

A NEW APPROACH TO FORECASTING EXCHANGE RATES⁺

by

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Abstract

Building on purchasing power parity theory, this paper proposes a new approach to forecasting exchange rates using the Big Mac data from The Economist magazine. Our approach is attractive in three aspects. Firstly, it uses easily-available Big Mac prices as input. These prices avoid several serious problems associated with broad price indexes, such as the CPI, that are used in conventional PPP studies. Secondly, this approach provides real-time exchange-rate forecasts at any forecast horizon. Such real-time forecasts can be made on a day-to-day basis if required, so that the forecasts are based on the most up-to-date information set. These high-frequency forecasts could be particularly appealing to decision makers who want up-to-date forecasts of exchange rates. Finally, as our forecasts are obtained through Monte Carlo simulation, estimation uncertainty is made explicit in our framework which provides the entire distribution of exchange rates, not just a single point estimate. A comparison of our forecasts with the random walk model shows that although the random walk is superior for very short horizons, our approach tends to dominate over the medium to longer term.

Keywords: Exchange-rate forecasting, Big Mac prices, purchasing power parity, Monte Carlo simulation

JEL Classification Code: F30, C53

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“Most people dealing in the foreign exchange market have no clue about the fundamental value of the dollar (the “quality” of the dollar). Specialists and professors do not know either, at least within a broad range of dollar-euro rates between say, \$1.0 and \$1.3. For every specialist telling us that the fundamental value of the dollar is close to \$1.3 to the euro there will be another one affirming that \$1.0 is near the fundamental value. Anything in between is a fair game.”

Paul de Grauwe, Financial Times. Jan 13, 2006. p. 19.

1. Introduction

Since the breakdown of the Bretton Woods system of fixed exchange rates in the early 1970s, forecasting currency values has become crucial for many purposes such as international comparisons of incomes, earnings and the costs of living by international agencies, management and alignment of exchange rates by governments, and corporate financial decision making. Even though it is widely agreed that forecasting exchange rates is a notoriously difficult task (as indicated by de Grauwe’s comments above), there are still many attempts to do so. This paper builds on purchasing power parity theory and introduces a new approach to forecast exchange rates based on the Big Mac data published by The Economist magazine.

In the exchange-rate forecasting literature, the paper by Meese and Rogoff (1983) remains highly influential as it demonstrates that structural models are unable to outperform the random walk model, which simply predicts that the exchange rate would not change at all. Though the random walk model has occupied center stage for many years, practitioners and researchers continue to employ a variety of techniques in an effort to beat the random walk. Generally speaking, there are three distinct approaches to exchange-rate forecasting:

- *Surveys*, which are popular among practitioners. But it is found that while survey forecasts provide some predictive power (Lai, 1990, Chinn and Frankel, 1994a), sometimes they are biased (Chinn and Frankel, 1994b) and unreliable (Harrison and Mogford, 2004).
- *Model-based approaches*, which include (i) fundamentals models, (ii) linear time series models and (iii) non-linear time series models. The monetary approach is a popular fundamentals model, with explanatory variables including relative prices levels, interest rate differentials, and other determinants of equilibrium in the money market. Abhyabkara et al. (2005) show that the economic value, as opposed to the statistical accuracy, of exchange-rate forecasts based on a fundamentals model, can be greater than that based on the random walk model. The traditionally-used linear time series models are the random walk, ARIMA, or multivariate systems models such as the VAR model and the VECM. A recent stream of research focuses on non-linear time series models, which includes the simultaneous nearest-

neighbour approach by Fernandez-Rodriguez et al. (1999), and the neural networks of Zhang and Hu (1998).

- *The composite forecast approach*, which involves taking weighted averages of forecasts from alternative approaches. MacDonald and Marsh (1994) review the earlier literature and their examination of various methods of forecast combination shows that they can lead to improvements in forecast accuracy. More recent examples of composite forecasts include Qi and Wu (2003) in which neural networks and monetary fundamentals are used to model exchange rates, and Alvarez-Diaz and Alvarez (2005) who combine forecasts from two non-linear models.

PPP-based exchange-rate forecasts belong to the fundamentals stream of the model-based approach, and use the relative price levels in two countries in question as fundamentals. There are three versions of PPP: the absolute version, the relative version, and the stochastic relative version. While the first two versions are often explained in textbooks, it is the third version that of particular interest to researchers. Relative PPP implies that the exchange rate and the relative prices are exactly proportional, so that the real exchange rate (the exchange rate deflated by relative prices) is a constant. Stochastic relative PPP, on the other hand, allows for systematic deviations from this constant, and treats this constant as the center of gravity to which the real exchange rate reverts in the long run. Research on this weaker version of PPP examines the time-series properties of exchange rates, and tests for mean reversion and the speed of adjustment to long-run equilibrium values. The estimated long-run exchange rates and the speed-of-adjustment parameters are then used for the purpose of exchange-rate forecasting.

In most studies of PPP, the real exchange rate is usually defined using the price index based on a broad basket of goods, such as the consumer price index, wholesale price index, or GDP deflator.¹ The use of broad indexes is subject to several serious problems however. First, many price indexes are published only at infrequent intervals; in Australia, for example, the CPI is published only quarterly and then with a considerable lag, which limits its usefulness for timely forecasts. Second, differences in consumption patterns in different countries mean that broad indexes relate to the prices of baskets of goods and services that can differ substantially internationally.² In PPP theory the ratio of prices at home to those abroad is meant to reflect differing monetary conditions only, but when broad indexes are used, this ratio could be dominated by heterogeneity of

¹ For an analysis of the impact of using differing broad price indexes on exchange-rate forecasts, see Xu (2003).

² For example, food occupies less than 10 percent of total consumption in rich countries, while it absorbs something like 50 percent in the poorest.

consumption patterns. Thus, rather than comparing like with like to isolate the underlying monetary factors, the CPI-based price ratios could be subject to substantial biases or be contaminated with measurement error. Finally, most statistical agencies construct price indexes by carrying out surveys of prices and derive the index weights from household expenditure surveys for CPIs, and use similar procedures for other types of indexes. Accordingly, these indexes are subject to sampling error, a problem that is ignored by most PPP studies.³ In this paper, we largely avoid these problems by using a single-good basket -- a McDonald's Big Mac hamburger.

The main contributions of the paper are twofold: (i) It develops a new approach to forecasting exchange rates, based on easily-available Big Mac prices. In this approach, we model not only real exchange rates, but also the evolution of Big Mac prices.⁴ (ii) This new approach is sufficiently flexible to be able to provide forecasts of exchange rates in real time. The real time attraction is that the approach incorporates the most recent shocks into the model, thus allowing the forecasts to be made on the basis of a comprehensive information set. Such real-time forecasts are of practical significance for decision makers in government, the corporate world and those in financial markets, who require up-to-date forecasts.

The structure of the paper is as follows. Section 2 briefly describes the Big Mac data, while Section 3 models these prices. In Section 4 we draw on Lan (2006) to model Big Mac real exchange rates, to estimate exchange rate equations, and to test for PPP. This leads to a convenient way to forecast real exchange rates for any horizon, using a Monte Carlo approach to derive the whole distribution of future rates, rather than single point estimates. Section 5 then merges the forecasts of Big Mac prices and real exchange rates to yield forecasts of nominal exchange rates. Using the random walk model as the benchmark, in Section 6 we evaluate the performance of our approach, and find that although the random walk is superior for short forecast

³ There is possibly a further problem with broad price indexes in that they are dominated by the prices of goods that do not enter into international trade, such as rents, retail margins, much of medical care, utility services, etc. For the prices of such nontraded goods, it is far from clear exactly how they are related (if at all) to the exchange rate. While it cannot be claimed that the use of Big Mac prices completely avoids this problem, the traded component of a Big Mac is likely to be larger than that of the basket underlying the CPI for instance.

⁴ A previous Burgernomics approach to forecasting exchange rates took the forecast of Big Mac prices as being the in-sample means, based on signal-extraction techniques (Lan, 2006). By contrast, the current paper explicitly models the time-series dynamics of Big Mac prices. We also extend Lan (2006) by introducing the idea of real-time forecasts whereby the horizon is not restricted to be integer. For reviews of the literature on Burgernomics, see Lan (2006) and Ong (2003). For reviews of the whole PPP area, see the surveys by Froot and Rogoff (1995), Lan and Ong (2003), Rogoff (1996), Sarno and Taylor (2002), Taylor and Taylor (2004), and Taylor (2006). While there is still considerable controversy, it is possible to summarise current thinking as follows: As supportive evidence for PPP as a long-run proposition has emerged in recent years, PPP has been resurrected as a theory of long-run exchange rate determination.

horizons, the Big Mac model tends to do better over the medium to longer term. Section 7 presents a refinement to the procedure by adjusting the forecasts to reflect systematic tracking errors in the immediately preceding period. Concluding remarks are presented in the final section.

2. Big Mac Real Exchange Rates

The real exchange rate (RER) is conventionally defined in terms of natural logarithms as

$$(1) \quad q_{ct} = \log \frac{P_{ct}}{S_{ct} P_t^*},$$

where P_{ct} is the price level in country c in terms of domestic currency in year t , P_t^* the corresponding price level in the US, and S_{ct} the nominal exchange rate quoted as the domestic currency cost of \$US1. According to PPP, a positive (negative) value of the RER q_{ct} implies that country c 's currency is overvalued (undervalued) in year t . The support for PPP comes from the stationarity of real exchange rates.

Instead of using broad indices such as the CPI or WPI, this paper uses a single-good basket -- a McDonald's Big Mac hamburger, whose prices have been published in The Economist magazine since 1986.⁵ This "basket" includes tradable items such as buns and beef, as well as nontradable items such as rent and wages. Though sometimes criticised as being too "narrow", the basket is attractive because Big Macs are produced in around 120 countries around the world using almost identical ingredients and the previous Big Mac literature shows that it performs at least as well as other indices used in PPP studies (see, e.g., Chen et al., 2003, Cumby 1996, Ong 1997, 2003, and Parsley and Wei, 2003).

Table 1 presents the Big Mac prices in six major countries and the US and the corresponding nominal exchange rates from 1994 to 2006.⁶ Figure 1 presents the RERs q_{ct} for $c=1, \dots, 6$ countries and $t=1, \dots, 13$ years, calculated using the Big Mac prices.⁷ It can be seen that there are

⁵ In view of the substantial opportunity cost of a full page of The Economist, that the magazine continues to publish the Big Mac article after 20 years indicates its perceived value to its readers. See Lan (2006) and Lan and Ong (2003).

⁶ The exchange rates we consider refer to the six most important currencies. The start of the sample period, 1994, is determined by the earliest year when the bilateral exchange rates of the euro and its member countries are available (http://ec.europa.eu/budget/inforeuro/index.cfm?fuseaction=dsp_html_monthly_rates&Language=en).

⁷ The currency over/under-valuation employed by The Economist magazine is the percentage difference between the PPP exchange rate P_{ct}/P_t^* and the actual rate S_{ct} , $r_{ct} = (P_{ct}/P_t^* - S_{ct})/S_{ct}$. Mathematically, $\log(1+r_{ct}) \approx q_{ct}$ when r_{ct} or q_{ct} is small.

TABLE 1
BIG MAC PRICES AND NOMINAL EXCHANGE RATES

Year	Australia	Britain	Canada	Euro	Japan	Switzerland	US
A. <u>Big Mac prices (Domestic currency units)</u>							
1994	2.45	1.81	2.86	2.51	391	5.70	2.30
1995	2.45	1.74	2.77	2.50	391	5.90	2.32
1996	2.50	1.79	2.86	2.53	288	5.90	2.36
1997	2.50	1.81	2.88	2.50	294	5.90	2.42
1998	2.65	1.84	2.79	2.44	280	5.90	2.56
1999	2.65	1.90	2.99	2.52	294	5.90	2.43
2000	2.59	1.90	2.85	2.56	294	5.90	2.51
2001	3.00	1.99	3.33	2.57	294	6.30	2.54
2002	3.00	1.99	3.33	2.67	262	6.30	2.49
2003	3.00	1.99	3.20	2.71	262	6.30	2.71
2004	3.25	1.88	3.19	2.74	262	6.29	2.90
2005	3.24	1.88	3.27	2.91	250	6.30	3.06
2006	3.25	1.94	3.52	2.94	250	6.30	3.10
B. <u>Nominal exchange rate (Domestic currency cost of US\$1)</u>							
1994	1.42	0.68	1.39	0.88	104	1.44	-
1995	1.35	0.62	1.39	0.74	84	1.13	-
1996	1.27	0.66	1.36	0.79	107	1.23	-
1997	1.29	0.61	1.39	0.87	126	1.47	-
1998	1.51	0.60	1.42	0.92	135	1.52	-
1999	1.59	0.62	1.51	0.93	120	1.48	-
2000	1.68	0.63	1.47	1.08	106	1.70	-
2001	1.98	0.70	1.56	1.14	124	1.73	-
2002	1.86	0.69	1.57	1.12	130	1.66	-
2003	1.61	0.63	1.45	0.91	120	1.37	-
2004	1.44	0.56	1.38	0.83	113	1.28	-
2005	1.30	0.55	1.26	0.82	108	1.25	-
2006	1.33	0.53	1.12	0.78	112	1.21	-

Source: The Economist (various issues).

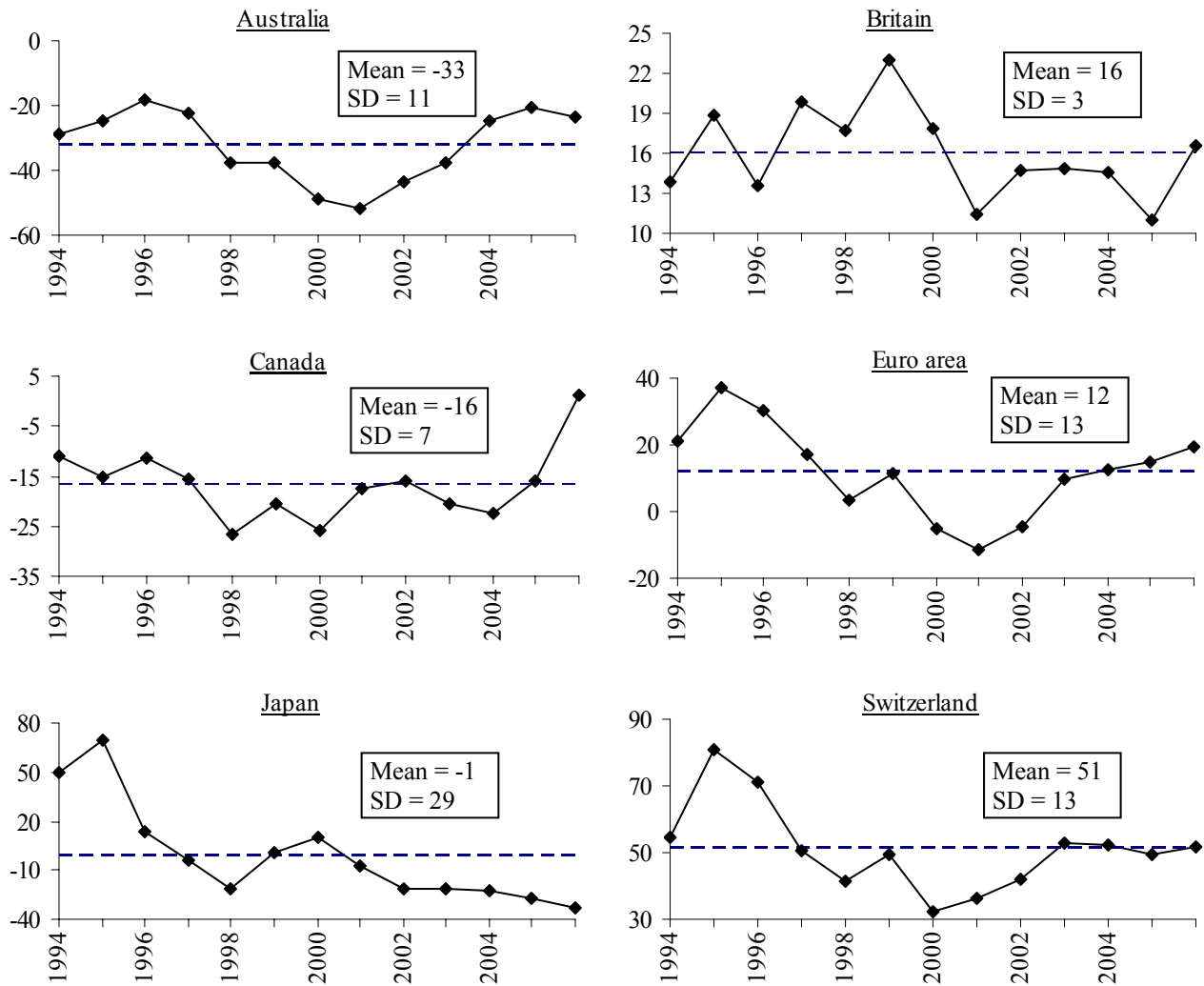
always departures from absolute PPP, i.e., $q_{ct} \neq 0$, and q_{ct} is usually very volatile (except for Britain). In addition, except for Japan and the euro area, the means of q_{ct} are significantly different from zero according to a t-test, suggesting systematic deviations from absolute PPP.

The focal point of our new approach to forecasting exchange rates is the definition of RER, equation (1). In the next three sections, we forecast prices and RERs and then use definition (1) to derive forecasts of nominal rates.

3. Big Mac Price Modeling and Forecasting

Preliminary analysis of the Big Mac prices indicates that it is difficult to model these prices simultaneously in a parsimonious multivariate framework. We thus model the prices for each country as a univariate time series.

FIGURE 1
 BIG MAC REAL EXCHANGE RATES
 (Log difference of relative price from nominal exchange rate $\times 100$)



Due to short time span of the data available, we only examine three alternative models for the prices: (i) a linear trend model; (ii) an AR(1) model; (iii) a linear trend and AR(1) model. Analysis based on a battery of model fit criteria leads to the conclusion that the following linear trend model best describes the data:

$$(2) \quad p_t = \mu + \beta t + v_t,$$

where p_t is the log of the price of a Big Mac in year t , μ and β are parameters, v_t is the disturbance term, and for convenience the country subscript c is omitted. The Durbin-Watson and Lagrange multiplier tests show that the OLS regression residuals for Britain, the Euro area and the US are serially correlated. We thus assume that

$$(3) \quad v_t = \lambda v_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma_\varepsilon^2) \quad \text{for Britain, the Euro area and the US}$$

$$(4) \quad v_t \sim N(0, \sigma_v^2) \quad \text{otherwise.}$$

We then use the Cochrane-Orcutt method to estimate (2) and (3) for the Big Mac prices in the above-mentioned three countries, and OLS to estimate (2) and (4) for those in the remaining four countries.

Suppose that the forecast horizon is h years ahead of the last year of the sample period τ . One attraction of using the linear trend model is that we can forecast the price at any forecast horizon h , as the trend value $h = t$ is not constrained to integer years, but can be a fraction of a year such as one month, one week, one hour or even a few seconds. As discussed below, this has the substantial advantage of allowing high-frequency forecasts that start with the most up-to-date values of the actual exchange rate. To take forecast uncertainty into consideration, we use Monte Carlo simulation techniques as follows. Let $\hat{\mu}$, $\hat{\beta}$, $\hat{\lambda}$, $\hat{\sigma}_e^2$ and $\hat{\sigma}_v^2$ be the data-based estimates of the corresponding parameters. In the j^{th} trial ($j=1, \dots, 10,000$ replications), according to (3) or (4) we generate an error term, denoted by $v_{\tau+h}^{(j)}$, and then use equation (2) to simulate 10,000 values of the price based on the estimates $\hat{\mu}$ and $\hat{\beta}$ and the generated error terms: $p_{\tau+h}^{(j)} = \hat{\mu} + \hat{\beta}(\tau + h) + v_{\tau+h}^{(j)}$, $j=1, \dots, 10,000$. The 10,000 forecasts of the price will be used in Section 5 to obtain real-time forecasts of the nominal exchange rate of the country in question.

4. Real Exchange Rate Modeling and Forecasting

PPP theory implies that the RER has a constant mean and deviations from this constant are temporary and dissipate over time. On the other hand, if PPP does not hold, the RER will have a unit root, deviations from parity are cumulative and the RER does not have a well-defined centre of gravity in the long run. Whether or not RERs are stationary has been a controversial issue in the literature, but in the past decade there is mounting evidence that they are, so that PPP holds in the long run. In this section, we first use the procedures introduced by Lan (2006) to model and test the six Big Mac RERs in a seemingly-unrelated framework, and then extend the methodology to accommodate non-integer forecast horizons.

We assume that the data-generating process for RERs is as follows:

$$(5) \quad \Delta q_{ct} = \alpha_c + \rho q_{c,t-1} + u_{ct}, \quad c = 1, \dots, 6, \quad t = 2, \dots, 13,$$

where α_c is the country-specific intercept, ρ is the common speed-of-adjustment parameter, and u_{ct} is a disturbance term with $E(u_{ct}) = 0$. As there are only 13 years of Big Mac data available,

we have to use a parsimonious specification and therefore only include one lagged value of the RER on the right-hand side of equation (5). We use the first difference of the RER on the left-hand side to ensure that (i) it is stationary under the null hypothesis that each RER evolves as a unit root, and (ii) the standard errors of the estimates are well-defined. Under the null hypothesis, $\rho = 0$ and the alternative of PPP holding corresponds to $\rho < 0$. To take account of cross-currency correlation, equation (5) is estimated by SUR-GLS proposed by O’Connell (1998) in the context of PPP testing.⁸

Due to the presence of the lagged dependent variable in the panel data setting, the SUR-GLS estimates are biased. The existing literature derives analytical expressions for the approximate bias of estimators based on large-sample asymptotics (see, e.g., Kiviet et al., 1995, 1999). For the case of a small sample, Lan (2006) proposes a novel Monte Carlo approach to detect for the presence of bias and then adjust for it.⁹ In what follows, we briefly describe the procedures.

- *Bias detection.* We first examine whether our SUR-GLS estimates are biased. Assume that the error terms in equation (5) for $c = 1, \dots, 6$ are drawn from a multivariate normal distribution with zero mean vector and the covariance matrix Σ , which we estimate by $\hat{\Sigma}$, the matrix of mean squares and cross products of the residuals.¹⁰ The RER changes are then simulated from equation (5) using the SUR-GLS estimates given in column 2 of Table 2 as true values, the values of RER in the previous period and error terms drawn from $N(\mathbf{0}, \hat{\Sigma})$. Using these generated data, we re-estimate equation (5) by SUR-GLS. This procedure is repeated 10,000 times and we compute the mean of 10,000 estimates. For any parameter θ_i , let $\hat{\theta}_i$ be its data-based SUR-GLS estimate, θ_i^* be its “true value” in the simulation, and $\bar{\theta}_i$ be the mean over 10,000 trials. Then the initial proportionate bias is $p_i^{(0)} = [\bar{\theta}_i - \theta_i^*] / \theta_i^*$ with $\theta_i^* = \hat{\theta}_i$. It is found that SUR-GLS leads to the underestimation of point estimates, with the bias ranging from 5 to 39 percent.
- *Iterative scheme for bias adjustment of estimates.* In iteration k , we start with the data-based

⁸ As in Lan (2006), we follow Parkes and Savvides (1999) to conduct an F-test to investigate whether the restriction of ρ being the same across countries in equation (5) is valid in the SUR setting. The test results show that a common speed of adjustment cannot be rejected.

⁹ There is a slight difference between Lan (2006) and the approach taken in this paper. As the time dimension is less than the cross-sectional dimension in Lan (2006), she patterns the covariance matrix to get around this problem. Since there is no such a problem in this paper, we use the data-based estimate of covariance matrix of disturbances $\hat{\Sigma}$ for the SUR-GLS estimation.

¹⁰ The multivariate normal distribution rather than the bootstrap is used in the simulation because it can better capture the cross-currency correlations.

TABLE 2
REAL EXCHANGE RATE ESTIMATION RESULTS

Country c / Estimate (1)	Parameter estimate of RER equation			Equilibrium exchange rate for country c	
	Data-based SUR- GLS estimate (2)	Bias-adjusted estimate (3)	Corrected SE (4)	Mean (5)	RMSE (6)
Country-specific intercept α_c					
Australia	-15.57	-9.35	3.52	-32.72	7.53
Britain	7.95	4.74	1.85	16.53	4.30
Canada	-7.78	-4.81	2.45	-15.92	7.21
Euro area	5.35	2.61	2.61	10.12	9.98
Japan	-6.09	-6.29	9.69	-16.11	20.19
Switzerland	24.56	14.12	5.42	49.82	11.99
Speed of adjustment ρ	-0.48	-0.31	0.08	-	-

Note: All entries except those in the last row are to be divided by 100.

SUR-GLS estimates, and use the proportionate biases from iteration $k-1$, $p_i^{(k-1)}$, to obtain the “true” values of estimates for the simulation $\theta_i^{*(k)}$. In the j^{th} trial ($j=1, \dots, 10,000$) we generate RERs in equation (5) using these true values of estimates and the generated errors, re-estimate (5) by SUR-GLS, and compute bias-adjusted SUR-GLS estimates $\hat{\theta}_i^{\text{ba}(j)}$ using the same proportionate biases used to compute the true values. Finally we calculate the mean of 10,000 $\hat{\theta}_i^{\text{ba}(j)}$, denoted by $\bar{\theta}_i^{\text{ba}}$. The new proportionate bias $p_i^{(k)}$ is then $p_i^{(k)} = \left[\bar{\theta}_i^{\text{ba}} - \theta_i^{*(k)} \right] / \theta_i^{*(k)}$. The procedure ends when from one iteration to the next the changes in the proportionate bias $p_i^{(k)}$ for all estimates are sufficiently small.

- *Correction of standard errors* of the bias-adjusted estimates. Upon convergence, there are 10,000 simulated values of the point estimates and the asymptotic standard errors, $\hat{\theta}_i^{\text{ba}(j)}$, $\text{ASE}_{\theta_i}^{(j)}$, $j=1, \dots, 10,000$. Consider the ratio of the root-mean-square of the 10,000 estimates around their true value to the root-mean-square of the 10,000 asymptotic standard errors. Write ϕ_i for this ratio. If the estimation procedure is working satisfactorily, then ϕ_i should be close to unity. However, it is quite different from one for a majority of parameter estimates, suggesting that the conventionally-defined SUR-GLS asymptotic standard errors do not reflect the true sampling variability of the parameters. We thus correct the asymptotic standard error for $\hat{\theta}_i^{\text{ba}}$ by multiplying its asymptotic standard error by ϕ_i . We conduct another Monte Carlo simulation experiment to confirm that this correction procedure works satisfactorily.

The bias-adjusted estimates and their corrected standard errors are presented in columns 3 and 4 of Table 2. As can be seen, out of the seven estimates, only $\hat{\alpha}_c^{ba}$ for $c = \text{euro area}$ and Japan are not significantly different from zero. To test whether the speed-of-adjustment parameter ρ is equal to zero, we use the t statistic $\tau = \hat{\rho}^{ba} / \text{SE}(\hat{\rho}^{ba})$, which has a value of -3.98. As the iteration-based estimate is used to calculate τ , the distribution of τ is non-standard under the null. We thus derive its critical values by simulating 10,000 values of τ under the null; we then pick the α -percentile of the 10,000 simulated values corresponding to the confidence interval $(100 - \alpha)$ percent. The 1 percent, 5 percent and 10 percent critical values are -4.59, -3.68 and -3.09 respectively, suggesting that the unit root null is rejected at the 5 percent level.¹¹

The conclusion of stationarity enables us to derive the long-run equilibrium value of the real exchange rate for country c as $q_c^E = -\alpha_c / \rho$, obtained by taking expectation of both sides of equation (5). The estimated equilibrium exchange rate involves a ratio of estimated parameters, but under normality such a ratio is typically not normally distributed and does not possess finite moments.¹² We thus employ a Monte Carlo simulation to measure the sampling variability of \hat{q}_c^E , whose 10,000 estimated values follow directly from the bias-adjustment procedure described above. The means and the root-mean-squared errors for the six equilibrium RERs are given in columns 5 and 6 of Table 2. The ratio of the mean to the root-mean-squared error of \hat{q}_c^E provides a t -test on whether an equilibrium RER is significantly different from zero. These t -tests reveal that in the long run, Australian and Canadian dollars are significantly undervalued, the British pound and Swiss franc are overvalued, while the euro and Japanese yen are not significantly different from parity. This result for the euro and yen agrees with Figure 1, where the means of q_{ct} for these two currencies tend not to be too far away from zero (and are not significantly different therefrom).

From the data-generating process of the real exchange rate, equation (5), we can derive by successive substitution the exchange rate for forecast horizon h years ahead of the last year of the sample τ :

$$(6) \quad q_{c,\tau+h} = q_c^E + (\rho + 1)^h (q_{c,\tau} - q_c^E) + \sum_{k=0}^{\tau-1} (\rho + 1)^{h+k} u_{c,\tau-k} + \sum_{m=1}^{\lfloor h \rfloor} (\rho + 1)^{h-m} u_{c,\tau+m} + (\rho + 1)^{h-\lfloor h \rfloor} u_{c,\tau+h},$$

¹¹ We also examined the power of the tests by successively increasing the number of stationary series in two alternative data-generating possibilities: (i) All exchange rates are stationary; and (ii) a sub-set of exchange rates are stationary. The results show that our test has high power only when five or more exchange rates series are stationary. This gives some confidence in our finding that the RERs are stationary.

¹² See, e.g., Bewley and Fiebig (1990), Chen (1999) and Zellner (1978).

where h can be non-integer and we use the floor function $\lfloor h \rfloor \equiv \text{greatest integer} \leq h$. The five components on the right of equation (6) are as follows:

- The equilibrium exchange rate q_c^E , to which the rate moves in the long run;
- The adjustment from the initial deviation $(q_{c,\tau} - q_c^E)$ with the adjustment speed $(\rho + 1)$;
- A weighted sum of in-sample shocks, with the weight $(\rho + 1)^{h+k}$ being accorded to the shock $(h+k)$ years before the year $(\tau + h)$;
- A weighted sum of out-of-sample shocks associated with forecast horizon integer years; and
- The final shock, the influence of which depends on the non-integer time interval, $h - \lfloor h \rfloor$.

To account for forecast uncertainty, we again use simulation techniques to forecast real exchange rates based on equation (6). In each of 10,000 simulation experiments, we generate $\lfloor h \rfloor + 1$ error terms for $c = 1, \dots, 6$ countries from a multivariate normal distribution with zero mean vector and the data-based estimate of the covariance matrix $\hat{\Sigma}$. The 10,000 simulated values of the real exchange rate for country c are obtained using equation (6) based on the biased-adjusted estimate of ρ , the corresponding estimated q_c^E and the generated shocks. In the next section, we merge these RERs with the 10,000 forecast Big Mac prices to obtain real-time forecasts of the nominal exchange rate.

5. Real-Time Exchange-Rate Forecasts

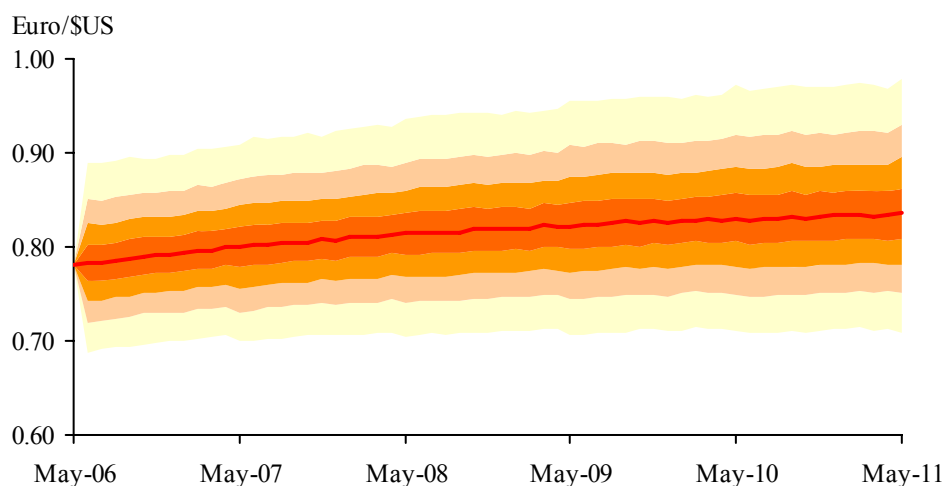
The term “real time” was first used in the computer science literature to describe the level of computer responsiveness that a user senses as being sufficiently immediate to keep up with some external process; one example is the visualisations of the weather as it constantly changes. By a real-time forecast of exchange rates, we mean we use as input “the most recent” or “current” exchange rate data that we can obtain -- for example, from the Yahoo Finance web site. The forecasts we make are thus real time in the sense that the input exchange rates are updated as they constantly evolve, with a minimal “acquisition lag”.

As Big Mac prices and real exchange rates are forecast independently, equation (1) implies that the forecast of the nominal exchange rate in the j^{th} trial for the forecast horizon of h years is $S_{c,\tau+h}^{(j)} = \exp \left[p_{c,\tau+h}^{(j)} - p_{c,\tau+h}^{*(j)} - q_{c,\tau+h}^{(j)} \right]$, $j = 1, \dots, 10,000$. This procedure is used to forecast the six currencies from the last period of the sample for various horizons of up to five years in the future.

Figure 2 contains the fan chart of the euro forecasts made on 22nd May 2006, the date of the most recent publication of the annual Big Mac data.¹³ To illustrate the workings of the non-integer horizon, we express the forecast horizon in terms of years and examine month-by-month forecasts up to 60 months into the future, from June 2006 to May 2011, so that in terms of the notation of Sections 3 and 4, $h = \frac{1}{12}, \frac{2}{12}, \dots, \frac{60}{12}$. The middle dark curve in Figure 2 corresponds to the median of the 10,000 forecast values and the border between any two adjacent sections is the appropriate decile. The lower and upper bounds of each chart contain 80 percent of the simulated forecast values, so that the corresponding vertical distance can be regarded as the 80 percent confidence band. It can be seen that the nominal exchange rate for the euro converges to its equilibrium value over this period with only modest fluctuations, and that as the forecast horizon becomes longer, the confidence band get wider, reflecting the greater uncertainty of the more distant future.

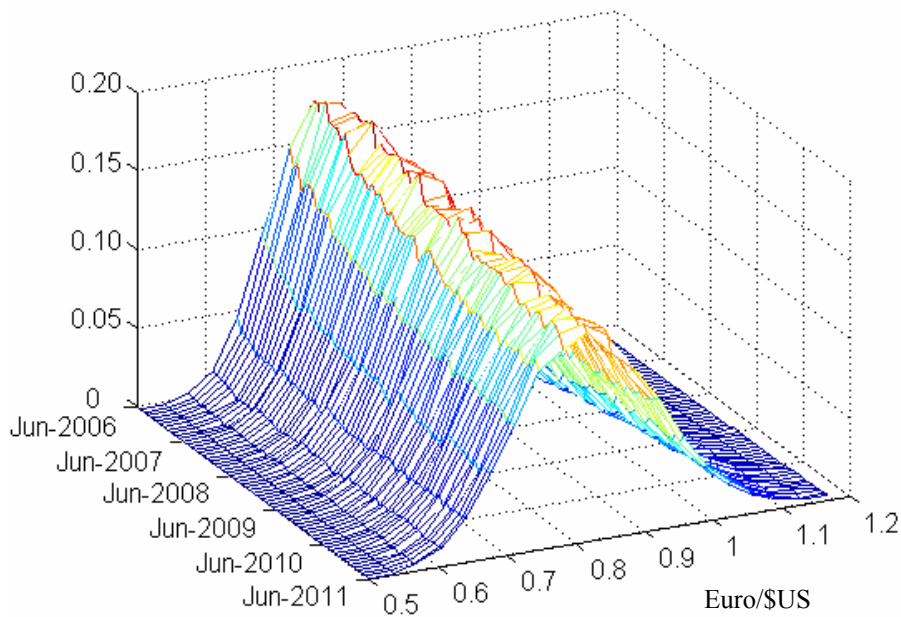
To visualise further the forecasts, in Figure 3 we present a three-dimensional view of the probability distribution for the euro. Consistent with Figure 2, Figure 3 shows that as we move further into the future, the larger the spread of the distributions. Figure 4 gives the conditional distributions of the forecasts for the euro at three points in time in the future: June 2006, December 2008, and May 2011. The mean forecast value changes from €0.79 to €0.82 and finally approaches to the equilibrium of €0.84, with the standard deviation increasing from €0.08 to €0.11.

FIGURE 2
FAN CHART OF REAL-TIME EXCHANGE-RATE FORECASTS: THE EURO



¹³ The fan chart was invented by the Bank of England for reporting its probability forecasts of inflation and output growth (Britton et al., 1998, Wallis, 1999).

FIGURE 3
DISTRIBUTION OF EXCHANGE-RATE FORECASTS: THE EURO



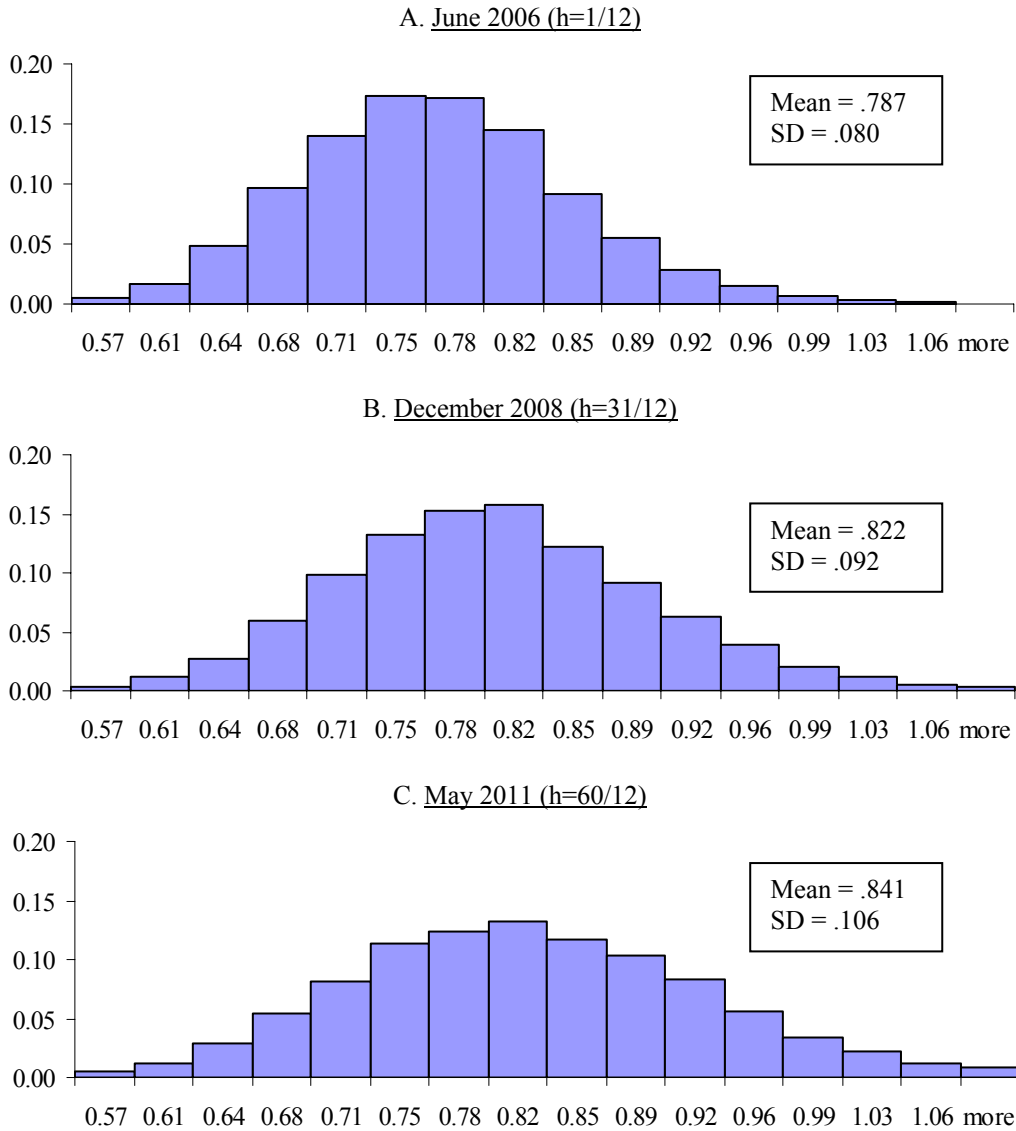
Note: For the purpose of clarity of presentation, some small frequencies for extreme values are not displayed.

6. An Evaluation of Forecasts

Since the influential paper by Meese and Rogoff (1983), the random walk (RW) model remains the standard metric by which to judge the forecast accuracy of an exchange rate model. To evaluate the performance of our approach and compare it to the RW model, in this section we employ a test-set methodology by dividing the existing 13-year sample into two sub-periods. The first ten-years' data are used for estimation and the remaining three years' for out-of-sample forecasts. To compare the two sets of forecasts, we apply three commonly-used criteria for forecast evaluation: (i) direction of change, (ii) bias, and (iii) Theil's (1966) U statistic.

The ability to identify the direction of change in exchange rates is important for short-term currency traders. We use the realised direction of change from the time we make the forecast to the forecast horizon as the gauge, to determine whether the BM model gives the correct direction of change. If the BM model is indistinguishable from the RW model, then the expected probability of the BM winning is 0.5, so that for 36 forecast horizons the number of the correct direction-of-change predictions should be around 18. It takes the value of 22 for the Australian dollar and the Japanese yen, as seen in the last entries of columns 2 and 6 of Table 3. For the remaining four currencies, the direction of change is correct in at least 30 out of 36 cases,

FIGURE 4
 CONDITIONAL DISTRIBUTIONS OF \$A FORECASTS



indicating the superior forecast performance of the BM model. In summary, on the basis of the direction of change, the RW never does substantially better than the BM; additionally, the BM substantially outperforms the RW for all currencies except the Australian dollar and Japanese yen.

We denote the mean forecast of country c 's currency from the BM model for horizon h by F_{ch} , the forecast from the RW by \tilde{F}_{ch} , and the corresponding realised exchange rate by S_{ch} . To avoid cancellation errors, we use the absolute bias, the difference between forecast and actual values, ignoring the sign. To put the forecasts on the same footing, we eliminate different currency units by using (absolute) logarithmic forecast errors $\delta_{ch} = |\log(F_{ch}/S_{ch})|$ and $\tilde{\delta}_{ch} = |\log(\tilde{F}_{ch}/S_{ch})|$. If $\delta_{ch} < \tilde{\delta}_{ch}$, then the BM model is less biased than that from the RW model. Columns 8 to 25 of

TABLE 3
FORECAST EVALUATION

Forecast horizon	Does the Big Mac model predict the right direction? (+ yes, - no)						Bias															Theil's U statistic								
	SA	£	SC	€	¥	SF	SA			£			SC			€			¥			SF			SA	£	SC	€	¥	SF
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	BM	RW	Win	BM	RW	Win	BM	RW	Win	BM	RW	Win	BM	RW	Win	BM	RW	Win	(26)	(27)	(28)	(29)	(30)
May-03	+	+	+	+	+	+	4	4	-	3	2	-	5	5	+	5	5	+	3	2	-	5	4	+	1.03	1.15	1.00	1.06	1.41	1.10
Jun-03	+	+	+	+	+	+	7	7	-	5	5	-	7	7	+	6	6	+	1	1	-	5	4	+	1.00	1.04	.97	1.02	.92	1.22
Jul-03	+	+	+	+	+	+	6	6	-	2	2	-	4	5	+	3	3	+	1	1	-	1	1	-	1.00	1.01	.93	1.00	.44	1.94
Aug-03	+	+	+	+	+	+	5	5	-	0	0	-	3	4	+	1	1	-	0	1	-	0	1	-	.96	.65	.87	.99	.19	.25
Sep-03	+	+	+	+	+	+	6	7	+	1	2	-	6	6	+	2	2	+	3	4	-	0	0	-	.97	.81	.90	.91	.64	.67
Oct-03	+	+	+	+	-	+	11	11	+	5	6	+	8	9	+	6	6	+	7	9	+	4	4	+	.98	.91	.91	.96	.79	1.05
Nov-03	+	+	+	+	-	+	14	14	+	6	6	+	9	10	+	6	6	+	7	9	+	3	3	-	.99	.90	.91	.94	.69	1.11
Dec-03	+	+	+	+	-	+	17	17	+	9	10	+	9	10	+	11	11	+	7	11	+	8	8	+	.98	.92	.89	.95	.67	1.03
Jan-04	-	+	+	+	-	+	21	22	+	13	14	+	10	11	+	13	14	+	8	12	+	10	10	+	.98	.93	.89	.96	.63	1.00
Feb-04	-	+	+	+	-	+	22	22	+	15	16	+	7	9	+	14	14	+	7	12	+	10	10	+	.97	.93	.84	.96	.57	1.00
Mar-04	+	+	+	+	-	+	18	19	+	13	14	+	7	9	+	10	11	+	5	10	+	7	7	+	.97	.91	.83	.94	.46	1.01
Apr-04	+	+	+	+	-	+	17	18	+	11	13	+	6	8	+	8	9	+	5	11	+	5	5	+	.97	.88	.78	.92	.47	1.01
May-04	+	+	+	+	+	+	12	13	+	10	12	+	3	5	+	8	9	+	0	7	-	6	7	+	.94	.87	.65	.86	.06	.98
Jun-04	+	+	+	+	+	+	10	11	+	12	14	+	5	7	+	9	10	+	2	9	-	9	9	+	.93	.87	.71	.89	.23	.98
Jul-04	+	+	+	+	+	+	13	14	+	13	15	+	7	9	+	10	11	+	1	9	-	9	10	+	.94	.87	.77	.91	.14	.98
Aug-04	+	+	+	+	+	+	13	14	+	12	14	+	8	10	+	9	10	+	0	9	-	8	8	+	.93	.84	.78	.89	.05	.96
Sep-04	+	+	+	+	+	+	12	12	+	10	12	+	10	12	+	9	11	+	0	9	-	8	8	+	.94	.81	.80	.86	.01	.95
Oct-04	+	+	+	+	+	+	16	17	+	11	13	+	13	15	+	12	13	+	1	10	+	10	11	+	.95	.82	.84	.89	.06	.96
Nov-04	-	+	+	-	+	-	21	22	+	13	16	+	17	19	+	15	17	+	4	14	+	15	16	+	.95	.83	.86	.90	.29	.97
Dec-04	-	-	+	-	+	-	20	21	+	17	19	+	15	17	+	18	20	+	4	14	+	17	18	+	.95	.86	.84	.92	.27	.97
Jan-05	-	+	+	-	+	-	20	21	+	14	17	+	14	17	+	16	18	+	4	15	+	14	15	+	.95	.82	.83	.89	.28	.95
Feb-05	-	-	+	-	+	-	22	23	+	14	17	+	13	16	+	15	17	+	2	13	+	13	14	+	.95	.82	.81	.90	.12	.94
Mar-05	-	-	+	-	+	-	22	23	+	15	18	+	15	18	+	16	18	+	1	13	+	14	15	+	.95	.82	.83	.90	.08	.94
Apr-05	-	-	+	-	+	-	21	22	+	14	18	+	13	16	+	14	16	+	1	11	+	13	14	+	.95	.81	.82	.87	.08	.95
May-05	-	+	+	+	+	+	20	21	+	12	16	+	11	14	+	12	14	+	1	12	+	11	12	+	.95	.78	.78	.85	.11	.91
Jun-05	-	+	+	+	+	+	20	21	+	10	14	+	12	16	+	8	10	+	3	10	-	7	8	+	.94	.73	.79	.77	.34	.89
Jul-05	-	+	+	+	+	+	18	19	+	6	10	+	14	17	+	7	9	+	7	7	-	4	6	+	.94	.61	.81	.74	1.07	.78
Aug-05	-	+	+	+	+	+	19	20	+	8	12	+	15	19	+	9	11	+	7	8	-	7	8	+	.94	.68	.81	.77	.79	.85
Sep-05	-	+	+	+	+	+	20	21	+	9	13	+	17	21	+	8	11	+	8	8	-	7	8	+	.94	.68	.83	.78	1.01	.83
Oct-05	-	+	+	+	-	+	18	19	+	6	11	+	17	21	+	6	9	+	12	4	-	5	6	+	.93	.60	.82	.72	2.67	.78
Nov-05	+	+	+	+	-	+	16	17	+	4	9	+	17	21	+	4	7	+	15	1	-	3	4	+	.92	.50	.82	.62	11.76	.61
Dec-05	+	+	+	+	-	+	17	18	+	5	10	+	18	22	+	5	8	+	15	1	-	3	5	+	.93	.52	.83	.63	12.58	.68
Jan-06	+	+	+	+	-	+	18	19	+	6	11	+	19	23	+	7	10	+	13	4	-	5	7	+	.94	.56	.83	.72	3.39	.77
Feb-06	+	+	+	+	-	+	16	18	+	5	10	+	19	23	+	5	8	+	16	2	-	3	5	+	.92	.49	.82	.65	8.94	.64
Mar-06	+	+	+	+	-	+	14	16	+	4	9	+	18	23	+	6	9	+	16	2	-	3	5	+	.91	.46	.81	.69	7.11	.65
Apr-06	+	+	+	+	-	+	16	17	+	6	11	+	20	24	+	8	11	+	16	3	-	5	7	+	.92	.52	.83	.71	6.32	.71
No. of “+”	22	32	36	30	22	30				32			31					36			35			15			32			

Notes: 1. The bias for the BM and RW models are to be divided by 100.
2. In the “win” columns, “+” (“-”) indicates that the bias from the BM model is lower (higher) than that from the RW model.

Table 3 contain δ_{ch} and $\tilde{\delta}_{ch}$, as well as the information on whether the BM model wins based on biasness of the forecasts (i.e., whether $\delta_{ch} < \tilde{\delta}_{ch}$ is true). The results show that for the Canadian dollar, the BM model outperforms the RW for each of the 36 forecast horizons considered. For the Australian dollar, British pound and Japanese yen, the RW model dominates for each of the first four/five months of the forecast horizon. Over similar short-term horizons, the BM tends to beat the RW for the euro, while for the Swiss franc the two models are about the same. For all currencies except the yen, over the medium to longer term the BM wins unambiguously on the basis of bias. This is an impressive result. The failure of the BM model for the Japanese yen stems from the substantial volatility of that country's real exchange rate over the estimation period, as can be seen in Figure 1, which leads to its equilibrium exchange rate being estimated very imprecisely (see the fifth entries of column 5 and 6 of Table 2). As its equilibrium value is highly uncertain, the BM forecasts of Japan's real and nominal exchange rates are also problematic. To summarise the bias results, except for the yen (i) the BM model dominates the RW at medium and longer term horizons; and (ii) over the short term, the RW tends to do better, but not always.

The U statistic is the ratio of the root-mean-squared (logarithmic) error (RMSE) from the BM model to the RMSE of the RW model. Since we have 10,000 simulated forecast exchange rates from the BM model, we can calculate its RMSE for each horizon. For the RW model, its RMSE for country c and horizon h is just $\tilde{\delta}_{ch}$. If U is less than 1.0, the BM model is better than the RW, and the closer it is to 0, the better the BM model. Columns 26 to 31 of Table 3 show that over short horizons the RW model tends to dominate, as before with the bias. But over the medium to longer terms, the BM beats the RW for all currencies except the yen (as before). Note also that the BM model works best over the medium to longer terms for the British pound. The BM also works well for the Canadian dollar and the euro, while it is satisfactory for the Swiss franc. The BM model performs marginally better than the RW model for the Australian dollar, with U decreasing slowly over time to end up around 0.9. For Japanese yen, U is erratic, which is again related to the underlying volatility of its real exchange rate.

Table 4 summarises the evaluation results. Column 2 shows that based on the direction of change, the BM model has a clear advantage over the RW model for 4 out of 6 currencies, and it yields marginally more correct predictions than the RW for the other two currencies. In broad terms, the pattern of results from the bias and the U statistic are fairly similar -- the BM model defeats the RW over the medium and longer terms for all currencies except the Japanese yen; see column 4. In terms of the overall score (column 7), the BM model wins for four out of the six currencies, loses for one currency -- the Japanese yen -- and ties with the RW for the Australian dollar.

TABLE 4
SUMMARY OF FORECAST EVALUATION

Country /area	Direction of change	Bias and U statistic		Score		
		Short horizons	Medium and longer horizons	RW	BM	BM-RW
(1)	(2)	(3)	(4)	(5)	(6)	(7)=(6)-(5)
Australia	BM≈RW	RW wins	BM wins	1½	1½	0
Britain	BM wins	RW wins	BM wins	1	2	1
Canada	BM wins	BM wins	BM wins	0	3	3
Euro area	BM wins	BM wins	BM wins	0	3	3
Japan	BM≈RW	RW wins	RW wins	2½	½	-2
Switzerland	BM wins	BM≈RW	BM wins	½	2½	2

Note: For columns 5-6, we employ the scoring convention for the evaluation criteria of columns 2-4. We award the score of ½ if the two models are approximately the same and 1 (0) if the model in question wins (loses).

7. A Tracking-Error Adjustment

Recall from Section 5 that the out-of-sample real-time exchange rate forecasts were derived from the forecasts of Big Mac prices and real exchange rates. In order to evaluate our new approach, in Section 6 we divided the 13-years' in-sample data into two sets -- the first 10-years' data were used for estimation and the rest were used as the test set for the evaluation of forecasts. The results in Section 6 show that the BM model performs no worse than the RW model over the medium and longer horizons for all currencies except Japan. For these five currencies, a comparison of the BM and RW forecasts with actual exchange rates reveals that the mean forecasts from both models consistently exceed the realised rates. Figure 5 gives as an example the euro test-set forecasts. Such persistence of tracking errors suggests a way to further improve our out-of-sample forecasts.

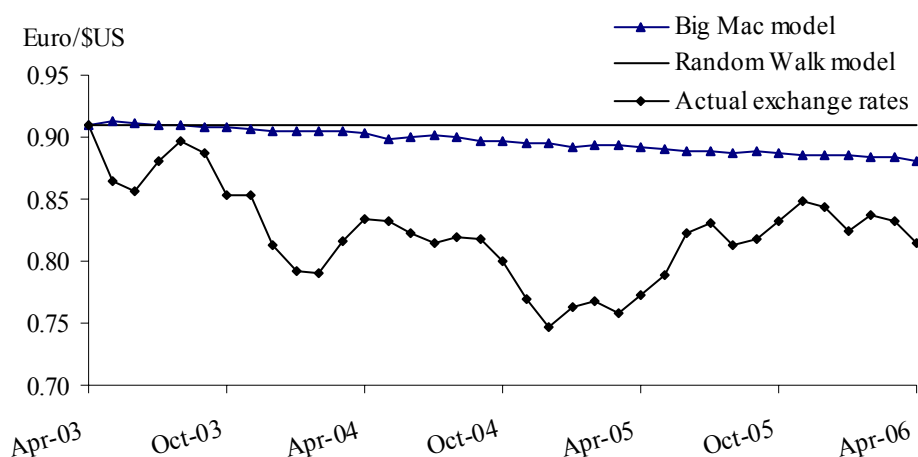
From equation (1), we obtain $\log S_{ct} = \log P_{ct} - \log P_t^* - q_{ct}$. This also holds for the exchange rate and price forecasts, i.e., $\log S_{ct}^F = \log P_{ct}^F - \log P_t^{*F} - q_{ct}^F$ with the superscript "F" denoting forecasts.

Thus

$$\log S_{ct}^F - \log S_{ct} = (\log P_{ct}^F - \log P_{ct}) - (\log P_t^{*F} - \log P_t^*) - (q_{ct}^F - q_{ct}),$$

where the left-hand side is the bias of the nominal exchange rate, which consists of three components, as seen from the right-hand side -- the bias of the domestic price, that of the foreign price and that of the real exchange rate. It seems reasonable to attribute all of the bias in the nominal rate to the real rate. We thus revise the above simulation procedure as follows. Writing γ for the tracking error of the real exchange rate, our revised expression for the equilibrium real exchange rate is $q_c^{E(j)} = -\alpha_c^{(j)} / \rho^{(j)} + \gamma$, where $\alpha_c^{(j)}$ and $\rho^{(j)}$ are the parameter estimates from the

FIGURE 5
TWO SETS OF FORECASTS FOR THE EURO AS AT APRIL 2003



j^{th} ($j=1, \dots, 10,000$) simulation experiments of model (5). The distribution of γ is taken to be normal with mean and variance equal to those of the tracking error of the log of the nominal rate obtained from the test set data. We then proceed exactly as before to simulate the distribution of each nominal rate in each future period.

Table 5 gives the mean of q_{ct}^{E} before and after the tracking-error revision. As can be seen, the impact is to increase algebraically the equilibrium exchange rates in all cases except for the Japanese yen. The root-mean-squared errors of q_{ct}^{E} after revision are slightly larger, as the uncertainty of the biases are now included. Figure 6 presents the tracking-error-revised exchange rate forecasts in the form of fan charts. For the euro, the impact of the adjustment is quite noticeable, as can be seen by comparing the second graph in the right panel of Figure 6 with Figure 2. Rather than depreciating on average against the dollar (Figure 2), the euro now appreciates. Because of the rise in its equilibrium real exchange rate due to the tracking error adjustment, from 10 to 19 percent, at the start of the forecast period the euro is now undervalued, so that it subsequently appreciates as it converges to the new equilibrium value. Figure 7 gives the distributions of exchange rate forecasts after the tracking-error adjustment.

TABLE 5
EQUILIBRIUM REAL EXCHANGE RATES BEFORE AND AFTER TRACKING-ERROR ADJUSTMENT

Country	Before adjustment	After adjustment
Australia	-32.72 (7.53)	-17.13 (7.59)
Britain	16.53 (4.30)	25.41 (4.38)
Canada	-15.92 (7.21)	-4.54 (7.25)
Euro area	10.12 (9.98)	19.11 (10.00)
Japan	-16.11 (20.19)	-17.69 (20.22)
Switzerland	49.82 (11.99)	56.99 (12.01)

Note: Root-mean-squared errors are in parentheses.

In summary, this tracking error adjustment would seem to be a useful final step in producing the forecasts. As it uses information on the performance of the procedure in the test set data that

FIGURE 6
TRACKING-ERROR ADJUSTED FAN CHARTS OF REAL-TIME EXCHANGE-RATE FORECASTS

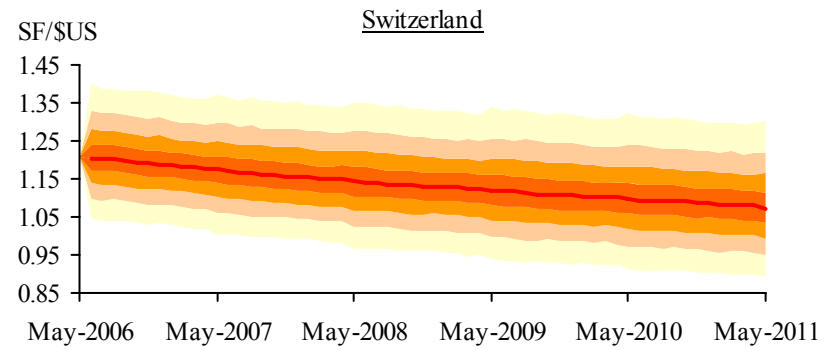
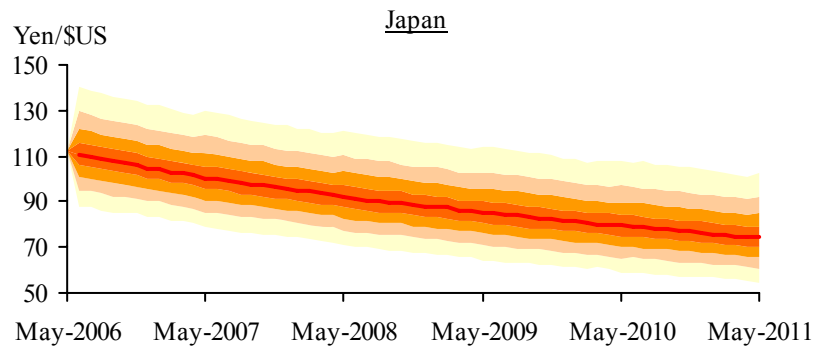
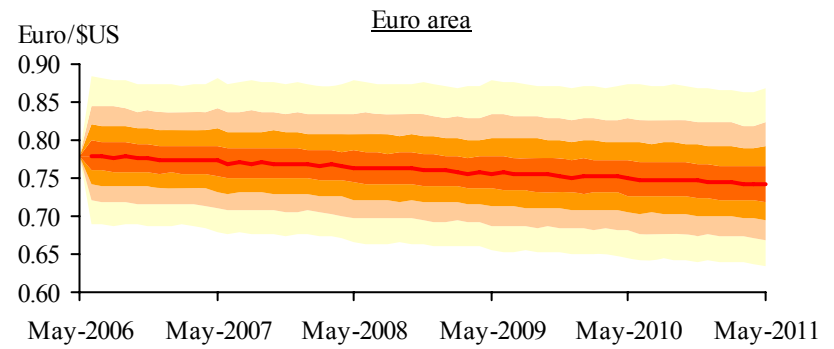
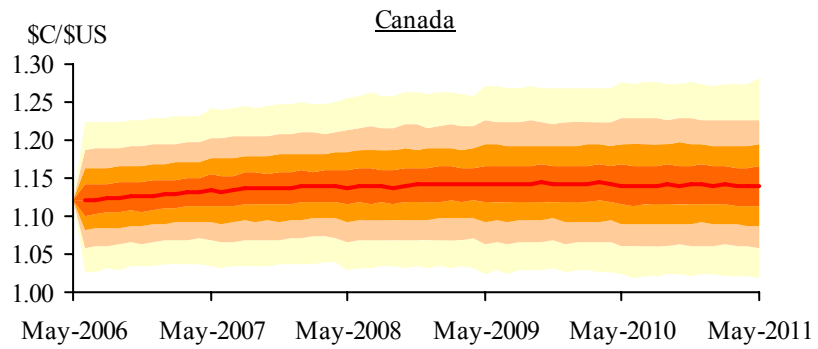
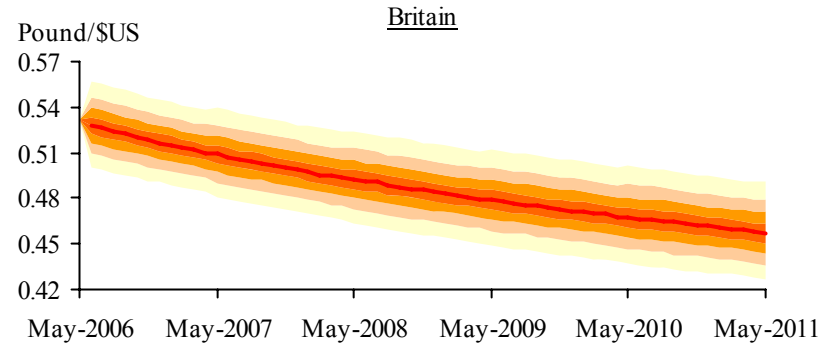
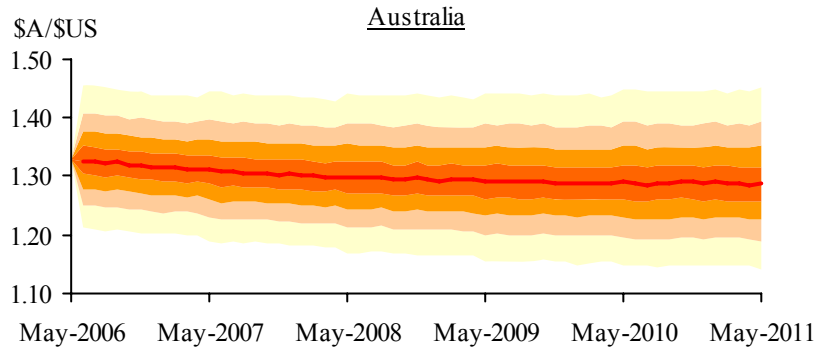
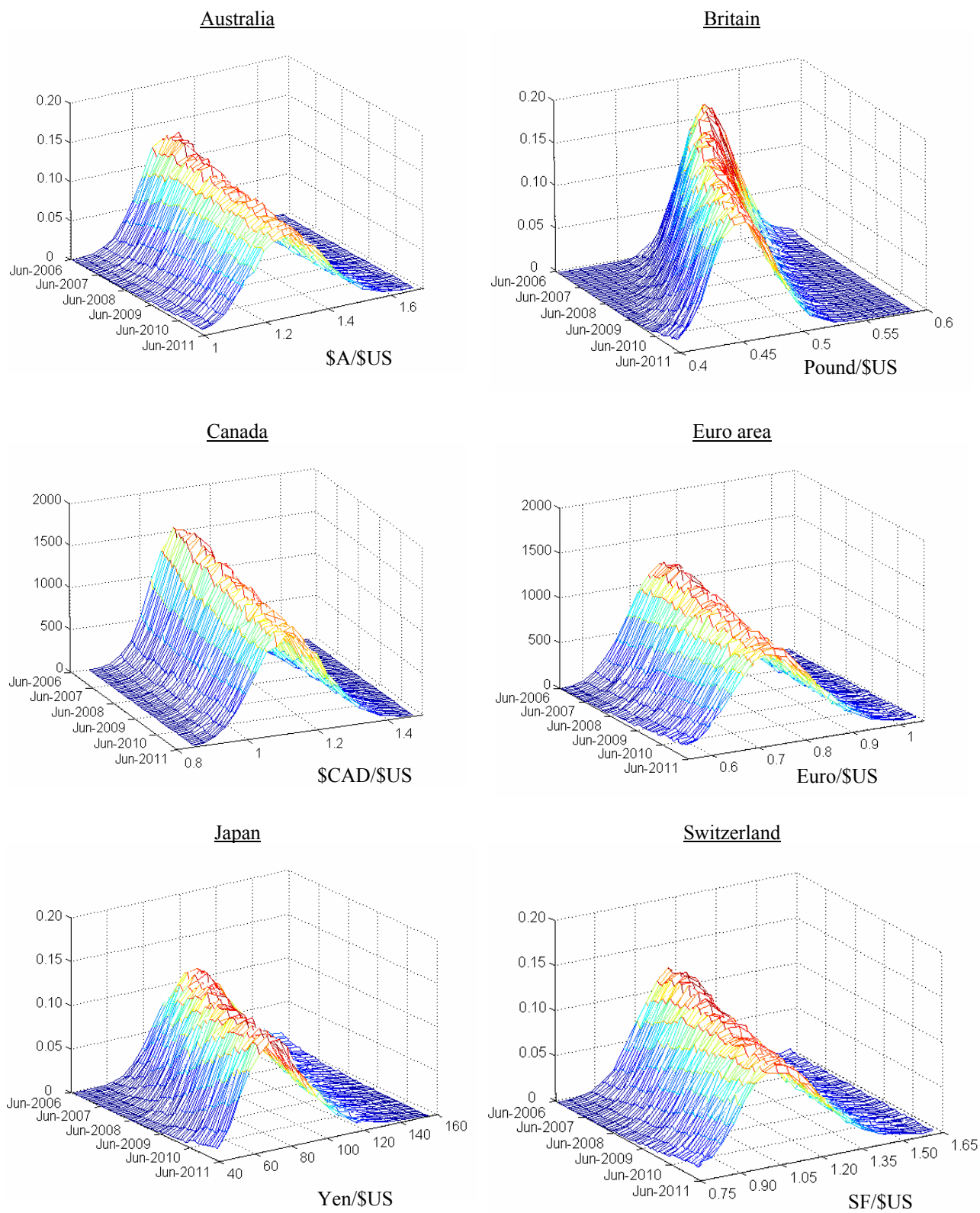


FIGURE 7
TRACKING-ERROR ADJUSTED DISTRIBUTIONS OF EXCHANGE-RATE FORECASTS



Note: For the purpose of clarity of presentation, some small frequencies for extreme values are not displayed.

immediately proceeds the forecast period, this approach is consistent with the idea of incorporating in the forecasts all of the most up-to-date information.

8. Concluding Comments

While forecasting exchange rates is a formidable task, the availability of Big Mac prices provides a convenient way to make currency forecasts in real time. Rooted in purchasing power parity theory, our Big Mac approach to forecasting exchange rates follows four steps:

- (i) Time-series modelling of Big Mac prices to make price forecasts.
- (ii) Testing for a unit root in real exchange rates in a seemingly-unrelated framework. Testing and estimation are carried out in the context of bias-adjusted estimates and standard errors. This model leads to estimates of equilibrium real exchange rates and forecasts of real exchange rates.
- (iii) Using a Monte Carlo simulation approach, the whole distribution of forecasts of nominal exchange rates is then derived by merging the forecasts of the Big Mac prices and the real exchange rates.
- (iv) Based on the tracking errors of test-set forecasts, the out-of-sample forecasts are revised so that they are unbiased.

The results shows that while the random walk model still dominates over the short forecast horizons, i.e., within six months, the Big Mac model has a superior performance in forecasting exchange rates over medium and long horizons.

Our approach to exchange-rate forecasting is attractive in three aspects. Firstly, it uses easily-available Big Mac prices as input. These prices avoid several serious problems associated with broad price indexes, such as the CPI, that are used in conventional PPP studies. Secondly, this approach provides real-time exchange-rate forecasts at any forecast horizon. If required, such real-time forecasts can be made on a day-to-day basis and adjust for recent tracking errors that reflect swings in market sentiment. As these high-frequency forecasts are based on an up-to-date and comprehensive information set, they could be particularly appealing to decision makers in government, business and financial markets who want up-to-date forecasts of exchange rates. Finally, as our forecasts are obtained through Monte Carlo simulation, estimation uncertainty is made explicit in our framework which provides the entire distribution of future values of the exchange rate, not just single point estimates. The dispersion of this distribution provides a realistic measure of the riskiness of the forecasts.

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