0.180	−0.000	0.056	−0.449	0.039	−0.198	−0.864	−0.091	−0.396	−0.274	−0.075	−0.132
	8	1.188	0.076	0.155	−0.451	−0.057	−0.088	−0.312	−0.045	−0.067	−3.998	−0.952	−0.730
	12	−2.563	−0.329	−0.211	−1.377	−0.242	−0.155	−0.044	−0.068	−0.006	−8.525	−0.897	−0.848
	16	−16.720	−0.845	−0.948	−6.074	−0.277	−0.440	−5.245	0.279	−0.437	−8.887	−0.452	−0.538

	Statistics	Horizon 1	Horizon 4	Horizon 8	Horizon 12	Horizon 16
FE	$\hat{\gamma}_k$	−0.494	−1.916	−5.386	−13.425	−22.574
	$t(0)$	−1.111	−0.777	−0.898	−1.302	−1.363
	$t(4)$	−1.154	−0.839	−0.909	−1.312	−1.414

B. Vector error-correction model

	Horizon	Pound $\hat{\beta}_k$	Pound asy.t	Pound R^2	Deutschmark $\hat{\beta}_k$	Deutschmark asy.t	Deutschmark R^2	Swiss franc $\hat{\beta}_k$	Swiss franc asy.t	Swiss franc R^2	Yen $\hat{\beta}_k$	Yen asy.t	Yen R^2
Implied long horizon statistics	1	−1.091	−1.206	0.021	−0.353	−0.420	0.002	−1.010	−1.300	0.019	−0.381	−0.840	0.009
	4	−3.753	−1.294	0.047	−1.370	−0.461	0.007	−3.378	−1.226	0.051	−0.316	−0.276	0.001
	8	−4.819	−1.280	0.038	−2.314	−0.461	0.010	−5.733	−1.220	0.073	−0.275	−0.258	0.000
	12	−5.042	−1.273	0.027	−2.949	−0.461	0.011	−7.405	−1.215	0.080	−0.278	−0.260	0.000
	16	−5.089	−1.270	0.021	−3.375	−0.460	0.011	−8.592	−1.208	0.081	−0.278	−0.260	0.000

	variable	Pound coef.	Pound asy.t	Pound χ^2_3 (m.s.l.)	Deutschmark coef.	Deutschmark asy.t	Deutschmark χ^2_3 (m.s.l.)	Swiss franc coef.	Swiss franc asy.t	Swiss franc χ^2_3 (m.s.l.)	Yen coef.	Yen asy.t	Yen χ^2_3 (m.s.l.)
Exchange rate equation	constant	−0.005	−0.839	3.988	0.005	0.699	0.351	0.009	1.185	1.625	0.010	1.504	2.388
	Δs_t	−0.495	−0.402	(0.263)	−0.310	−0.216	(0.950)	0.144	0.087	(0.654)	0.419	0.753	(0.496)
	$\Delta \tilde{p}_t$	0.645	0.528		0.351	0.242		−0.145	−0.087		−0.289	−0.539	
	z_t	−1.104	−1.230		−0.377	−0.435		−0.992	−1.194		−0.247	−0.523	

slope coefficient, its asymptotic t-ratio, and the regression R^2 implied by the VECM, the coefficient estimates of the exchange-rate equation from the VECM, and Wald statistics for the test that the slope coefficients in this equation are jointly zero.[13]

PPP Fundamentals

Beginning with Table 1, under the PPP fundamentals we see that the slope coefficients, asymptotic t-ratios, and implied long-horizon regression R^2 display the familiar pattern of increasing, at least initially, with horizon.

Table 3. Characterizing long-horizon predictability with fixed coefficient monetary-model fundamentals.

A. Backward-averaged regression

Estimation technique	Horizon	Pound			Deutschmark			Swiss franc			Yen		
		$\hat{\gamma}_k$	$t(0)$	$t(4)$	$\hat{\gamma}_k$	$t(0)$	$t(4)$	$\hat{\gamma}_k$	$t(0)$	$t(4)$	$\hat{\gamma}_k$	$t(0)$	$t(4)$
	1	0.052	1.854	1.646	0.030	1.078	1.033	0.068	1.841	1.786	0.024	0.762	0.668
	4	0.249	2.086	1.926	0.141	1.196	1.169	0.307	1.939	2.008	0.165	1.210	1.088
OLS	8	0.616	2.346	2.225	0.367	1.423	1.394	0.680	1.919	2.036	0.506	1.658	1.550
	12	1.039	2.433	2.490	0.830	1.950	1.968	1.416	2.339	2.570	1.081	2.050	1.978
	16	1.396	2.225	2.274	1.316	1.987	2.018	2.586	2.709	3.088	1.677	1.994	1.904
	1	0.040	1.135	1.870	0.025	1.423	1.561	0.067	2.711	3.426	0.034	1.233	1.131
	4	0.208	1.366	2.399	0.131	1.643	1.860	0.300	2.493	3.740	0.216	1.818	1.692
SUR	8	0.474	1.540	2.422	0.273	1.525	1.765	0.556	1.763	3.087	0.543	2.034	2.024
	12	0.790	1.590	2.494	0.560	1.615	2.213	0.745	1.004	2.371	1.017	1.685	2.214
	16	1.048	1.552	2.272	0.795	1.250	2.070	1.200	0.998	2.413	1.576	1.209	2.099

	Statistics	Horizon				
		1	4	8	12	16
FE	$\hat{\gamma}_k$	0.036	0.181	0.485	0.912	1.224
	$t(0)$	1.880	2.277	2.754	3.101	2.761
	$t(4)$	1.735	2.128	2.624	3.188	2.857

B. Vector error-correction model

	Horizon	Pound			Deutschmark			Swiss franc			Yen		
		$\hat{\beta}_k$	asy.t	R^2	$\hat{\beta}_k$	asy.t	R^2	$\hat{\beta}_k$	asy.t	R^2	$\hat{\beta}_k$	asy.t	R^2
Implied	1	0.056	2.373	0.046	0.031	1.126	0.021	0.068	1.868	0.035	0.058	2.022	0.034
long	4	0.259	2.573	0.197	0.127	1.147	0.083	0.262	2.001	0.134	0.263	2.089	0.137
horizon	8	0.496	2.920	0.369	0.243	1.202	0.155	0.441	2.170	0.213	0.503	2.213	0.240
statistics	12	0.673	3.258	0.476	0.346	1.265	0.216	0.544	2.318	0.242	0.697	2.361	0.310
	16	0.786	3.471	0.514	0.438	1.332	0.267	0.597	2.409	0.241	0.847	2.519	0.355

	variable	coef.	asy.t	χ^2_3 (m.s.l.)	coef.	asy.t	χ^2_3 (m.s.l.)	coef.	asy.t	χ^2_3 (m.s.l.)	coef.	asy.t	χ^2_3 (m.s.l.)
Exchange	constant	−0.005	−0.757	7.178	0.005	0.701	1.395	0.008	0.770	3.602	0.010	1.525	8.327
rate	Δs_t	0.187	1.741	(0.127)	0.050	0.455	(0.845)	0.054	0.495	(0.463)	0.119	1.085	(0.080)
equation	$\Delta \tilde{p}_t$	−0.420	−0.875		0.046	0.086		0.071	0.135		0.989	2.169	
	z_t	0.120	0.268		−0.127	−0.220		0.294	0.414		0.260	0.461	
	z_t	0.067	2.152		0.032	1.057		0.068	1.703		0.054	1.639	

For the backward-averaged regression, $t(0)$ and $t(4)$ under OLS yield generally similar implications. The exception occurs for the BP at $k = 16$, but even here $t(4) = 3.44$ exceeds $t(0) = 3.06$ by only 12%. Across the four currencies at $k = 1$, with $t(0)$ values of 1.3, 1.4, 1.6 and 0.20 for the BP, DM, SF and yen respectively. There is little evidence that the exchange rate is predictable. At $k = 16$, there is marginal evidence that PPP fundamentals contain predictive power for the DM ($t(0) = 2.0$) and SF ($t(0) = 1.9$) while the evidence for the BP is rather strong with $t(0) = 2.6$.

The SUR coefficient estimates are similar to the OLS estimates for the DM and yen, but are much smaller for the SF at the 12 and 16 quarter horizons and for the BP at the 8 and 12 quarter horizons. There is considerable divergence between $t(0)$ and $t(4)$ for the SUR estimates with $t(4)$ typically being the larger value. While these t-values are larger than their OLS counterparts for the DM, SF and yen, they are smaller for the BP. The estimates associated with SUR appear to be somewhat erratic.

Table 4. Characterizing long-horizon predictability with fitted DOLS monetary-model fundamentals.

A. Backward-averaged regression

Estimation technique	Horizon	Pound			Deutschmark			Swiss franc			Yen		
		$\hat{\gamma}_k$	$t(0)$	$t(4)$	$\hat{\gamma}_k$	$t(0)$	$t(4)$	$\hat{\gamma}_k$	$t(0)$	$t(4)$	$\hat{\gamma}_k$	$t(0)$	$t(4)$
	1	0.048	1.554	1.379	0.034	1.219	1.167	0.071	1.882	1.821	0.055	1.488	1.297
	4	0.236	1.790	1.633	0.156	1.327	1.303	0.316	1.963	2.033	0.328	2.040	1.865
OLS	8	0.564	1.945	1.821	0.401	1.567	1.546	0.706	1.969	2.094	0.865	2.396	2.333
	12	1.259	2.704	2.902	0.858	2.035	2.068	1.432	2.347	2.578	1.798	2.895	3.001
	16	2.009	2.897	3.202	1.343	2.046	2.090	2.541	2.652	3.000	3.011	3.039	3.205
	1	0.023	0.874	0.979	0.027	1.682	1.749	0.064	2.897	3.158	0.072	2.649	2.161
	4	0.127	1.138	1.337	0.135	1.970	2.016	0.276	2.764	3.300	0.420	3.565	3.149
SUR	8	0.284	1.239	1.350	0.273	1.831	1.898	0.494	2.062	2.719	0.934	3.395	3.332
	12	0.873	1.963	2.587	0.555	1.986	2.233	0.757	1.542	2.376	1.565	2.960	3.157
	16	1.470	2.285	2.952	0.804	1.689	2.095	1.261	1.580	2.506	2.421	2.550	2.970

	Statistics	Horizon				
		1	4	8	12	16
FE	$\hat{\gamma}_k$	0.041	0.205	0.520	1.151	1.821
	$t(0)$	1.844	2.171	2.467	3.272	3.357
	$t(4)$	1.706	2.067	2.451	3.737	4.019

B. Vector error-correction model

	Horizon	Pound			Deutschmark			Swiss franc			Yen		
		$\hat{\beta}_k$	asy.t	R^2	$\hat{\beta}_k$	asy.t	R^2	$\hat{\beta}_k$	asy.t	R^2	$\hat{\beta}_k$	asy.t	R^2
Implied	1	0.048	1.563	0.028	0.035	1.272	0.024	0.070	1.914	0.037	0.076	2.465	0.051
long	4	0.226	1.810	0.121	0.143	1.301	0.095	0.272	2.048	0.140	0.344	2.647	0.208
horizon	8	0.397	1.909	0.193	0.271	1.369	0.176	0.458	2.232	0.224	0.637	3.030	0.352
statistics	12	0.491	1.909	0.207	0.382	1.446	0.242	0.565	2.399	0.356	0.846	3.453	0.431
	16	0.523	1.811	0.183	0.477	1.527	0.293	0.620	2.505	0.256	0.984	3.804	0.466

	variable	coef.	asy.t	χ^2_3 (m.s.l.)	coef.	asy.t	χ^2_3 (m.s.l.)	coef.	asy.t	χ^2_3 (m.s.l.)	coef.	asy.t	χ^2_3 (m.s.l.)
Exchange	constant	−0.005	−0.795	5.467	0.005	0.701	1.718	0.008	0.777	3.747	0.010	1.561	8.543
rate	Δs_t	0.191	1.751	(0.243)	0.050	0.461	(0.787)	0.055	0.508	(0.441)	0.126	1.146	(0.074)
equation	$\Delta \tilde{p}_t$	−0.056	−0.126		0.032	0.060		0.068	0.129		0.742	1.682	
	z_t	0.176	0.384		−0.140	−0.243		0.283	0.389		0.338	0.599	
	z_t	0.055	1.723		0.036	1.200		0.071	1.744		0.064	1.700	

$t(0)$ and $t(4)$ in the pooled FE regression display only small differences. Here, the evidence that the PPP fundamentals have predictive power is firm at horizons of 12 and 16 quarters with asymptotic t-ratios exceeding 2.0.

Turning to the VECM and looking across the four currencies at $k = 1$ we again see little evidence of exchange of exchange-rate predictability. The implied slope coefficients are not significant at the 5% level, and the Wald test of the zero restrictions on the exchange-rate equation is marginally significant only for the BP. At the 3- and 4-year horizons, however, the implied regression statistics indicate that the PPP fundamentals have predictive power for the SF, and (marginally) for the DM.

To sum up, the FE regression provides the strongest evidence that PPP fundamentals contain long-horizon predictive power. For a given currently, the results across estimation techniques are not uniform. The OLS backward-averaged regression slope coefficients are significant at the 5% level at $k = 16$ for the BP, DM and SF, while the implied VECM slopes are significant only for the SF. Exploiting cross-currency information by pooling, apparently results in more precise estimates than those of the multivariate VECM.

UIP Fundamentals

Table 2 displays estimation results using the forward premium. The slope coefficients are again seen to increase in magnitude with horizon, and displays the characteristic 'wrong' sign associated with exchange-rate regressions on the forward premium. However, the evidence of predictive power is very weak as none of the asymptotic t-ratios in the table exceed 2.0. Although the backward-averaged regression slope coefficients and the VECM implied long-horizon regression slope coefficients are large in magnitude compared with those obtained with the PPP fundamentals, the VECM-implied R^2s are very low at each of the horizons considered.

A Priori Specified Monetary-Model Fundamentals.

Table 3 contains results using the monetary-model fundamentals with the income-elasticity of money demand set to 1. Here, we observe that the slope coefficients, asymptotic t-ratios, and implied R^2s increase with the forecast horizon, up through $k = 12$.

The asymptotic ts for the backward-averaged regression estimated by OLS are robust to the two choices of lag length and present reasonably strong evidence that the exchange rate is predictable at the 4-year horizon for the BP ($t(0) = 2.22, t(4) = 2.27$) and the SF ($t(0) = 2.71, t(4) = 3.10$). The evidence is slightly weaker for the other two exchange rates ($t(0) = 1.99, t(4) = 2.02$ for the DM, $t(0) = 1.99$, $t(4) = 1.90$ for the yen).

The SUR coefficient estimates tend to lie below the OLS estimates. The associated asymptotic t-ratios again appear to be unreliable as their values are somewhat erratic and sizeable differences between $t(0)$ and $t(4)$ are displayed.

The estimated slope coefficients in the FE regression increase with horizon while the t-ratios display a hump shape reaching a maximum at $k = 12$. These asymptotic ts are robust to the choice of lag length, and with values of both $t(0)$ and $t(4)$ exceeding 2.0 at $k = 4, 8, 12$ and 16, the evidence that the monetary models contain long-horizon predictive power for the exchange rate is strong.

The implied long-horizon statistics from the VECM increase with the forecast horizon as well. We note that these implied R^2s exceed those obtained under the PPP fundamentals, that the implied asymptotic t-ratios of the slope coefficients exceed 2.0 at $k = 4, 8, 12$ and 16 for the BP, SF and yen, and that the Wald tests marginally reject the null hypothesis that quarterly changes in the log exchange rate are unpredictable for the BP and yen.

Overall, the monetary-model fundamentals appear to contain significant long-horizon predictive power for the exchange rate.

Monetary-Model Fundamentals Estimated by DOLS

Table 4 reports results with λ estimated by DOLS. In the OLS backward-averaged regressions the evidence that the log exchange rate is predictable at the 3- and 4-year horizons is stronger (compared with setting $\lambda = 1$), as $t(0)$ and $t(4)$ exceed 2.0 for each of the four currencies at these horizons. SUR again produces erratic results which are contrary to the OLS estimates. The SUR slope coefficient estimates lie below the OLS estimates, and $t(4)$ typically exceeds $t(0)$ by sizeable amounts. While the OLS $t(0)$ increases with k for the yen and SF, the SUR $t(0)$ displays a hump shape for the yen and declines with k for the SF.

The pooled FE regression provides strong evidence that the DOLS-estimated monetary-model fundamentals have predictive power. Both $t(0)$ and $t(4)$ values exceed 2.0 at horizons of 1 year or more.

From the VECM estimates, long-horizon predictability is apparent for the SF and yen. These results are less supportive for the BP than those in which λ is set to 1. The Wald test marginally rejects the exclusion restrictions only for the yen.

Monetary-Model Fundamentals Estimated by Joint DOLS

Table 5 reports the results using monetary-model fundamentals by pooling the cointegrating regres-

Table 5. Characterizing long-horizon predictability with fixed JDOLS monetary-model fundamentals.

A. Backward-averaged regression

Estimation technique	Horizon	Pound			Deutschmark			Swiss franc			Yen		
		$\hat{\gamma}_k$	$t(0)$	$t(4)$	$\hat{\gamma}_k$	$t(0)$	$t(4)$	$\hat{\gamma}_k$	$t(0)$	$t(4)$	$\hat{\gamma}_k$	$t(0)$	$t(4)$
	1	0.054	1.822	1.615	0.025	0.915	0.879	0.057	1.668	1.632	0.043	1.189	1.037
	4	0.257	2.057	1.895	0.122	1.041	1.014	0.266	1.818	1.878	0.270	1.723	1.563
OLS	8	0.630	2.293	2.174	0.322	1.251	1.217	0.572	1.714	1.800	0.764	2.162	2.075
	12	1.132	2.550	2.650	0.782	1.836	1.838	1.311	2.264	2.479	1.635	2.665	2.700
	16	1.585	2.427	2.529	1.258	1.901	1.914	2.639	2.848	3.318	2.718	2.746	2.790
	1	0.036	1.047	1.637	0.028	1.822	1.741	0.064	3.226	3.598	0.060	2.243	1.816
	4	0.201	1.338	2.271	0.140	2.054	1.999	0.289	3.175	3.980	0.359	3.047	2.593
SUR	8	0.447	1.533	2.238	0.265	1.755	1.715	0.507	2.280	3.018	0.825	3.028	2.839
	12	0.862	1.770	2.640	0.558	1.763	2.148	0.712	1.432	2.341	1.405	2.501	2.753
	16	1.196	1.804	2.484	0.809	1.428	2.032	1.332	1.542	2.768	2.228	2.048	2.639

	Statistics	Horizon				
		1	4	8	12	16
FE	$\hat{\gamma}_k$	0.038	0.189	0.500	1.013	1.411
	$t(0)$	1.908	2.209	2.570	3.077	2.799
	$t(4)$	1.736	2.081	2.540	3.387	3.176

B. Vector error-correction model

	Horizon	Pound			Deutschmark			Swiss franc			Yen		
		$\hat{\beta}_k$	asy.t	R^2	$\hat{\beta}_k$	asy.t	R^2	$\hat{\beta}_k$	asy.t	R^2	$\hat{\beta}_k$	asy.t	R^2
Implied	1	0.056	2.169	0.043	0.026	0.959	0.018	0.056	1.678	0.028	0.073	2.387	0.046
long	4	0.263	2.389	0.184	0.107	0.971	0.069	0.221	1.802	0.109	0.329	2.518	0.187
horizon	8	0.493	2.668	0.333	0.208	1.012	0.130	0.375	1.919	0.173	0.618	2.794	0.319
statistics	12	0.653	2.896	0.413	0.299	1.059	0.184	0.464	2.012	0.195	0.832	3.102	0.399
	16	0.745	2.981	0.426	0.382	1.109	0.231	0.510	2.067	0.191	0.982	3.383	0.440

	variable	coef.	asy.t	χ^2_3 (m.s.l.)	coef.	asy.t	χ^2_3 (m.s.l.)	coef.	asy.t	χ^2_3 (m.s.l.)	coef.	asy.t	χ^2_3 (m.s.l.)
Exchange	constant	−0.005	−0.768	6.802	0.005	0.703	1.072	0.007	0.740	3.035	0.010	1.541	8.668
rate	Δs_t	0.189	1.752	(0.146)	0.048	0.444	(0.899)	0.049	0.448	(0.552)	0.125	1.139	(0.070)
equation	$\Delta \tilde{p}_t$	−0.318	−0.683		0.065	0.120		0.090	0.170		0.867	1.962	
	z_t	0.141	0.312		−0.117	−0.202		0.337	0.464		0.303	0.539	
	z_t	0.066	2.066		0.026	0.892		0.005	1.528		0.063	1.734	

Table 6. Out-of-sample prediction with fixed coefficient PPP fundamentals. Sample extends through 1994,4 and forecasting begins at 1982,1.

		Pound		Deutschmark		Swiss franc		Yen	
Description	k	U	$\mathcal{DM}$	U	$\mathcal{DM}$	U	$\mathcal{DM}$	U	$\mathcal{DM}$
OLS	12	1.120	0.374	1.520	0.972	0.777	−1.075	0.916	−0.489
	16	1.226	0.838	1.659	1.343	0.697	−3.252	0.977	−0.074
GMM-	12	1.095	0.362	1.311	0.789	0.736	−1.299	0.950	−0.324
SUR	16	1.191	0.688	1.195	0.939	0.520	−3.601	1.026	0.086
GMM-	12	1.220	1.017	0.844	−1.222	0.787	−1.368	0.881	−0.856
FE	16	1.205	1.383	0.546	−4.174	0.535	−2.915	0.955	−0.143
Complete	12	1.018	0.264	1.335	1.384	0.892	−3.862	0.809	−1.942
VECM	16	1.006	0.243	1.300	4.785	0.607	−3.067	0.677	−2.518
VECM implied	12	1.262	1.319	1.109	1.096	0.916	−2.443	0.830	−2.563
regression	16	1.374	2.941	1.023	0.681	0.652	−2.480	0.715	−3.545

sions across countries and estimating a common value of λ. Compared to fixing $\lambda = 1$, the OLS evidence that the exchange rates are predictable over long horizons remains strong for the BP, SF and yen, but becomes less forcible for the DM.

The SUR estimates characteristically lie below the OLS coefficients and two versions of the t-ratios display widely differing values.

The FE t-ratios again display the hump shape reaching a maximum at $k = 12$ and continue to provide support in favour of exchange rate predictability at horizons of 1 to 4 years ahead.

Summary of the Full-Sample Estimates

The monetary-model fundamentals provide the strongest and most consistent evidence that exchange rate changes over long horizons are predictable. Results employing estimated values of λ are marginally more supportive than those using λ fixed at 1. The PPP fundamentals also appear to contain predictive power at long horizons as well, but the evidence here is less forcible. The long-horizon predictive content of the UIP fundamentals enjoy little statistical support.

Out-of-Sample Prediction

We generate out-of-sample predictions by the long regressions and the VECM. The long-horizon regressions are estimated by OLS, and by GMM as an SUR system and as an FE regression. From the VECM, we report two predictions—the full-information VECM forecast incorporating both the short-run and long-run dynamics of the system, and the forecast from the VECM's implied long-horizon regression.[14]

We employ the standard rolling estimation strategy in which the models estimated with data available through 1982,1 are used to form an initial set of k-period ahead predictions for $1982{,}1 + k$. We then update the sample with observations from 1982,2 and repeat the drill, continuing this way through the end of the dataset at 1994,4.

As in Chinn and Meesee (1995), Flood and Rose (1993) and Mark (1995), we find that macroeconomic fundamentals are pretty useless for understanding exchange-rate movements over short horizons of 2 years or less. To reduce the proliferation of tables and to keep with our emphasis on long horizons, we thus report our prediction results only for $k = 12$ and 16.

We employ two measures of forecast accuracy. The first, which we denote by U, is the ratio of the root-mean-square-prediction errors of the econometric model being evaluated to that of the driftless random walk. Values of U will be less than 1.0 when point predictions of econometric model are more accurate than the naive 'no change' prediction. Secondly, we employ the method of Diebold and Mariano (1995) to test the null hypothesis that the forecasts from the econometric model and the random walk are equally accurate. Let t_0 be the date at which the first forecast is formed, $u_{i,t}, (i = 1, 2)$ be the prediction error of model i, $N_f = T - t_0 - k + 1$ be the number of forecasts, $\bar{d} = (1/N_f)\sum_{t=t_0+k}^{T}(u_{1,t}^2 - u_{2,t}^2)$ be the sample mean-squared-error-differential, $f_d(0)$ be the spectral density of $\{u_{1,t}^2 - u_{2,t}^2\}$ at frequency 0. Diebold and Mariano's test statistic is

$$\mathscr{D}\mathscr{M} = \frac{\bar{d}}{\sqrt{\frac{2\pi\hat{f}_d(0)}{N_f}}}. \tag{18}$$

We use $\hat{f}_d(0) = \hat{\omega}_0 + \sum_{j=1}^{k-1}(\hat{\omega}_j + \hat{\omega}_{-j}), \hat{\omega}_j = (1/N_f)\sum_{t=t_0+k+j}^{T}(u_{1,t}^2 - u_{2,t}^2)(u_{1,t-h}^2 - u_{2,t-j}^2)$ which is a consistent estimate of $f_d(0)$ assuming that the forecast errors display $(k-1)$th order serial correlation. Under the null hypothesis of equal forecast accuracy, the mean-square-error differential is zero and $\mathscr{D}\mathscr{M}$ has an asymptotic standard normal distribution. Our normalization sets the random walk to be model '2' so that values of $\mathscr{D}\mathscr{M}$ will be negative when the fundamentals outperform the random walk.

Forecasting with PPP Fundamentals

We find in Table 6, that the PPP fundamentals have predictive power for the SF and the yen as indicated by the preponderance of U-statistic values less than 1. The yen results are surprising in light of the insignificant results from the full-sample regressions (Table 1). PPP apparently does not work in forecasting the BP.

Comparing the alternative estimators and formulations finds that only the fixed-effects long-horizon regression generates forecasts for the DM that outperform the random walk with $U = 0.84$ and $\mathscr{D}\mathscr{M} = -1.22$ at $k = 12$ and $U = 0.55$ and $\mathscr{D}\mathscr{M} = -4.17$ at $k = 16$. The FE long-horizon regression beats the random walk for the SF and the yen as well, but the statistical significance of their VECM forecasts are higher. The complete VECM performs better than its implied long-horizon regression for all but the DM. The contribution to prediction accuracy of the short-run dynamics is noticeable in this case.

Forecasting with UIP Fundamentals

Table 7 also contains surprising results for the yen. Whereas the full-sample estimates in Table 2 were uniformly insignificant, the forward-premium predictions of the yen significantly outperform the random walk at both the 3- and 4-year horizons.

Comparing the alternative formulations, there is little difference among the full-information VECM forecasts, the implied long-horizon regression from the VECM, the FE and the SUR estimates of the long-horizon regression. At the 4-year horizon, forecasts of the DM from pooled estimates either through SUR ($U = 0.97$, $\mathscr{D}\mathscr{M} = -1.57$) or the FE regression ($U = 0.91$ $\mathscr{D}\mathscr{M} = -2.32$) outperforms the random walk. Similarly, SUR and FE point predic-

Table 7. Out-of-sample prediction with fixed coefficient covered interest parity fundamentals. Sample extends through 1994,4 and forecasting begins at 1982,1.

		Pound		Deutschmark		Swiss franc		Yen	
Description	k	U	$\mathscr{D}\mathscr{M}$	U	$\mathscr{D}\mathscr{M}$	U	$\mathscr{D}\mathscr{M}$	U	$\mathscr{D}\mathscr{M}$
OLS	12	1.419	1.869	1.160	1.493	1.185	0.531	0.861	−3.031
	16	1.754	2.539	1.058	5.866	1.146	0.359	0.792	−10.977
GMM-	12	1.361	1.490	1.027	0.793	0.957	−0.285	0.878	−2.486
SUR	16	1.807	2.300	0.974	−1.573	0.896	−0.377	0.791	−9.576
GMM-	12	1.412	1.521	1.035	0.951	0.050	−0.971	0.863	−2.527
FE	16	1.661	3.027	0.913	−2.317	0.706	−1.472	0.765	−10.467
Complete	12	1.383	1.899	1.080	2.127	1.116	0.418	0.838	−2.614
VECM	16	1.549	3.572	0.973	−1.733	0.904	−0.272	0.736	−4.409
VECM implied	12	1.368	1.765	1.054	2.025	0.986	−0.097	0.844	−2.650
regression	16	1.534	3.576	0.967	−2.976	0.797	−0.766	0.733	−4.283

Table 8. Out-of-sample prediction with fixed coefficient monetary-model fundamentals. Sample extends through 1994,4 and forecasting begins at 1982,1.

		Pound		Deutschmark		Swiss franc		Yen	
Description	k	U	$\mathcal{DM}$	U	$\mathcal{DM}$	U	$\mathcal{DM}$	U	$\mathcal{DM}$
OLS	12	0.751	−1.132	1.025	0.069	0.666	−2.765	0.851	−0.863
	16	1.087	0.280	0.928	−0.166	0.344	−2.676	0.882	−0.742
GMM-	12	0.656	−1.939	0.948	−0.183	0.677	−2.603	0.852	−1.120
SUR	16	0.874	−0.432	0.902	−0.254	0.339	−2.617	0.813	−0.943
GMM-	12	0.887	−1.704	0.956	−0.249	0.746	−3.091	0.810	−1.525
FE	16	0.802	−0.943	0.820	−0.642	0.356	−2.633	0.761	−1.303
Complete	12	1.005	0.152	1.018	0.209	0.795	−2.050	0.701	−1.489
VECM	16	0.943	−2.902	0.852	−1.061	0.512	−2.189	0.621	−1.599
VECM implied	12	1.174	1.161	0.997	−0.290	0.877	−1.835	0.797	−2.968
regression	16	1.224	3.087	0.897	−1.901	−0.616	−2.184	0.697	−3.196

tions for the SF are more accurate than the random walk, but these are not significant. The forward premium exhibits no ability to predict the BP at either the 3- and 4-year horizons.

Forecasting with A Priori Fixed Coefficient Monetary-Model Fundamentals

The results in Table 8 are consistent with the full sample estimates in the sense that the monetary-model fundamentals display some measure of predictability for each of the four exchange rates at both the 3- and 4-year horizons. The ability to predict is highest for the SF, followed by the yen, the BP, and the DM. At $k = 16$, the U-statistics indicate that the FE regression achieves reductions in RMPSE relative to the random walk of 64% for the SF, 24% for the yen, 20% for the BP, and 18% for the DM.

In comparing the SUR and FE predictions to OLS we see that pooling helps to produce improved forecasts for the BP and DM, but less so for the SF and yen. Both the full-information VECM and the VECM's implied long-horizon regression forecasts outperform the random walk for the SF and the yen. The full-information forecasts are significantly better for the SF, while the implied regression forecasts are significantly better for the yen. Overall, the FE regression generates the most accurate predictions for the BP, DM and SF while the full-information VECM appears to work best for the yen.

Figure 1 displays plots of the actual 4-year changes in the log exchange rate and the full-information VECM's in-sample and out-of-sample forecasts. Figure 2 displays the same information for the FE regression. These figures illustrates the improvement in fit and forecastability of the FE regression over the VECM for the BP and the DM. Note also that the divergence between the in-sample fitted values and out-of-sample predictions is largely eliminated from about 1990 on.

Forecasting with DOLS Estimated Monetary-Model Fundamentals

The results reported in Table 9 display only minor variations from the forecast results λ fixed at 1. Based on the U-statistics, each of the 5 yen predictions are an improvement over the fixed $\lambda = 1$ predictions, whereas the OLS, SUR and FE predictions for the BP, DM and SF are worse.

The best overall predictor employing these fundamentals appears to be the full-information VECM. At $k = 4$, these forecasts have U-statistic values of 0.64, 0.80, 0.53, and 0.51 for the BP, DM, SF and yen, respectively.

Forecasting with Joint DOLS Estimated Monetary-Model Fundamentals

The results displayed in Table 10 show that only the DM FE and VECM forecasts benefit from estimating a common value of λ as opposed to fixing $\lambda = 1$. Otherwise, the $\lambda = 1$ results dominate.

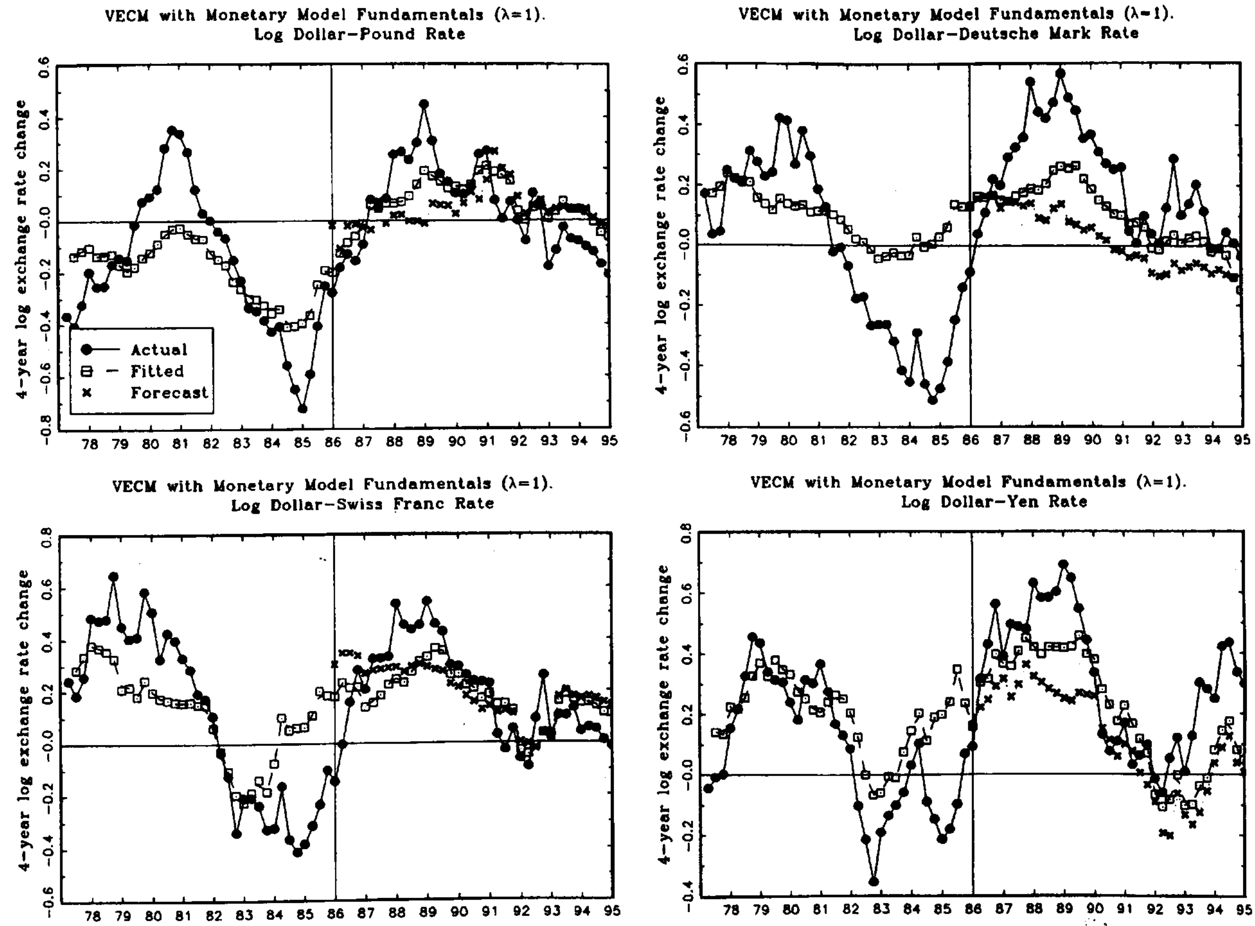

Figure 1. Plots of 4-year changes in the log exchange rate and the full-information VECM's in-sample and out-of-sample forecasts.

Table 9. Out-of-sample prediction with fitted DOLS monetary-model fundamentals. Sample extends through 1994,4 and forecasting begins at 1982,1.

		Pound		Deutschmark		Swiss franc		Yen	
Description	k	U	$\mathcal{D}.\mathcal{M}$	U	$\mathcal{D}.\mathcal{M}$	U	$\mathcal{D}.\mathcal{M}$	U	$\mathcal{D}.\mathcal{M}$
OLS	12	1.743	1.136	0.977	−0.060	1.174	0.681	0.798	−2.497
	16	1.767	2.664	1.059	0.206	1.088	5.160	0.647	−1.585
GMM-	12	1.416	0.950	0.906	−0.326	1.005	0.045	0.817	−3.902
SUR	16	1.441	10.308	0.953	−0.154	0.842	−1.872	0.649	−1.632
GMM-	12	0.785	−9.378	0.863	−0.473	0.679	−2.973	0.739	−2.718
FE	16	0.717	−1.269	0.932	−0.284	0.493	−2.523	0.639	−2.183
Complete	12	0.774	−1.732	0.906	−0.514	0.853	−2.637	0.655	−2.575
VECM	16	0.636	−6.853	0.803	−1.218	0.528	−2.559	0.511	−2.307
VECM implied	12	1.107	0.835	0.902	−2.586	0.906	−1.902	0.774	−3.335
regression	16	1.105	3.321	0.798	−2.151	0.592	−2.676	0.648	−3.235

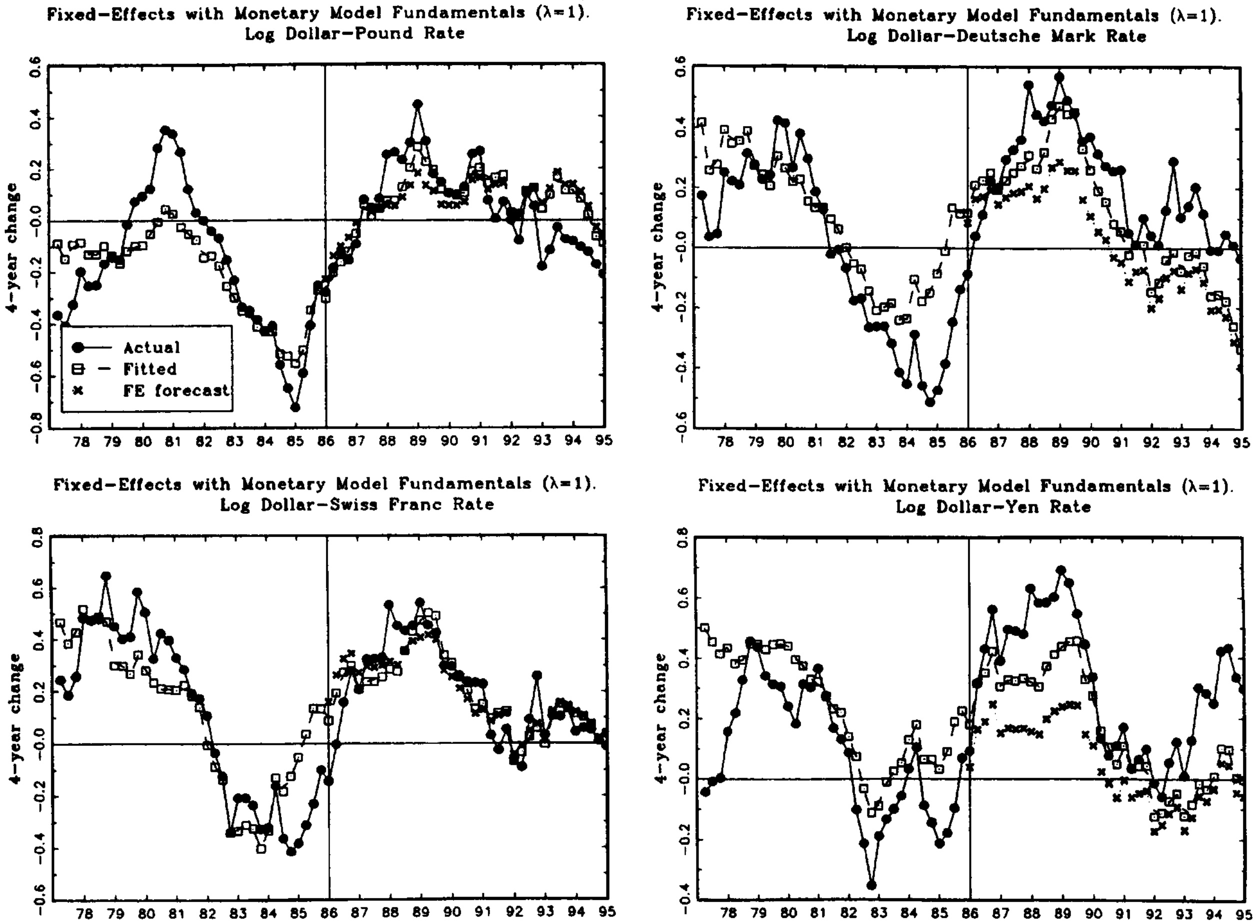

Figure 2. As Figure 1 for the FE regression.

Table 10. Out-of-sample prediction with fitted JDOLS monetary-model fundamentals. Sample extends through 1994,4 and forecasting begins at 1982,1.

		Pound		Deutschmark		Swiss franc		Yen	
Description	k	U	$\mathcal{D}.\mathcal{M}$	U	$\mathcal{D}.\mathcal{M}$	U	$\mathcal{D}.\mathcal{M}$	U	$\mathcal{D}.\mathcal{M}$
OLS	12	1.105	1.981	1.040	0.106	0.857	−0.731	0.871	−1.374
	16	1.246	4.482	0.988	−0.026	0.472	−5.870	0.925	−2.703
GMM-	12	0.873	−1.096	0.974	−0.088	0.831	−0.905	0.874	−1.962
SUR	16	1.022	0.387	0.989	−0.025	0.439	−3.781	0.957	−1.231
GMM-	12	0.957	−2.047	0.924	−0.383	0.795	−1.284	0.930	−2.383
FE	16	0.780	−1.182	0.847	−0.499	0.393	−3.200	0.991	−0.152
Complete	12	0.986	−0.321	1.008	0.092	0.859	−2.551	0.700	−2.026
VECM	16	0.851	−2.987	0.841	−1.047	0.528	−2.622	0.744	−16.018
VECM implied	12	1.182	1.203	0.993	−0.306	0.906	−2.075	0.813	−4.294
regression	16	1.215	3.611	0.892	−1.817	0.617	−2.437	0.752	−7.032

CONCLUSIONS

We conclude by returning to the questions raised in the introduction.

1. 'Which of the three alternative fundamentals proposed in the literature has the highest predictive ability?' Of the three fundamental exchange-rate values that we examined, the monetary-model fundamentals appear to be the most robust predictors of long-run changes in nominal exchange rates. It is interesting and somewhat anomalous that the monetary-model fundamental performs better than fundamental values implied by two of the monetary approach's building blocks.

   Whether on the basis of in-sample fit or out-of-sample prediction, none of the fundamentals were found to have significant predictive power at short horizons, thus confirming Chinn and Meese's (1995), Flood and Rose's (1993), and Mark's (1995) findings that macroeconomic fundamentals are pretty useless in understanding short-run exchange-rate dynamics.
2. 'How important is the empirical modelling strategy?' and 'Can more efficient estimates and predictions be obtained from pooling or do multivariate techniques such as vector error correction methods prove superior?' The full-sample fixed-effect regressions generally provided the most forceful evidence that the exchange rate is predictable. While SUR t-ratios appear to be somewhat unreliable for drawing inference. SUR out-of-sample forecasts illustrated that sizeable benefits can be obtained by pooling the data across even our very small cross-section of four currencies. The RMPSE's from the SUR and fixed-effects regressions are systematically lower than those from the OLS regression forecasts. The relative success of the fixed-effects regression suggests the various markets may be characterized by common speeds of adjustment toward a common set of fundamental values.

   The contribution from explicitly incorporating the short-run dynamics in prediction is marginal. The full-information VECM forecasts are roughly as accurate as the fixed-effects regression and only marginally more accurate than the VECM implied long-horizon regression. Apparently, the additional parameter uncertainty had only a modest effect on the predictions due to the small size of the VECM systems. The problem of possible misspecification in the VECM seems not to have been an issue here.
3. 'Does one draw the same conclusions from the standard analysis of econometric estimates as from an evaluation of out-of-sample predictions?' For three of the currencies, the answer we found is yes. The yen, however, is an exception. While there is little statistical evidence from the in-sample results to suggest that PPP or UIP fundamentals contained predictive power for the yen, their out-of-sample predictions were significantly better than the random walk at the longer horizons.

   The significance levels of tests for predictability were higher when the fundamental value was estimated from cointegrating regressions than when fixed *a priori*, but the results on out-of-sample prediction accuracy are reversed.

APPENDIX

A description of the data sources is provided. The procedures used to estimate λ for the monetary model fundamentals are described and the closed form solution to the GMM estimator of the seemingly-unrelated system is presented.

The Data

We employed data obtained from the OECD *Main Economic Indicators, CITIBASE*, the Harris Bank *Foreign Exchange Weekly Review* (Harris), and *International Financial Statistics*, (IFS). We collected observations from 1970,1 to 1994,4.

United States Real GDP (s.a.), M1 and CPI (n.s.a.) from *CITIBASE*.

Switzerland Real GDP (s.a.), M1 and CPI (n.s.a.) from OECD *Main Economic Indicators*.

Germany Real GDP (s.a.), M1 (n.s.a.) from OECD *Main Economic Indicators*. CPI (n.s.a.) from *CITIBASE*.

Britain Real GDP (s.a.) from OECD *Main Economic Indicators*. Real GDP (s.a.) from OECD *Main Economic Indicators*. M0 (n.s.a.) from the IMF's

International Financial Statistics, CPI (n.s.a.) from *CITIBASE.*

Japan Real GDP (s.a.) and M1 (n.s.a.) from OECD *Main Economic Indicators.* CPI (n.s.a.) from *CITIBASE.*

For regressions run with PPP and monetary model fundamentals, the spot exchange rates are end-of-month US dollar prices of the foreign currency from OECD *Main Economic Indicators.* The analysis of UIP fundamentals employs spot and 3-month forward rates from the Harris Bank's *Foreign Exchange Weekly Review.* Our measure of money and prices takes a moving average of the current and previous three quarter's observations to estimate the seasonal and fluctuations in these data.

Estimating λ

For country i, let $\tilde{s}_{i,t} = s_{i,t} - (m_{i,t} - m^*_{i,t})$ and $\tilde{y}_{i,t} = y_{i,t} - y_{i,t}$. Stock and Watson's (1993) DOLS estimate of λ is obtained by running OLS on the regression

$$\tilde{s}_{i,t6} = \delta + \lambda_i \tilde{y}_{i,t} + \sum_{j=1}^{3} (\Delta\tilde{y}_{i,t-j}\phi_j + \Delta\tilde{y}_{i,t+j})\psi_j) + v_{i,t}. \tag{A.1}$$

The deviation of the current log spot rate from its fundamental value is given by,

$$z_{i,t} = \tilde{s}_{i,t} - \delta - \lambda_i \tilde{y}_{i,t}. \tag{A.2}$$

We get our joint estimate of λ by setting $Y_{i,t} = (1, \tilde{y}_{i,t}, \Delta\tilde{y}_{i,t-3}, \ldots, \Delta\tilde{y}_{i,t+3})$. We constrain λ to be equal across the four currencies and stack Equation (A.1) into a system of equations which we estimate by GMM using

$$\begin{pmatrix} v_{1,t} & Y_{1,t} \\ v_{2,t} & Y_{2,t} \\ v_{3,t} & Y_{3,t} \\ v_{4,t} & Y_{4,t} \end{pmatrix}$$

as the orthogonality conditions. The deviations of the log spot rate from its fundamental value is again formed from Equation (A.2).

The GMM Estimator of the SUR System

Let y^i_t be the k-period change in the log exchange rate for currency i. We are interested in the system of equations,

$$y_t = Z_t\eta + u_t \tag{A.3}$$

where

$$y_t = \begin{bmatrix} y^i_t \\ \vdots \\ y^n_t \end{bmatrix}, Z_t = \begin{bmatrix} (1, z^1_t) & & 0 \\ 0 & \ddots & \\ & & (1, z^n t) \end{bmatrix},$$

$$\eta = \begin{bmatrix} \eta_1 \\ \vdots \\ \eta_n \end{bmatrix}, u_t = \begin{bmatrix} u^1_t \\ \vdots \\ u^n_t \end{bmatrix}.$$

Using $\tilde{z}_t = (1, z^1_t, \ldots, z^n_t)'$ as the instrument vector, the GMM estimator of the parameter vector η is,

$$\eta_T = (D'_T W_T D_T)^{-1} D'_T W_T \left(\frac{1}{T}\sum_{t=1}^{T} (\tilde{z}_t \otimes y_t)\right) \tag{A.4}$$

with

$$\mathrm{Var}(\eta_T) = \frac{1}{T}[D'_T W_T D_T]^{-1} \tag{A.5}$$

where

$$D_T = \frac{1}{T}\sum_{t=1}^{T} (\tilde{z}_t \otimes z'_t),$$

$$\tilde{Q}_{T,j} = \frac{1}{T}\sum_{t=j+1}^{T} \tilde{z}_t \tilde{z}'_{t-j};$$

$$\Sigma_{t,j} = \frac{1}{T}\sum_{t=j+1}^{T} u_t u'_{t-j}$$

$$S_{T,w} = \Omega_{T,0} + \sum_{j=1}^{m} \omega_j(\Omega_{T,j} + \Omega'_{T,j});\ \omega_j = 1 - j/(m+1)$$

$$\Omega_{T,j} = \tilde{Q}_{T,j} \otimes \Sigma_{T,j}.$$

ENDNOTES

1. Research to date has been less successful in exploiting non-linearities in the exchange-rate process for prediction. Random walk predictions dominate Diebold and Nason's (1990) non-parametric exchange-rate predictions at weekly horizons from

1986 to 1987. Engel and Hamilton (1990) find that one-year-ahead forecasts of their quarterly Markov-switching model during 1984–1988 for US dollar prices of the Deutschmark, French franc, and pound are beaten by the random walk. When Engel (1994) extended that data set to include six US dollar nominal exchange rates, however, his point predictions from the Markov-switching model have lower mean-square error than the driftless random walk for three of the six exchange rates during the forecast period 1986,2–1991,1.
2. This result was originally noted, but not for forcibly pursued in Meese and Rogoff (1983b).
3. Long-run PPP has attracted widespread interest. For recent surveys on the state of PPP research, see Breuer (1994) and Froot and Rogoff (1995). For a recent broad-based survey on exchange rate economics, (including PPP), see Taylor (1995).
4. We do not entertain real variables such as fiscal policy or productivity shocks. Chinn (1994) has shown these variables have been found to have little explanatory and predictive power for exchange rates.
5. We note that the out-of-sample predictions should do badly if the cointegration assumption is violated.
6. There are sound theoretical arguments from Balassa (1964)–Samelson (1964) models with traded and non-traded goods sectors emphasizing productivity differenced that call for relaxing unit-valued coefficients and specifying the PPP fundamentals as $\phi_t = \alpha_1 p_t + \alpha_2 p_t^*$. Since the imposition of unit-valued coefficients is supported by the recent literature on long-run PPP we do not pursue this tack. We note that we have experimented by modelling $\phi_t = \alpha(p_t - p_t^*)$ and estimating the coefficient α. Doing so did not lead to an improvement.
7. We assume that z_t is known. Taking z_t as the error term from a cointegrating regression puts us in Pagen's (1984) generated regressor framework. Estimation of z_t in this way may induce conditional heteroscedasticity into the regression error term but causes no additional complications.
8. Campbell (1993) describes how the positive relation between the slope coefficient and forecast horizon and the R^2 and forecast horizon depends on the persistence of $\{z_t\}$. He also shows how mean-reversion in the dependent variable induces negatively serially correlated error terms $\{\varepsilon_{t,k}\}$, which at least initially contributes to a shrinking of the asymptotic standard errors relative to point estimates of the slope coefficients as the forecast horizon is lengthened.
9. Using a monthly dataset of 431 observations on equity returns and dividend yields to calibrate his data generating process. Hodrick finds that the empirical critical level of a one-tail test that the slope coefficient is zero, is approximately 2.0 at each of the horizons that he investigates.
10. Again, we rely on Hodrick (1992) to justify doing asymptotic inference. Assuming that the lag length of the dynamical system is known, Hodrick shows that the small sample distributions of his VAR generated long-horizon statistics are very close to their asymptotic distributions.
11. The extension to include an arbitrary finite number of lags is straightforward, but redundant in our case.
12. In implementing this procedure, we truncate the summations at 200.
13. We perform this test because, in the VECM, if there is no short-horizon predictability, there will be no long-horizon predictability either.
14. The full-information VECM prediction $E_t(s_{t+k}) = s_t + e_1 E_t(\sum_{j=1}^{k} y_{t+j}) = s_t + e_1(\sum_{j=0}^{k} B_j)y_t$.

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