DIRECT AND INDIRECT FORECASTING OF CROSS EXCHANGE RATES*

ABSTRACT

The objective of this paper is to determine whether direct forecasting is more or less accurate than indirect forecasting when applied to the cross exchange rate as a defined variable. By using the flexible price monetary model to represent three cross rates, the results show that indirect forecasting is better than direct forecasting, when forecasting accuracy is measured in terms of the root mean square error (RMSE), for two of the three cross rates examined while the opposite is true for the third rate. However, no difference is apparent when performance is measured in terms of directional accuracy. It is concluded that the choice between direct and indirect forecasting is an empirical issue and that the results of such an exercise are case-specific.

Keywords: Forecasting, Random Walk, Exchange Rate Models, Cross Exchange Rates
JEL Classification: F31, F37, C53

RIASSUNTO

Previsione diretta e indiretta dei tassi di cambio cross

Lo scopo di questo studio è determinare se la previsione diretta è più o meno accurata di quella indiretta se applicata ai tassi di cambio cross. Utilizzando modelli monetari a prezzi flessibili per rappresentare tre tassi cross, i risultati mostrano che la previsione indiretta è migliore della previsione diretta (se l’accuratezza delle previsioni si misura in termini di root minimum square error), per due dei tre tassi di cambio, mentre è vero il contrario per il terzo tasso. Comunque, non c’è apparente differenza se la performance è misurata in termini di accuratezza direzionale. Si conclude che la scelta tra previsione diretta o indiretta è un problema empirico e che i risultati dipendono dal caso considerato.

* We are grateful to an anonymous referee for useful comments.
1. INTRODUCTION

A cross exchange rate is typically defined as the exchange rate between two currencies calculated from the exchange rates of the two currencies against a third currency, the numeraire. While the numeraire could be the domestic currency, it is more common to use the U.S. dollar as the numeraire as exchange rates are typically quoted against the U.S. dollar. If the dollar is the numeraire, then a cross exchange rate may be defined the exchange rate between two currencies calculated from their exchange rates against the U.S. dollar.

This paper examines the accuracy (or lack thereof) of direct relative to indirect forecasting. Since the cross exchange rate is a defined variable – defined as the ratio of two U.S. dollar exchange rates – forecasting cross rates may be direct or indirect. Direct forecasting entails the fitting of a model to the cross exchange rate and using the estimated model to generate forecasts. The indirect method requires fitting separate models to the exchange rates of the two currencies against the U.S. dollar, then using the forecasts of the two individual rates to calculate the corresponding cross rate.

This is not simply an exercise in number crunching, because there is some underlying economic theory. Take for example the monetary model of exchange rates, which tells us (among other things) that a country that has faster monetary growth than other countries will experience currency depreciation\(^1\). It is not clear how this model works or how the effect is transmitted from monetary growth to the exchange rate, but let us assume that the mechanism works at the market micro level. This means that if foreign exchange dealers observe rapid monetary expansion in country A relative to that in country B, they will sell or short sell the currency of country A against the currency of country B. To trade this way, foreign exchange dealers must observe what happens in a vast number of country pairs. The simpler alternative would be to observe each country against the U.S., derive implications for the U.S. dollar exchange rates and consequently for the cross rates. This line of reasoning is consistent with the fact that the cross rates quoted by foreign exchange dealers and money changers are invariably calculated from the dollar exchange rates. In particular, the exchange rates of currencies that are pegged to the U.S. dollar or currency baskets (typically with a dominant dollar component) are calculated as cross rates by determining the dollar exchange rate (of the pegged currency) first. If this reasoning is

\(^1\) This phenomenon is quite conspicuous under a hyperinflationary environment but not so under normal moderate inflation.
valid, one would expect indirect forecasting to produce better forecasts of the cross rates than direct forecasting.

The objective of this paper is to find out if indirect forecasting of cross exchange rates is indeed superior to direct forecasting by applying the flexible price monetary model to three cross exchange rates involving the Japanese yen, British pound and the Canadian dollar. Apart from the exchange-rate-specific reasoning given above for why indirect forecasting is likely to be more accurate, the literature on direct versus indirect forecasting portrays the same idea in general terms. Some economists maintain the opposite view that direct forecasting is better or at least preferable. And there is the neutral view that either can be better or worse, implying that this is an empirical issue. Therefore, we start with a brief examination of the literature on direct versus indirect forecasting.

2. DIRECT VERSUS INDIRECT FORECASTING

In choosing between direct and indirect forecasting, economists have been primarily concerned with the aggregation problem. In this case the direct method is used to generate forecasts from a model of the aggregated series, while the indirect method boils down to adding up the forecasts generated from disaggregated time series. Earlier studies of this issue were based on structural models, including Grunfeld and Griliches (1960), Orcutt et al. (1968) and Edwards and Orcutt (1969). These studies produced no clear-cut evidence on the superiority of one method over the other. Subsequent studies employed ARIMA modelling, including those of Tiao and Guttman (1980), Wei and Abraham (1981), Kohn (1982) and Lütkepohl (1984). The conclusion derived from these studies is that, although one could have theoretical conditions under which a particular choice can be made, these conditions are so restrictive and unrealistic that the choice should be made entirely on an empirical basis. For example, Wei and Abraham (1981) conclude that there is no guarantee that the indirect method is more efficient than the direct method.

Hendry and Hubrich (2005) investigate the issue as applied to the Euro-zone inflation forecasts, arguing that an implication of a theory of prediction is that indirect forecasting (by forecasting the components) should outperform direct forecasting of the aggregated variable. However, they point out that the empirical evidence suggests that more information can help, more so by including macroeconomic variables than disaggregate components. Lütkepohl (1984) suggests
that the superiority of indirect forecasting is no longer assured if the DGPs are not known and
must be estimated. Fliedner (1999) brings in the effect of correlation, as his results support the
proposition that strong correlation leads to improved forecasting performance at the aggregate
level. In general he finds that direct forecasts of an aggregate variable are more accurate than
derived (indirect) forecasts.

Bermingham and D’agostino (2011) argue that forecast aggregation is an empirical issue and that
empirical results in the literature often go unexplained, which leaves forecasters in the dark
when confronted with the option of forecast aggregation. They analyse two price data sets, one
for the U.S. and one for the Euro Area, and consider multiple levels of aggregation for each data
set. The models include an autoregressive model, a factor augmented autoregressive model, a
large Bayesian VAR and a time-varying model with stochastic volatility. They find that once the
appropriate model has been found, forecast aggregation can improve forecast performance
significantly. However, Wei and Abraham (1981) conclude that a forecast based on component
series is not necessarily more efficient than the forecast from a single univariate aggregate
series.

Kang (1986) puts forward the argument that the conclusions reached on the superiority or
otherwise of direct over indirect forecasting as applied to aggregated variables can be extended
to defined variables. The distinction between aggregated and defined variables, for the purpose
of the underlying issue, may look superfluous because an aggregated variables is typically
measured as the sum of its components, \( x_t = x_{1t} + \cdots + x_{nt} \), while a defined variable may be
expressed as the sum of other variables, \( x_t = z_{1t} + \cdots + z_{mt} \). Indirect forecasting entails fitting
models to \( x_{1t}, \cdots , x_{nt} \) to forecast \( x_t \) as an aggregated variable. To forecast \( x_t \) as a defined variable,
models are fitted to \( z_{1t}, \cdots , z_{mt} \). Kang, therefore, suggests that the way in which indirect forecasts
are constructed for defined variables is similar to that of aggregated variables, concluding that
the preference for either method is based on empirical considerations\(^2\). Furthermore, Kang
argues that forecasting defined variables appears to be more fundamental than forecasting

\(^2\) Unlike aggregation, definition is not necessarily additive. As a defined variable, \( x_t \) may be expressed as \( z_{1t} / z_{mt} \) or
a variety of other forms.

\(^3\) Engel (1984) provides a unified approach to time series aggregation by identifying three types of aggregation: sums,
products and intertemporal aggregations. This is why Silhan (1986) argues that the defined variables examined by
Kang (1986) can be viewed as multiplicative aggregation.
aggregated variables. This is because (i) aggregation can be viewed as a special case of definitional relationships among variables; (ii) defined variables can be developed at every level of aggregation; and (iii) definitions can embrace variables of diverse characters.

One reason why indirect forecasting of a defined variable makes more sense than direct forecasting is that the different components of a definition may have different time series properties. In this respect, Kang (1986) asserts that the components of a defined variable are more heterogeneous than those comprising an aggregated variable. This heterogeneity does not only pertain to the time series properties of the components but also to the units of measurement. Hence, the generating processes of the components are more heterogeneous for defined variables than for aggregated variables. Kang concludes that the study of defined variables should be “richer” and “more concrete” than the study of aggregated variables.

Moosa and Kim (2001) explain this point with respect to the definition of the real exchange rate, arguing that the indirect method may be superior since, unlike the direct method, it does not implicitly assume that the three components of the real exchange rate have the same time series properties and thus can be represented by the same model. They point out that the behaviour of the nominal exchange rate is significantly different from that of the price level: while the former moves predominantly in cycles, the latter moves along strong upward trends. They also suggest that the indirect method should be more efficient because more information is used, while arguing that the direct method may be preferred because it involves fitting a simple model with a small number of parameters to be estimated (which involves less sampling variability than under the indirect method).

Kang (1986) compares the accuracy of direct and indirect forecasting using four defined variables: real interest rate, money multiplier, real output and the velocity of circulation. The bulk of the evidence he provides, which is based on ARIMA modelling, shows that indirect forecasting tends to outperform direct forecasting using the mean absolute error, mean squared error and mean absolute percentage error as criteria for measuring performance. However, the evidence is mixed for monetary variables as direct forecasting outperformed indirect forecasting in this case according to certain criteria. Following up on Kang’s study, Silhan (1986) compared

---

4 For example, two of the components of the real exchange rate (domestic and foreign prices) are measured as indices (without units), while the third component (the nominal exchange rate) is measured in units of two currencies (assuming that we are talking about a bilateral exchange rate).
direct and indirect ARIMA forecasts of corporate profit margins and found that the indirect approach did not on average outperform direct forecasting.

Other economists have also indulged in the same exercise on the U.S. money multiplier. Johannes and Rasche (1979, 1981) attempted to forecast the money multiplier indirectly by forecasting the ratios comprising the multiplier. They suggested that indirect forecasting is more useful because certain events that influence the individual ratios may be masked in a model of the total multiplier series. Johannes and Rasche (1979) provide some evidence on cross correlations among the ratios’ residuals to demonstrate another gain in forecasting accuracy resulting from the use of the indirect method. This gain results if the movements in the affected components do not have negligible variances. On the other hand, Hafer and Hein (1984) conclude that the evidence based on forecasts of the M1 multiplier for the period from January 1980 to December 1982 indicates that the direct method produces as good forecasts as those produced by using the indirect method.

Bidarkota (1998) examined the problem by using the unobserved component model to forecast the U.S. real interest rate. Again, the results seem to be mixed. On the basis of one-step ahead forecasting within the estimation sample period, Bidarkota found out that indirect forecasting provides more accurate forecasts in terms of the mean prediction error, while forecasts derived from the direct method are more precise in that they have a smaller prediction error variance. Out of sample, indirect forecasting outperforms direct forecasting both in terms of the accuracy of the forecasts and their precision. However, when multi-step ahead forecasting is used both methods yield very poor forecasts.

In a series of papers, Moosa and Kim (2001, 2004a, 2004b, 2004c) applied direct and indirect forecasting techniques to three defined variables – real exchange rate, money multiplier and the velocity of circulation in a number of countries. These studies produced results that mostly supported direct forecasting. First, indirect forecasting of real exchange rates does not produce superior forecasting results as compared with direct forecasting. Second, mixed results were obtained for the U.K. money multiplier and velocity of circulation, although the overall evidence seems to be in favour of direct forecasting, which they explained in terms of the effect (reduction) of time series pooling on the noise associated with individual series. Third, the superiority of direct forecasting for the Japanese velocity of circulation, which is again explained
in terms of the pooling effect. Fourth, mixed results were found when forecasting the U.S. money multiplier and velocity of circulation.

It seems, therefore, that the choice between direct and indirect forecasting is indeed an empirical issue. While arguments are available for why indirect forecasting may or may not be superior to direct forecasting, the empirical results are mixed, providing no indication as to why one approach should be preferred to the other a priori.

3. METHODOLOGY

The analysis is based on the flexible price monetary model

\[ s_t = \beta_0 + \beta_1 (m_t - m_t^*) + \beta_2 (y_t - y_t^*) + \beta_3 (i_t - i_t^*) + \epsilon_t \tag{1} \]

where \( s \) is the log of the exchange rate (measured as the domestic currency price of one unit of the foreign currency), \( m \) is the log of the money supply, \( y \) is the log of industrial production, and \( i \) is the short-term interest rate (an asterisk indicates the foreign variable). Out-of-sample forecasts are generated by estimating the model over the estimation period \( t = 1, 2, \ldots k \), then generating a forecast for the period in time \( m+1 \) from the equation

\[ \hat{s}_{k+1} = \hat{\beta}_0 + \hat{\beta}_1 (m_{k+1} - m_{k+1}^*) + \hat{\beta}_2 (y_{k+1} - y_{k+1}^*) + \hat{\beta}_3 (i_{k+1} - i_{k+1}^*) \tag{2} \]

where \( \hat{\beta}_i \) is the estimated value of \( \beta_i \). The process is then repeated by estimating the model over the period \( t = 1, 2, \ldots k + 1 \) to generate a forecast for point in time \( k+2 \), \( \hat{s}_{k+2} \), and so on until we get to \( \hat{s}_n \), where \( n \) is the total sample size. This analysis is restricted to one-period ahead forecasts, not that the results will change qualitatively if longer horizons are used.

Consider three currencies, \( a, b \) and \( c \). The cross exchange rate between \( a \) and \( b \) is derived from their exchange rates against the numeraire, \( c \), as follows:

\[ S(a/b) = \frac{S(a/c)}{S(b/c)} \tag{3} \]

---

5 Any other model, including an ARIMA model, can be used instead but that does not matter. The objective of this study is to compare direct and indirect forecasting when implemented in conjunction with the same model. The objective is not to compare the forecasting accuracy of two or more models or to determine the best model.

6 This means that the estimation period is \( t = 1, 2, \ldots k \), while the forecasting period is \( t = k + 1, \ldots n \).
Since the forecasting model is written in terms of the log exchange rate, the forecast level of the exchange rate is calculated as

$$\hat{S}(a/b) = \exp[\hat{s}(a/b)]$$  \hspace{1cm} (4)

Direct forecasting is carried out by estimating equation (1) for \(s(a/b)\), in which case the explanatory variables \(m, y\) and \(i\) are those of the country whose currency is \(a\), while the explanatory variables with stars are those of the country whose currency is \(b\). The forecast is derived directly as in (4). Indirect forecasting entails estimating equation (1) for two exchange rates, \(s(a/c)\) and \(s(b/c)\) to obtain the forecast log values, \(\hat{s}(a/c)\) and \(\hat{s}(b/c)\). It follows that

$$\hat{s}(a/b) = \hat{s}(a/c) - \hat{s}(b/c)$$  \hspace{1cm} (5)

which gives

$$\hat{S}(a/b) = \exp[\hat{s}(a/c) - \hat{s}(b/c)]$$  \hspace{1cm} (6)

Forecasting accuracy is judged in terms of the root mean square error and directional accuracy, which are calculated as

$$RMSE = \sqrt{\frac{1}{n-k} \sum_{t=k+1}^{n} \left( \frac{\hat{S}_t - S_t}{S_t} \right)^2}$$  \hspace{1cm} (7)

$$DA = \frac{1}{n-k-1} \sum_{t=k+1}^{n} z_t$$  \hspace{1cm} (8)

where

$$z = \begin{cases} 1 & \text{if } (\hat{S}_{t+1} - S_t)(S_{t+1} - S_t) > 0 \\ 0 & \text{if } (\hat{S}_{t+1} - S_t)(S_{t+1} - S_t) < 0 \end{cases}$$  \hspace{1cm} (9)

Tests of significance are conducted on both measures of forecasting accuracy. The significance of \(DA\) is judged by using conventional tests of proportions. The AGS test – suggested by Ashley et al. (1980) – is used to test the significance of the difference between two root mean square errors. It requires the estimation of the linear regression

$$D_t = \alpha_0 + \alpha_1(M_t - \bar{M}) + u_t$$  \hspace{1cm} (10)

where \(D_t = w_{1t} - w_{2t}, M_t = w_{1t} + w_{2t}, \bar{M}\) is the mean of \(M\), \(w_{1t}\) is the forecasting error at time \(t\) of the model with the higher RMSE, \(w_{2t}\) is the forecasting error at time \(t\) of the model with the
lower RMSE$. The null hypothesis of the equality of the two root mean square errors is $H_0: \alpha_0 = \alpha_1 = 0$. If $\alpha_0$ and $\alpha_1$ are both positive, then a Wald test of the joint hypothesis $H_0: \alpha_0 = \alpha_1 = 0$ is appropriate. However, if one of the estimates is negative and statistically significant then the test is inconclusive. But if the estimate is negative and statistically insignificant the test remains conclusive, in which case significance is determined by the upper-tail of the t-test on the positive coefficient estimate.

4. DATA AND EMPIRICAL RESULTS

The empirical results are based on a sample of monthly data covering the period January 1990-September 2010. The data cover four countries: the U.S., Japan, the U.K. and Canada. The analysis is conducted on three cross rates: GBP/CAD, JPY/CAD and JPY/GBP, which are calculated from the exchange rates against the dollar: JPY/USD, GBP/USD and JPY/USD. Since this is an out-of-sample forecasting exercise, the sample period is split into an estimation period and a forecasting period – the latter extends between January 2005 and September 2010. The data were obtained from the IMF’s International Financial Statistics.

Figure 1 displays the actual and forecast cross exchange rates over the forecasting period, using both the direct and indirect methods. It can be immediately observed that indirect forecasting produces smaller forecasting errors than direct forecasting for the GBP/CAD and JPY/CAD rates but not for JPY/GBP. Notice, however, that the model seems to work better for the JPY/GBP rate, irrespective of the use of direct or indirect forecasting. Both forecasting methods produce biased forecasts of the GBP/CAD and JPY/CAD rates as the forecast values are (almost) consistently below the actual values. This is not the case for the JPY/GBP rate. Figure 2 displays the cumulative percentage errors derived from the direct and indirect forecasts as compared to the random walk for the three cross rates. Because the forecasts of the first two rates are biased, the cumulative errors tend to increase (in absolute value) over the forecasting period. Again this is not the case for the JPY/GBP rate. The random walk forecasts, on the other hand, produce small cumulative errors because the individual errors are small and not consistently positive or negative.

---

$^7$ If the mean value of an error series is negative, it should be multiplied by -1 before running the regression.
FIGURE 1 - Actual and Forecast Cross Exchange Rates

GBP/CAD

JPY/CAD

JPY/GBP
FIGURE 2 - Cumulative Percentage Errors

GBP/CAD

NY/JPY

JPY/GBP
Table 1 reports the RMSE and directional accuracy, while Table 2 and Table 3 present the results of hypothesis testing on these metrics. The results of the AGS test show that, in terms of the RMSE, the model is inferior to the random walk, irrespective of whether direct or indirect forecasting is used. This is consistent with the Meese-Rogoff (1983) proposition that exchange rate models cannot outperform the random walk in out-of-sample forecasting. While this has become to be regarded as a puzzle, Moosa (2013) demonstrates, by using simulation, that we should expect nothing other than the inability of exchange rate models to outperform the random walk if accuracy is measured in terms of the RMSE. Based on testing the significance of ratios, all sets of forecast outperform the random walk in terms of directional accuracy, predicting the direction of change correctly on a fifty-fifty basis. The results reported in Table 3 show that the hypotheses $H_0 : DA_p = 0$ and $H_0 : DA_j = 0$ cannot be rejected while the hypotheses $H_0 : DA_p = 0.5$ and $H_0 : DA_j = 0.5$ are rejected. This is because Moosa and Burns (2012) show that exchange rate models can outperform the random walk in terms of directional accuracy and profitability.

The objective here is not to compare direct and indirect forecasting with the random walk. Rather, we want to compare direct and indirect forecasting for any model (in this case the flexible price monetary model), irrespective of how good or how bad the model is in relation to the random walk. In terms of the RMSE, indirect forecasting produces better (or less bad) forecasts than direct forecasting for the GBP/CAD and JPY/CAD rates as the results of the AGS test show. Since $\alpha_i$ is not positive, when the test is conducted for the direct versus indirect forecasts, the significance of $\alpha_0$ implies the rejection of the null that the two root mean square errors are equal. In the case of the JPY/GBP rate, direct forecasting produces better results. Notice, however, that direct and indirect forecasting produce similar results in forecasting the direction of change for all currency pairs. This is because the results reported in Table 3 show that the null hypothesis of the equality of two ratios, $H_0 : DA_p = DA_j$, cannot be rejected. Judged by these results, it is more likely that the performance of direct versus indirect forecasting is an empirical issue as the outcome is case-specific.

---

* The random walk without drift, which is what is used in this paper, predicts zero period-to-period changes in exchange rates. Evans and Lyons (2005) state explicitly that if the exchange rate follows a random walk (without drift), there is no forecast change in the spot rate. Since exchange rates invariably change, the random walk (without drift) consistently fails to predict the direction of change.
### TABLE 1 - Measures of Forecasting Accuracy

<table>
<thead>
<tr>
<th></th>
<th>RMSE</th>
<th>DA</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Direct</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GBP/CAD</td>
<td>26.28</td>
<td>0.46</td>
</tr>
<tr>
<td>JPY/CAD</td>
<td>19.22</td>
<td>0.47</td>
</tr>
<tr>
<td>JPY/GBP</td>
<td>11.08</td>
<td>0.59</td>
</tr>
<tr>
<td><strong>Indirect</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GBP/CAD</td>
<td>19.22</td>
<td>0.46</td>
</tr>
<tr>
<td>JPY/CAD</td>
<td>16.72</td>
<td>0.44</td>
</tr>
<tr>
<td>JPY/GBP</td>
<td>20.36</td>
<td>0.53</td>
</tr>
<tr>
<td><strong>Random Walk</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GBP/CAD</td>
<td>3.22</td>
<td>0.00</td>
</tr>
<tr>
<td>JPY/CAD</td>
<td>4.85</td>
<td>0.00</td>
</tr>
<tr>
<td>JPY/GBP</td>
<td>4.27</td>
<td>0.00</td>
</tr>
</tbody>
</table>

### TABLE 2 - Results of the AGS Test

<table>
<thead>
<tr>
<th></th>
<th>GBP/CAD</th>
<th>JPY/CAD</th>
<th>JPY/GBP</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Direct vs Indirect</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha_0$</td>
<td>7.950</td>
<td>40.645</td>
<td>3.931</td>
</tr>
<tr>
<td></td>
<td>(11.99)</td>
<td>(23.92)</td>
<td>(3.01)</td>
</tr>
<tr>
<td>$\alpha_1$</td>
<td>-0.028</td>
<td>-0.048</td>
<td>0.326</td>
</tr>
<tr>
<td></td>
<td>(-0.72)</td>
<td>(-0.33)</td>
<td>(7.12)</td>
</tr>
<tr>
<td>$\chi^2(\alpha_0 = \alpha_1 = 0)$</td>
<td>144.30</td>
<td>575.72</td>
<td>59.72</td>
</tr>
<tr>
<td><strong>Direct vs Random Walk</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha_0$</td>
<td>24.565</td>
<td>26.305</td>
<td>0.805</td>
</tr>
<tr>
<td></td>
<td>(35.03)</td>
<td>(23.95)</td>
<td>(0.98)</td>
</tr>
<tr>
<td>$\alpha_1$</td>
<td>0.697</td>
<td>0.599</td>
<td>0.608</td>
</tr>
<tr>
<td></td>
<td>(9.56)</td>
<td>(5.17)</td>
<td>(9.68)</td>
</tr>
<tr>
<td>$\chi^2(\alpha_0 = \alpha_1 = 0)$</td>
<td>1319.10</td>
<td>600.76</td>
<td>94.65</td>
</tr>
<tr>
<td><strong>Indirect vs Random Walk</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha_0$</td>
<td>16.615</td>
<td>13.956</td>
<td>4.735</td>
</tr>
<tr>
<td></td>
<td>(24.16)</td>
<td>(12.01)</td>
<td>(5.25)</td>
</tr>
<tr>
<td>$\alpha_1$</td>
<td>0.694</td>
<td>0.753</td>
<td>0.810</td>
</tr>
<tr>
<td></td>
<td>(10.33)</td>
<td>(5.79)</td>
<td>(19.15)</td>
</tr>
<tr>
<td>$\chi^2(\alpha_0 = \alpha_1 = 0)$</td>
<td>690.78</td>
<td>178.05</td>
<td>394.57</td>
</tr>
</tbody>
</table>
TABLE 3- Hypothesis Testing for Directional Accuracy

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>GBP/CAD</th>
<th>JPY/CAD</th>
<th>JPY/GBP</th>
</tr>
</thead>
<tbody>
<tr>
<td>$H_0 : DA_D = 0$</td>
<td>7.67*</td>
<td>7.82*</td>
<td>9.96*</td>
</tr>
<tr>
<td>$H_0 : DA_I = 0$</td>
<td>7.67*</td>
<td>7.36*</td>
<td>8.82*</td>
</tr>
<tr>
<td>$H_0 : DA_D = 0.5$</td>
<td>-0.67</td>
<td>-0.50</td>
<td>1.52</td>
</tr>
<tr>
<td>$H_0 : DA_I = 0.5$</td>
<td>-0.67</td>
<td>-1.00</td>
<td>0.50</td>
</tr>
<tr>
<td>$H_0 : DA_D = DA_I$</td>
<td>0.00</td>
<td>0.09</td>
<td>0.71</td>
</tr>
</tbody>
</table>

* Significant at the 5% level.

5. CONCLUSION

This paper addresses the issue whether the indirect forecasting of cross exchange rates is better or worse than direct forecasting. While direct forecasting entails generating forecasts from a model fitted directly to the cross exchange rate, indirect forecasting requires the generation of forecasts for the exchange rates against the dollar then combining these forecasts to obtain forecasts for the cross rate.

Several reasons have been suggested for why indirect forecasting is thought to be more accurate: (i) this proposition is implied by the theory of prediction; (ii) differences in the time series properties of the components; (iii) the utilisation of more information to enhance efficiency; (iv) certain events that affect individual components may be masked in a direct forecasting model; and (v) indirect forecasting utilises the information embodied in cross correlations. There is also a specific reason pertaining to the special case of cross exchange rates – that foreign exchange market participants pay more attention to macroeconomic developments relative to the U.S. economy (hence more attention to the bilateral exchange rates against the dollar).

On the other hand, views have been expressed in defence of direct forecasting, either because it produces better results or because it is preferable in terms of costs and benefits. These views include the following: (i) direct forecasting may be superior if the underlying processes are not known and have to be estimated; (ii) the information obtained from explanatory variables in the aggregate model may be more important than the information embodied in the components; (iii)
high correlation enhances forecasting accuracy at the aggregate level; and (iv) it may be preferred because it involves less work and data requirements. It has also been suggested that the choice between the two approaches depends on whether the exercise is conducted in sample or out of sample.

The mixed results produced by this strand of research support the view that the choice between the two approaches is an empirical issue – that is, doing both and picking the better set of forecasts. The results of this study show that indirect forecasting is better than direct forecasting, when forecasting accuracy is measured in terms of the RMSE, for two of the three cross rates examined while the opposite is true for the third rate. However, no difference is apparent when forecasting accuracy is measured in terms of directional accuracy.

REFERENCES


