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ASSESSMENT OF MODELS TO FORECAST EXCHANGE RATES: THE QUETZAL–U.S. DOLLAR EXCHANGE RATE

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Based on Cheung, Chinn and García-Pascual (2004) and Meese and Rogoff (1983), the forecasting performance of a wide variety of theoretical and empirical exchange rate models (PPP, UIP, flexible and sticky-price monetary models, portfolio balance, and a BEER model) is tested against the random walk specification to determine their assessment in predicting the quetzal–U.S. dollar nominal exchange rate. Such models are estimated by applying a recursive regression methodology to quarterly data for the period 1995-2009. Estimations are performed based on an innovative trend-gap data disaggregation methodology, and an error-correction specification to contrast short vs. long run prediction performance, which is evaluated up to eight periods ahead for all model specifications. Different from previous results, forecasts provided by most specifications in the very short run (up to 2 quarters ahead), particularly the BEER specification, consistently outperform those obtained from the random walk model.

JEL classification codes: C32, E44, F31, F41, F37
Key words: nominal exchange rate, econometric models, BEER

I. Introduction

Exchange rate forecasting has long been an important challenge for academics and empiricists. Although a wide range of theoretical and empirical models has

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been developed over the years to estimate and predict exchange rate behavior, the empirical literature suggests that such estimates are only useful for determining an exchange rate trend because in the short run they are usually outperformed by the random walk model. We challenge previous findings by testing the forecasting performance of a wide variety of theoretical and empirical exchange rate models against the random walk specification to determine their ability to predict the exchange rate of the Guatemalan quetzal over short and long horizons.

Based on the work of Meese and Rogoff (1983), and Cheung, Chinn and García-Pascual (2004), exchange rate forecasts obtained through the purchasing power parity model, the uncovered interest rate parity condition, the monetary model in its flexible and sticky-price versions, the portfolio balance model, and a behavioral empirical exchange rate (BEER) model are tested against forecasts generated by a random walk specification. Such models are estimated with quarterly data for 1995-2009 using a rolling regression methodology for the quetzal–U.S. dollar exchange rate. Estimates are performed based on an innovative trend-gap data disaggregation methodology specification as well as in error-correction form in order to contrast short vs. long run prediction performance which is evaluated up to eight periods ahead.

Unlike the results obtained in previous research, the prediction estimates of most exchange rate models in the very short run (2 quarters ahead), particularly with the BEER specification, consistently outperform those obtained through the random walk model.

Section II of this document presents the theoretical and empirical exchange rate models used as reference in this study. Section III describes the data and methodology employed. Section IV explains the comparative forecasts of each model with regard to the random walk specification, while Section V presents the conclusion.

II. Nominal exchange rate specifications

Since a large number of models has been developed to explain and forecast exchange rates, it would be difficult to describe each one. Nevertheless, there is a finite number of models that has survived and which are still being applied by policymakers to analyze and predict exchange rate behavior, mainly in the long run. These models are: i) the Purchasing Power Parity, ii) the Uncovered Interest Rate Parity Condition, iii) the Monetary Model, iv) the Portfolio Balance, and v) the Behavioral Empirical Exchange Rate (BEER). A description of each model together with a brief summary of its recent empirical performance is provided below.

A. The purchasing power parity model

The purchasing power parity (PPP) approach is the most widely used framework to assess exchange rate value, mainly for the long run. It is also one of the oldest approaches since its roots go back to 16th century Spain and it has been repeatedly restated in different versions. We focus on the relative version of PPP, which states that percentage changes in the quetzal's bilateral exchange rate, s , are determined by the difference between domestic and foreign inflation rates, $(\pi - \pi^*)$. In its functional form, the PPP equation can be stated as follows:

$$s_t = \rho_0 + \rho_1(\pi_t - \pi_t^*) + \varepsilon_t \,. \tag{1}$$

It is no exaggeration to say that since it was first established, equation (1) has been the most commonly used equation in empirical financial literature throughout the world. In fact, the simplicity of its formulation and its powerful economic intuition makes PPP a very appealing theory. Nevertheless, empirical results, such as those described in Frenkel (1980), Dornbush (1980), and Rosenberg (1996) have demonstrated departures from PPP, mainly over short term horizons, because of productivity shocks, terms of trade changes, resource discoveries, and structural differences in income elasticities and growth rates. Such elements could generate current account imbalances which may need significant exchange rate adjustments to correct, even when domestic and foreign price levels remain fixed.

In recent years, the compilation of wider and longer datasets, the development of new statistical methods, and the periodic emergence of improvements in information technology have contributed to the development of new forms of testing equation (1). Such a growing body of evidence, as summarized in Taylor (2009), suggests that exchange rates do indeed converge on their PPP values in the long run. Once again, PPP refuses to die.

B. The monetary approach

Another widely used model to estimate and forecast exchange rates is the monetary approach whose original specification is the flexible-price version established by Frenkel (1976) and Bilson (1978). According to this approach, changes in the relative supply of money lead to adjustments in prices, and, hence, in the exchange rate. Its functional form establishes that the nominal exchange rate is a function of domestic and foreign differentials of money supply $(m - m*)$, gross domestic product $(y - y*)$ and expected inflation $(\pi^e - \pi^{e*})$:

$$s_t = \rho_0 + \rho_1(m_t - m_t^*) + \rho_2(y_t - y_t^*) + \rho_3(\pi_t^e - \pi_t^{e*}) + \varepsilon_t \ . \tag{2}$$

Dornbusch (1976) argued that equation (2) should be modified given that the empirical evidence for PPP suggests that it does not hold continuously. Therefore, he suggested a monetary approach that relaxes the assumption of price flexibility, but that allows PPP to hold in the long run. Dornbusch's version of the monetary approach is known as the Sticky Price Monetary Model, defined as follows:

$$s_t = \rho_0 + \rho_1(m_t - m_t^*) + \rho_2(y_t - y_t^*) + \rho_3(i_t - i_t^*) + \varepsilon_t \ . \tag{3}$$

Empirical results based on the monetary models are mixed. Frankel (1984), Meese and Rogoff (1983), Schinasi and Swamy (1989), Eichenbaum and Evans (1993), and others have obtained poor results when trying to estimate exchange rate forecasts based on the monetary model. They argue that the failure of PPP to hold in the short run, the assumption of money demand stability, reliance on fixed regression coefficients, and overly simplified equations describing how expectations are formed are the main reasons that explain the failure of the monetary model in practice. Nevertheless, empirical studies by MacDonald and Taylor (1994), McNown and Wallace (1994), Lütkepohl and Wolters (1999), and Groen (2002) have obtained favorable results when applying innovations, such as variable coefficients, lagged dependent variables, or cointegration techniques. These new approaches for exchange rate testing have contributed to the development of renewed interest in the monetary model in recent years.

C. The portfolio balance approach

The portfolio balance approach differs slightly from the monetary model by assuming that domestic and foreign bonds are not perfect substitutes. Therefore, the exchange rate value can be affected by relative bond supply variations and shifts in asset preferences. Thus, besides the fundamentals described in equation (3), the nominal exchange rate is also a function of the domestic and foreign real interest rate differential $(r - r*)$, and the percentage change between the supply of domestic and foreign bonds $(b - b*)$, as described below:

$$s_t = \rho_0 + \rho_1(m_t - m_t^*) + \rho_2(y_t - y_t^*) + \rho_3(\pi_t^e - \pi_t^{e*}) + \rho_4(r_t - r_t^*) + \rho_5(b_t - b_t^*) + \varepsilon_t \quad . \quad (4)$$

Empirical results from the portfolio balance model have generally been poor. According to Rosenberg (1996) and Taylor (2004), the failure of this model to forecast exchange rate trends is due to misspecification of asset demand functions, inadequate data on the size and currency composition of private sector portfolios, simultaneity bias between exchange rate changes and changes in the current account balance, and inadequate treatment of exchange rate expectations.

D. The uncovered interest rate parity condition

According to the uncovered interest rate parity (UIP) specification, the expected value of the exchange rate, s^e, will differ from the current exchange rate, s, whenever there are differences between domestic and foreign interest rate differentials (i – i*) adjusted by a country risk premium, ρ. Although several versions have been constructed based on this approach, in this document we test the uncovered version of the parity, which is stated as follows:

$$i_t - i_t^* = (s_t^e - s_t) + \rho_t + \varepsilon_t \ . \quad (5)$$

Equation (5) implicitly states that arbitrage opportunities arise whenever the exchange rate differs from the established interest rate parity. Until recently, empirical results of the UIP hypothesis have been poor. Froot and Thaler (1990), and MacDonald and Taylor (1992) concluded that interest rate differentials are not predictors of future exchange rate movements. However, recent findings by Alexius (2001), Chinn and Meredith (2005), and MacDonald and Nagayasu (2000) have found supportive evidence of UIP parity when using long term (+5 years) interest differentials. Such results show correct sign coefficients which are closer to the predicted value of unity than to zero.

E. The behavioral equilibrium exchange rate model

The behavioral equilibrium exchange rate (BEER) model features the nominal exchange rate as a function of its main fundamentals. This specification was the result of an extensive search for nominal exchange rate fundamentals performed through dynamic cross correlations between the quetzal–US dollar exchange rate and a series of variables during the 2001-2010 period.[1] The BEER specification described in equation (6) represents the best fit obtained.

$$s_t = \rho_0 + \rho_1 s_{t-1} + \rho_2 m_t + \rho_3 y^*_{t-1} + \rho_4 sug_{t-1} + \rho_5 rem_t + \varepsilon_t, \tag{6}$$

where m stands for domestic money supply, y^* represents foreign (US) output, sug symbolizes international sugar prices, and *rem* denotes net inflows of family remittances. Although equation (6) resembles the original formulation established by Clark and MacDonald (1998), or its modified version described in Cheung, Chinn and Garcia-Pascual (2004), the last two terms are particularly significant to the Guatemalan economy. Specifically, sugar exports registered an annual average growth rate of about 52%, the highest among the country's traditional export products, during the last six years (2005-2010).[2] This increase has been prompted by higher international prices of this commodity due to an increase in the demand for sugar from emerging market economies, particularly China. As a result, in 2010 Guatemalan sugar became the country's most important export product (in terms of value), displacing coffee for the first time in the country's history. This event has increased the domestic supply of foreign exchange and influenced the bilateral quetzal–US dollar value. Moreover, family remittances represent the highest inflow of foreign currency to the Guatemalan economy, even surpassing proceeds from all traditional Guatemalan export commodities together. In fact, they have more than doubled during the last 8 years, so by 2010 they represented 48.2% of total Guatemalan exports (about 10% of the Guatemalan GDP). Although fluctuations in sugar prices and family remittances are procyclical with regard to the US GDP, y^*, they are modeled separately in equation (6) given their importance for the Guatemalan economy. Therefore, American output fluctuations capture the effects from additional factors, such as US Import Services, Tourism or Foreign Direct Investment in the Guatemalan economy, that generate fluctuations in the quetzal–US dollar exchange rate.

[1] We calculated dynamic cross-correlations between quarterly Q/US$ percentage variations and quarterly percentage fluctuations for 134 variables during the 2001-2010 period. From the total set of variables studied, 46 are from the monetary sector, 30 from the real sector, 12 from the fiscal sector and 46 from the external sector. Then we selected all significant variables and performed a series of multiple regression exercises and short run forecasts. The specification described in equation (6) represents the most suitable specification found to explain quetzal/dollar short run fluctuations.

[2] This rate rises to 71% when 2008, the year when Guatemalan exports were affected adversely by the international financial crisis, is taken out of the calculation.

III. Data, estimation and comparison tests

A. Data

Data estimations and forecasts are made based on quarterly data for 1995-2009 using recursive regression methodology for the quetzal–U.S. dollar exchange rate. In 1995, econometric estimations began to take into account the floating exchange rate period, which began to operate effectively in Guatemala in that year. A floating exchange rate system was established in Guatemala in 1989. However, during the initial years the Central Bank of Guatemala intervened considerably in the foreign exchange market to avoid severe fluctuations that could affect agents' expectations and economic decisions. The sample period includes two important dates in Guatemala's financial and monetary history. The first is related to changes in domestic financial legislation in 2001-2002. These began in 2001 with the establishment of the "Law on Freedom of Transactions in Foreign Exchange" which permitted bank deposits and credits in foreign currency as well as the freedom to perform any kind of transactions within the country in any currency denomination as decided by the parties. This law permitted the transparency of operations that were already taking place and its effect on the nominal exchange rate was null. In 2002, the Central Bank Law was modified as well as the Law on Banks and Financial Institutions. The former established the central bank's main goal, while the latter opened up the country for foreign banks to operate, thus increasing the competitiveness of the banking sector. The other important date was 2005 when Inflation Targeting was established as a framework for monetary policy. Prior to that year the central bank had established an inflation target, but from 2005 it committed to achieving that target annually. The data for Guatemalan variables were obtained from the Central Bank's website, while information for foreign variables was obtained from the IMF's International Financial Statistics and from the Federal Reserve website.

B. Estimation methodology

We follow the rolling regression methodology, applied by Meese and Rogoff (1983) and Cheung, Chinn and Garcia-Pascual (2004), which tends to control for parameter instability within the data sample, a common concern in the exchange rate literature. Estimations are performed for a trend-gap and an error-correction specification in order to contrast short vs. long run prediction performance which is evaluated up to 8 periods ahead from the sample end date.

With regard to the first type of estimations, we introduced a new methodology to test all exchange rate theories based on the long run trend of nominal exchange rate fluctuations. By doing this, we were implicitly enforcing each theory to explain short run nominal exchange rate fluctuations which might improve forecast accuracy. Therefore, the natural logarithm of the gap in each variable was obtained through a Hoddrick-Prescott filter, which gave us an approximation of the percentage difference in the variable from its long run trend. Consider the following functional form that shows the nominal exchange rate, s_t, as a function of its fundamentals:[3]

$$s_t = AX_t + \varepsilon_t \ , \tag{7}$$

where X_t is the vector of nominal exchange rate fundamental variables, A is a coefficient matrix, and ε_t represents an independently distributed error term. Breaking down each side into its trend and gap components, we have:

$$s_{tnd_t} = AX_{tnd_t} + \varepsilon_{1t} \ , \tag{8}$$

$$s_{gap_t} = AX_{gap_t} + \varepsilon_{2t} \ . \tag{9}$$

The addition of equations (8) and (9) is equivalent to equation (7). We assume that AX_{tnd_t} in equation (8), can be approximated by an n order lag polynomial, $L^n(s_{tnd_t})$. Consequently, the exchange rate trend component, equation (8), can be estimated and forecasted independently of each model specification. Therefore, each equation from (1) to (6) is estimated in a gap-form, as indicated by equation (9). As a result, forecasts from each exchange rate component are added up to obtain the exchange rate logarithm forecast for each period. Because of the rolling regression methodology applied in the estimation, this procedure is repeated for each forecast window. It is important to observe that the fundamental vector X_{gap_t} might contain contemporaneous variables so their forecasts are estimated through an AR(1) model.

[3] All variables in (7) are in log form, except for interest rates.

The error-correction specification is a two step procedure. In the first place, a Dickey-Fuller regression is estimated to check for the order of integration of each variable involved in the estimation. Since s_t is I(1), it is expected that the other variables have the same order of integration, a condition necessary to proceed with the second step and which holds in most cases.

$$dlog(s_t) = \omega_0 dlog(X_t) + \omega_1 dlog(s_{t-1}) + \omega_2 (log(s_{t-1}) - \Gamma log(X_{t-1})) + \mu_t \quad . \tag{10}$$

In the second step, equation (10) is estimated through least squares to take into account the short and long run effects of independent variables on nominal exchange rate dynamics.[4] Forecasts for exogenous variables were generated through an AR(1) specification of each variable's growth rate. A similar approach was employed in Chinn and Messe (1995). We also follow Cheung, Chinn and García-Pascual (2004) in assuming that the long run cointegrating relationship varies as the data window moves.

C. Comparison tests

In the spirit of Meese and Rogoff (1983) and Cheung, Chinn and García-Pascual (2004), each exchange rate forecast produced by the model specifications described in Section II was compared against those produced by a random walk model. The null hypothesis of no difference in the accuracy of both forecasts was tested using three different tests. First, we employed the Diebold and Mariano (1994) loss differential, d, to the mean squared forecast error (MSE). The statistic d was asymptotically distributed as a standard normal distribution, constructing its consistent standard deviation from the weighted sum of the sample autocovariances of the loss differential vector. A quadratic spectral kernel, like the one used by Andrews (1991), was used along with a data dependent bandwidth parameter.[5]

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[4] Cheung, Chinn and García-Pascual (2004) assume that $\omega_0 = \omega_1 = 0$ due to the difficulty of finding significant short run dynamics in exchange rate equations. However, as described in latter sections, we found significant short-run forecasts through model specifications 1-6 which could help strengthen long run comovements between forecast and observed exchange rates. Therefore, we included a complete error-correction specification, as shown in equation (10).

[5] Following Andrews (1993), the bandwidth parameter specification was as follows: $A(1) = 4 * (\frac{\rho}{(1-\rho)(1+\rho)})^2$, where ρ is the coefficient of an AR(1) model of the nominal exchange rate series.

The second test refers to the Direction of Change.[6] In this case, the proportion of correct sign predictions from the random walk model was subtracted from the proportion of correct sign forecasts obtained from each model specification. The result was that the proportion of correct direction of change predictions outnumbered (if positive) the forecasts made by the random walk specification. The null hypothesis of a greater proportion of correct direction of change predictions resulting from the theoretical models was therefore tested based on a normal distribution.

The third test was a consistency condition, developed by Cheung and Chinn (1998), which represents a more lenient criterion for evaluating forecasts since it is only concerned with the relative long run difference between forecasts and actual data. Nevertheless, it requires exchange rate forecasts to be cointegrated with actual realizations, and that the elasticity of expectations be equal to one, two conditions that are difficult to achieve for model forecasts. Cointegration was tested based on the Johansen methodology for two different out-of-sample forecast windows: 2002-2009 and 2005-2009. The first and longest period began in the year when financial legislation reforms were implemented. Such reforms included modifications to the Guatemalan Central Bank Law, which gave greater importance to exchange rate flexibility and established the transition from Monetary Targeting to Inflation Targeting. The second forecast window began in 2005, the year when Inflation Targeting was officially established as a monetary policy framework, and is characterized by a significant increase in trade openness. Despite the fact that different monetary policy regimes were operating during both periods, the bilateral quetzal–US$ exchange rate remained relatively stable, fluctuating at around Q/US$7.80.

IV. Forecasting results

This section presents the results and provides a brief analysis of the main findings. As mentioned above, each model's econometric estimation and out-of-sample forecast was performed through mobile and uniform windows to test for parameter and model robustness to changes in the sample period. Then their forecast performance was tested through the Diebold-Mariano loss differential

[6] A correct-sign forecast implies that the sign calculated through the difference of two consecutive forecasts for a given variable is equivalent to the sign calculated through the difference of such a given variable's observed values for the same two consecutive periods.

statistic, *d,* by comparing these forecasts with those provided by a random walk specification. Three different criteria were used for forecast comparison: A) mean squared error (MSE); B) direction of change; and C) consistency condition. Again, two specifications were performed for each model. The first one was a short run representation in which estimations were obtained from a trend-gap disaggregation, as indicated by equations (7)–(9), while the second was a long run representation in which an error-correction specification was used for each model like the one described by equation (10).

A. First forecast comparison criterion: mean squared error

Table 1 shows the results obtained from the loss differential statistic, *d*, which compares the MSE statistic generated for all of the eight-period-ahead forecasts produced by each model, relative to the MSE statistic produced by a random walk specification. The first column of Table 1 indicates the forecast period, while the remaining columns are divided according to the model specification used to obtain the results. The first five columns present the outcome estimated through the trend-gap data disaggregation for each of the following five models: 1) the purchasing power parity (PPP) model; 2) the flexible price monetary model; 3) the sticky price monetary model; 4) the portfolio balance model; and 5) the behavioral equilibrium exchange rate (BEER) model. The following six columns present the results estimated through an error-correction specification for each model mentioned and also for the uncovered interest rate parity (UIP) condition.[7]

The null hypothesis states that the loss differential is lower than zero, implying that the MSE calculated through each model forecast is lower than the MSE calculated through the random walk forecasts. The statistic *d* is asymptotically distributed through a standard normal distribution. As mentioned before, this criterion shows how close each model forecast was to the observed value in relation to the random walk forecast. For instance, a value such as -1.06, a result obtained in 8 out of 11 *d* statistics calculated for the first forecast period, indicated that the forecast produced by the random walk specification was, on average, 1.06 units further from the observed value than the forecast produced by the specific model which it was being compared.

[7] The UIP model was not estimated through the trend-gap data disaggregation criteria because it was a definition that provided the same result by any methodology used. Therefore, just one set of results was presented.

Table 1. Loss differential criterion over eight forecast periods

	Trend-gap specification					Error correction specification					
	(1) PPP	(2) Flexible	(3) Sticky	(4) Portfolio	(5) BEER	(1) PPP	(2) Flexible	(3) Sticky	(4) Portfolio	(5) BEER	(6) UIP
1	-1.06	-1.06	-1.06	-1.06	-1.07	-1.06	-1.06	-1.07	-1.06	-1.06	-1.03
	(0.03)**	(0.03)**	(0.03)**	(0.03)**	(0.03)**	(0.03)**	(0.03)**	(0.03)**	(0.03)**	(0.03)**	(0.03)**
2	-1.83	-1.82	-1.82	-1.82	-1.82	-1.79	-1.79	-1.80	-1.78	-1.78	-1.65
	(0.04)**	(0.04)**	(0.04)**	(0.04)**	(0.04)**	(0.06)*	(0.05)*	(0.06)*	(0.07)*	(0.06)*	(0.13)
3	-3.68	-3.67	-3.67	-3.67	-3.66	-3.59	-3.59	-3.60	-3.58	-3.56	-3.22
	(0.43)	(0.43)	(0.43)	(0.43)	(0.43)	(0.44)	(0.44)	(0.44)	(0.44)	(0.44)	(0.46)
4	-4.05	-4.05	-4.04	-4.04	-4.04	-3.92	-3.89	-3.93	-3.89	-3.89	-3.19
	(0.45)	(0.45)	(0.45)	(0.45)	(0.45)	(0.46)	(0.46)	(0.46)	(0.46)	(0.46)	(0.48)
5	-5.40	-5.40	-5.39	-5.39	-5.38	-5.24	-5.16	-5.23	-5.17	-5.17	-4.05
	(0.46)	(0.46)	(0.46)	(0.46)	(0.46)	(0.47)	(0.47)	(0.47)	(0.47)	(0.47)	(0.48)
6	-5.75	-5.75	-5.75	-5.75	-5.74	-5.58	-5.47	-5.57	-5.48	-5.49	-3.38
	(0.48)	(0.48)	(0.48)	(0.48)	(0.48)	(0.49)	(0.49)	(0.48)	(0.49)	(0.49)	(0.49)
7	-7.14	-7.14	-7.14	-7.14	-7.14	-6.95	-6.85	-6.95	-6.84	-6.83	-3.36
	(0.48)	(0.48)	(0.48)	(0.48)	(0.48)	(0.48)	(0.48)	(0.48)	(0.48)	(0.48)	(0.49)
8	-6.01	-6.02	-6.01	-6.01	-6.01	-5.79	-5.74	-5.79	-5.66	-5.64	-0.33
	(0.47)	(0.47)	(0.47)	(0.47)	(0.47)	(0.47)	(0.47)	(0.47)	(0.47)	(0.47)	(0.50)

Notes: Ho: the loss differential is lower than zero (implying that the MSE calculated through each model forecast is lower than the MSE calculated through the random walk forecasts). *** significant at 1% level; ** significant at 5% level; * significant at 10% level. (1) PPP: purchasing power parity model; (2) Flexible: flexible price monetary model; (3) Sticky: sticky price monetary model; (4) Portfolio: portfolio balance model; (5) BEER: behavioral equilibrium exchange rate model; (6) UIP: uncovered interest rate parity condition.

According to the estimated sign for all of the d statistics, all model forecasts seemed to be, on average, closer to the observed value than the random walk estimates. Nevertheless, in most cases the significance of such a forecast differential was relevant only for the first two period-ahead forecasts.[8] In fact, Table 1 shows in parenthesis the p-values for each of the d statistics calculated. By separating the results obtained through the trend-gap specification from those obtained through error-correction regressions, one can see that the d statistics are consistently significant at 5% for the first two period-ahead forecasts in the first type of models, while for the second type most of them are significant at the 5% level for the first period, but just at the 10% level in the second-period-ahead forecast. Therefore, the first kind of model specification provides better results.

Forecasts for the independent variables that feed each model specification were obtained through AR(1) processes. We also used observed data for these variables to determine whether the outcome generated for each model specification could improve over two periods ahead. However, no significant improvement was found in this exercise.

Comparison tests were also carried out between each of the model forecasts in order to determine the most reliable nominal exchange rate specification, particularly for the two periods ahead where model forecasts appeared to outperform those obtained through the random walk model. Therefore, by using the same methodology, but taking as a reference each of the model forecasts (instead of the random walk predictions), we determined that the trend-gap BEER specification provides slightly better forecasts than those obtained from the remaining models, particularly for the t+1 period .

These results contrast with empirical evidence from the nominal exchange rate forecasting literature which has usually failed to find short run exchange rate forecasts performed through structural models consistently superior to those from a random walk model. Although such results were obtained with both estimation methods, our evidence is more robust with the trend-gap methodology, particularly the BEER model. The final section presents some justifications to support these findings.

[8] The only exception is the forecast obtained through the UIP condition, which was more significant than the random walk specification only for the first-period-ahead forecast.

B. Second forecast comparison criterion: direction of change

The second criterion for evaluating model forecasts was the direction of change condition. The results obtained are presented in Table 2. The structure of this table is similar to the previous one. The null hypothesis in this test establishes that the proportion of correct-sign forecasts from each model specification was greater than the proportion of correct-sign forecasts obtained through the random walk model. Therefore, a *d* statistic calculated through this criterion is expected to have a positive sign.

As observed, the *d* statistics calculated were all positive. However, they were significant only from the second to the fourth forecasting periods and for the last (eighth) period projected. In fact, just 13 out of 88 possible results (14.8%) were significant, above the 5% critical level, and all of them belonged to the trend-gap specification. Even though the *d* statistic was greater than zero for the remaining periods, the results were not significant from the first period on since the random walk specification is also a good indicator of the direction of change for the first-period-ahead forecast.

As in the previous case, we also performed an alternative exercise by including observed data for all independent variables within the structural exchange rate models instead of forecasting those variables through AR(1) models. As a result, our second criterion test results show a significant improvement (see Table 3), particularly for exchange rate forecasts performed with the trend-gap specification methodology. In fact, 23 out of 88 forecasts (26.1%) were significant at the 5% level.

Furthermore, exchange rate forecasts generated through the BEER model appeared to be consistently superior, to the point that such forecasts were significantly better from the first- to the eighth-period-ahead forecasts than those generated by the random walk specification. Hence, the results improved significantly when employing observed data for all independent variables since we could predict an exchange rate appreciation or depreciation up to eight periods ahead. It was not possible to obtain the same kind of improvement through the first criterion because for evaluating the forecast error value, the MSE criterion is a more rigorous test.

Table 2. Direction of change criterion over eight forecast periods – independent variable forecasts generated through AR(1) models

	Trend-gap specification					Error correction specification					
	(1) PPP	(2) Flexible	(3) Sticky	(4) Portfolio	(5) BEER	(1) PPP	(2) Flexible	(3) Sticky	(4) Portfolio	(5) BEER	(6) UIP
1	0.19	0.19	0.16	0.16	0.25	0.25	0.25	0.25	0.25	0.28	0.16
	(0.76)	(0.50)	(0.96)	(0.96)	(0.24)	(0.86)	(0.64)	(0.64)	(0.92)	(0.36)	(0.76)
2	0.39	0.39	0.29	0.35	0.32	0.23	0.35	0.19	0.23	0.26	0.19
	(0.01)***	(0.00)***	(0.04)**	(0.02)**	(0.01)***	(0.50)	(0.24)	(0.76)	(0.64)	(0.08)*	(0.64)
3	0.30	0.27	0.27	0.27	0.23	0.23	0.30	0.23	0.20	0.20	0.23
	(0.03)**	(0.01)***	(0.07)*	(0.14)	(0.14)	(0.50)	(0.36)	(0.86)	(0.93)	(0.36)	(0.77)
4	0.28	0.21	0.28	0.28	0.21	0.31	0.31	0.28	0.28	0.24	0.24
	(0.00)***	(0.03)**	(0.03)**	(0.01)***	(0.07)*	(0.23)	(0.23)	(0.64)	(0.64)	(0.23)	(0.64)
5	0.21	0.14	0.14	0.14	0.18	0.18	0.18	0.14	0.21	0.18	0.18
	(0.22)	(0.50)	(0.65)	(0.65)	(0.35)	(0.97)	(0.78)	(1.00)	(0.97)	(0.78)	(1.00)
6	0.19	0.19	0.15	0.15	0.19	0.07	0.15	0.07	0.11	0.11	0.15
	(0.35)	(0.65)	(0.78)	(0.88)	(0.65)	(1.00)	(0.99)	(1.00)	(1.00)	(0.94)	(1.00)
7	0.27	0.23	0.27	0.23	0.27	0.15	0.19	0.19	0.23	0.19	0.15
	(0.12)	(0.22)	(0.12)	(0.22)	(0.06)*	(0.94)	(0.88)	(1.00)	(0.98)	(0.50)	(0.98)
8	0.24	0.28	0.24	0.24	0.28	0.16	0.28	0.12	0.16	0.20	0.08
	(0.05)**	(0.02)**	(0.05)**	(0.05)**	(0.00)***	(0.95)	(0.66)	(0.98)	(0.98)	(0.50)	(0.99)

Notes: Ho: The proportion of correct direction predictions is greater for each model than for the random walk specification. *** significant at 1% level; ** significant at 5% level; * significant at 10% level. (1) PPP: purchasing power parity model; (2) Flexible: flexible price monetary model; (3) Sticky: sticky price monetary model; (4) Portfolio: portfolio balance model; (5) BEER: behavioral equilibrium exchange rate model; (6) UIP: uncovered interest rate parity condition.

Table 3. Direction of change criterion over eight forecast periods – independent variable forecasts using observed data series

	Trend-gap specification					Error correction specification					
	(1) PPP	(2) Flexible	(3) Sticky	(4) Portfolio	(5) BEER	(1) PPP	(2) Flexible	(3) Sticky	(4) Portfolio	(5) BEER	(6) UIP
1	0.16	0.16	0.22	0.19	0.25	0.25	0.19	0.19	0.22	0.28	0.16
	(0.96)	(0.86)	(0.64)	(0.86)	(0.02)**	(0.24)	(0.86)	(0.64)	(0.86)	(0.14)	(0.76)
2	0.39	0.29	0.42	0.32	0.42	0.26	0.23	0.16	0.26	0.32	0.19
	(0.02)**	(0.04)**	(0.00)***	(0.04)**	(0.00)***	(0.04)**	(0.76)	(0.86)	(0.36)	(0.01)**	(0.36)
3	0.27	0.13	0.37	0.40	0.40	0.20	0.27	0.13	0.23	0.23	0.17
	(0.14)	(0.77)	(0.03)**	(0.01)**	(0.00)***	(0.50)	(0.77)	(0.97)	(0.86)	(0.14)	(0.93)
4	0.31	0.17	0.31	0.34	0.41	0.24	0.34	0.17	0.28	0.31	0.21
	(0.00)***	(0.23)	(0.01)**	(0.07)*	(0.00)***	(0.50)	(0.13)	(0.87)	(0.64)	(0.03)**	(0.77)
5	0.25	0.18	0.25	0.29	0.36	0.11	0.25	0.11	0.21	0.21	0.11
	(0.13)	(0.50)	(0.07)*	(0.13)	(0.00)***	(1.00)	(0.65)	(1.00)	(0.93)	(0.65)	(1.00)
6	0.26	0.19	0.22	0.19	0.30	0.04	0.19	0.11	0.11	0.15	0.07
	(0.03)**	(0.65)	(0.50)	(0.50)	(0.01)**	(1.00)	(0.97)	(1.00)	(1.00)	(0.88)	(1.00)
7	0.35	0.35	0.35	0.35	0.31	0.19	0.31	0.12	0.27	0.23	0.19
	(0.00)***	(0.06)	(0.12)	(0.06)	(0.00)***	(0.88)	(0.78)	(0.98)	(0.78)	(0.35)	(0.98)
8	0.32	0.32	0.32	0.32	0.28	0.24	0.32	0.16	0.28	0.24	0.24
	(0.01)**	(0.05)*	(0.02)**	(0.05)*	(0.01)**	(0.88)	(0.79)	(0.95)	(0.79)	(0.21)	(0.79)

Notes: Ho: The proportion of correct direction predictions is greater for each model than for the random walk specification. *** significant at 1% level; ** significant at 5% level; * significant at 10% level. (1) PPP: purchasing power parity model; (2) Flexible: flexible price monetary model; (3) Sticky: sticky price monetary model; (4) Portfolio: portfolio balance model; (5) BEER: behavioral equilibrium exchange rate model; (6) UIP: uncovered interest rate parity condition.

C. Third forecast comparison criterion: consistency condition

The third forecast comparison criterion is a consistency condition, aimed to find a long run comovement between out-of-sample forecasted and observed exchange rate observations. According to Cheung, Chinn, and García-Pascual (2004), observed and forecasted series are consistent if: i) both series have the same order of integration; ii) they are cointegrated; and iii) the cointegrating vector satisfies the unitary elasticity of expectations condition, which implies, from equation (10), that $\omega_2 = 1$, and $\Gamma = -1$. Therefore, it was necessary first to test for unit roots in order to determine whether both series (forecasted and observed exchange rate series) had the same order of integration. Then, the Johansen cointegration methodology was used to find a cointegrating vector. Finally, whenever significant results were found, a restriction was imposed on the normalized coefficient of the cointegrating vector to check whether its value was statistically different from one. As mentioned earlier, two forecast windows were tried in this case. The first one was for the 2002-2009 period, since the implementation of the new financial legislation reforms, while the second one was for 2005-2009, since the establishment of Inflation Targeting in Guatemala. The likelihood of finding a significant cointegration relationship was expected to be higher in the second forecast window, given the shorter number of exchange rate observations forecasted (4 years instead of 7).

The results obtained through the trend-gap specification are presented in Table 4. The first column indicates the forecast window. The rest of the table is classified into five different blocks, each of them representing the results based on one particular model: 1) the purchasing power parity (PPP) model; 2) the flexible price monetary model; 3) the sticky price monetary model; 4) the portfolio balance model; and 5) the behavioral equilibrium exchange rate (BEER) model. Furthermore, for any given period each block contains the three main results that allowed us to determine whether forecasted and observed exchange rate series were consistent for the long-run. The first column shows the Unit Root Tests for the exchange rate series forecasted by each model; the null hypothesis for this test indicates that the forecasted series had a unit root (which means that a series is non stationary). Given that observed exchange rate data are first order integrated, I(1), in both forecast-windows, we expected that exchange rate forecasts would also be non-stationary and I(1). If this were the case, we would proceed to test whether both series were cointegrated. The second column of Table 4 shows the results obtained through the Johansen Cointegration Tests between forecasted and observed exchange rate series; the null hypothesis in this case states that both forecasted and observed exchange rate series were not cointegrated. A rejection of such a null hypothesis led us to a third test. The final consistency test required that the cointegrating vector satisfy the unitary elasticity of the expectations condition. The null hypothesis in this case states that a cointegrating vector normalized coefficient is equal to one. The third column shows the statistic calculated to test for a unit value cointegrating coefficient.[9] The first row shows the estimated coefficient for each test, while the value in parenthesis in the second row represents its p-value. Long run consistency between forecasted and observed exchange rate series requires an acceptance of the first null hypothesis tests (implying that both series are non stationary), rejection of the second null hypothesis (implying that both series are cointegrated), and an acceptance of the third null hypothesis (implying that there is a unitary elasticity of expectations between forecasted and observed exchange rate series).[10]

As observed, exchange rate forecasts generated by every model between 2002 and 2009 were non-stationary; they appear to have a unit root. Since this was also the case for the observed series, we tested for cointegration. Out of the five model forecasts, none of them appeared to be cointegrated with the observed series. Hence, no results appear in the unitary restriction column because no tests were made. On the other hand, all model forecasts generated for forecast window 2005-2009 were stationary. Therefore, a similar conclusion was reached, implying the non-existence of a cointegrating relationship between the forecasted and the observed exchange rate series. Hence, the restriction could not be tested so no results appear in these columns. In conclusion, based on the trend-gap specification, we did not find any long run consistency between forecasted and observed nominal exchange rate data in the two forecast windows, a result that is in line with our findings through the MSE and the direction of change criteria.

Table 5 presents the third criterion test results obtained through the error-correction specification. The structure of the table is similar to that of Table 4 with the difference that it includes another block for presenting the results obtained through the UIP condition.

[9] The latter statistic, shown in the third column of each section, is distributed according to a Chi-Squared distribution.

[10] For the non-stationary forecasts, we ran Augmented Dickey-Fuller tests for the first differences and in all cases we found that all series were I(1).

Table 4. Consistency condition — trend-gap specification

Period	(1) PPP			(2) Flexible		
	Uroot	Coint	Restr	Uroot	Coint	Restr
2002-2009	-0.04	0.23		-0.05	0.22	5.54
	(0.95)	(0.36)		(0.95)	(0.37)	
2005-2009	-3.25			-6.50		
	(0.03)**			(0.00)***		
Period	**(3) Sticky**			**(4) Portfolio**		
	Uroot	Coint	Restr	Uroot	Coint	Restr
2002-2009	-0.08	0.23		-0.06	0.22	
	(0.94)	(0.36)		(0.95)	(0.40)	
2005-2009	-3.52			-5.95		
	(0.02)**			(0.00)***		
Period	**(5) BEER**					
	Uroot	Coint	Restr			
2002-2009	0.25	0.26				
	(0.97)	(0.24)				
2005-2009	-3.77					
	(0.01)***					

Notes: Ho^{Uroot}: there is a unit root (the series is not stationary). Ho^{Coint}: there is no cointegrating relationship. Ho^{Restr}: the normalized coefficient is different from one. *** significant at 1% level; ** significant at 5% level; * significant at 10% level. (1) PPP: purchasing power parity model; (2) Flexible: flexible price monetary model; (3) Sticky: sticky price monetary model; (4) Portfolio: portfolio balance model; (5) BEER: behavioral equilibrium exchange rate model.

As in the previous case, most exchange rate forecasts performed for 2002-2009 have a unit root. The only exceptions were forecasts obtained through the flexible price monetary model and the UIP condition (blocks 2 and 6 of Table 5). Therefore, we proceeded to test for cointegration in all the remaining cases. According to the results, only the forecasts obtained through the PPP model, the sticky price monetary model, and the BEER specification were cointegrated with observed exchange rate values for the same forecast window. Nevertheless, when testing for the unitary elasticity of expectations, only BEER model forecasts supported that condition.

Table 5. Consistency condition — error-correction specification

Period	(1) PPP			(2) Flexible		
	Uroot	Coint	Restr	Uroot	Coint	Restr
2002-2009	20.99	0.97	48.44	-343.02		
	(1.00)	(0.00)***	(0.00)***	(0.00)***		
2005-2009	12.51	0.94	39.45	5.91	0.77	25.28
	(1.00)	(0.00)***	(0.00)***	(1.00)	(0.00)***	(0.00)***
Period	(3) Sticky			(4) Portfolio		
	Uroot	Coint	Restr	Uroot	Coint	Restr
2002-2009	0.88	0.62	1.18	23.59	0.23	
	(0.99)	(0.00)***	(0.28)	(1.00)	(0.36)	
2005-2009	16.87	0.97	49.60	7.49	0.56	4.60
	(1.00)	(0.00)***	(0.00)***	(1.00)	(0.02)**	(0.03)**
Period	(5) BEER			(6) UIP		
	Uroot	Coint	Restr	Uroot	Coint	Restr
2002-2009	11.00	0.36		-36.78		
	(1.00)	(0.05)**		(0.00)***		
2005-2009	-26.47			6.36	0.77	0.02
	(0.00)***			(1.00)	(0.00)***	(0.90)

Notes: Ho^{Uroot}: there is a unit root (the series is not stationary). Ho^{Coint}: there is no cointegrating relationship. Ho^{Restr}: the normalized coefficient is different from one. *** significant at 1% level; ** significant at 5% level; * significant at 10% level. (1) PPP: purchasing power parity model; (2) Flexible: flexible price monetary model; (3) Sticky: sticky price monetary model; (4) Portfolio: portfolio balance model; (5) BEER: behavioral equilibrium exchange rate model; (6) UIP: uncovered interest rate parity condition.

Similar results were obtained with the second forecast window (2005-2009). Initially, unit root test results indicated that with the exception of the BEER specification, all remaining model forecasts were non-stationary. Furthermore, by running cointegration tests between forecasted and observed data, we found that all the remaining forecasts were cointegrated with observed data. However, when testing for unitary elasticity of substitution, only those forecasts performed through the UIP condition supported that criterion. In conclusion, through the error-correction specification, we found long run consistency for exchange rate forecasts performed through the BEER specification for the 2002-2009 period, and for exchange rate forecasts performed through the UIP model for the 2005-2009 period. Our results from such cointegration tests seem to support the conclusions obtained in the results of the MSE and the direction of change criteria presented earlier. In particular, the BEER specification seems to provide not only the more accurate short run exchange rate forecasts, but also consistent long run projections.

D. Additional discussion

In summary, the results indicate that forecasts obtained through the theoretical exchange rate models discussed in this document are suitable for explaining short run exchange rate fluctuations since they are significantly better than those obtained from a random walk specification within the first 2 out-of-sample forecasting periods. Such forecasts are more precise when performed through the trend-gap specification and particularly by using the BEER model specified in equation (6). In fact, BEER model forecasts are not only better in terms of the mean squared error criterion, but they were also found to be more significant (relative to a random walk specification) for correctly predicting the direction of change in nominal exchange rate forecasts up to 8 out-of-sample forecasting periods. Moreover, BEER model forecasts are consistent with observed exchange rate data in the long run.

Our results contrast with empirical evidence from the exchange rate literature, which, when employing the same type of models presented in this study, has usually failed to provide short run exchange rate forecasts consistently superior to those from a random walk model. This is particularly true for exchange rate forecasts performed through a PPP specification.[11] We believe that our significant results are mainly due to the solid co-movement of Guatemalan and US business cycles (as evidenced by Roache 2008) that result from the strong commercial and financial bonds between both economies which intensified after the 2004 trade agreement between the United States, the countries of Central America and the Dominican Republic (CAFTA-DR).[12] In fact, the full effect of a trade agreement becomes more consolidated over time given the dynamic effects associated with capital accumulation, changes in specialization patterns, growth of trade associated with services, and stronger productivity spillovers. Evidence

[11] See Taylor (2009) for a summary of recent empirical literature providing robust support for long run PPP across a diverse range of countries, periods and methodologies employed.

[12] The Dominican Republic-Central America-United States Free Trade Agreement (CAFTA-DR) was signed between the US, five Central American countries (Costa Rica, El Salvador, Guatemala, Honduras and Nicaragua) in May 2004. The Dominican Republic joined the agreement in August of the same year. The agreement's main objective is the gradual elimination of tariffs and non-tariff barriers during a period of 20 years.

of stretched trade and financial dynamic effects on business cycle synchronicity is well documented in the economic literature (Frankel and Rose 1998; Clark and van Wincoop 2001; and Kose and Yi 2005). In fact, there is significant evidence of a deeper and more persistent response of the Guatemalan economy to US economic activity shock (Kose, Rebucci and Schipke 2005).[13] Hence, such effect is also reflected on domestic money supply, interest rates and internal prices, which are the main fundamental variables to explain quetzal-dollar nominal exchange rate fluctuations, according to structural equations (1)–(6). As a result, short run fluctuations in these fundamental variables have a significant effect on the bilateral Q-US$ exchange rate.

As mentioned, the most suitable specification for performing Q-US$ short run forecasts was the BEER model, equation (6). We believe that this model's advantage over the remaining five specifications lies in the careful selection of the model's fundamental variables, chosen after an extended search for domestic and external variables through dynamic correlation analysis. However, to understand the particular effect of each of the model components on the two-period-ahead forecasts (which were found to be significant), we performed a sensitivity analysis by comparing the original exchange rate forecast, obtained through equation (6), with exchange rate forecasts obtained through all possible combinations of the six variables contained in the original BEER specification.[14] Forecast comparison was also made using seven different values for the Hodrick Prescott smoothing coefficient parameter, l, in order to determine the degree of sensitivity of our results to this parameter value.[15] As mentioned, this paper's main results were obtained using a value of l equal to 100 before estimating equations (8) and (9).

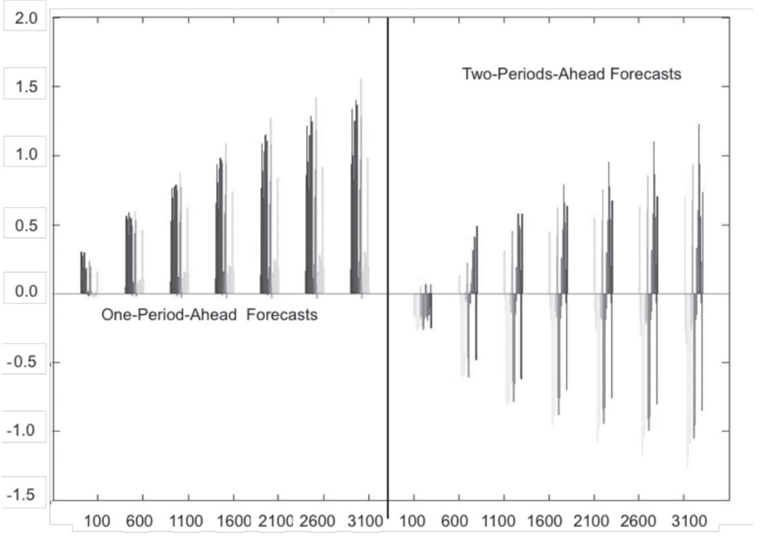
[13] It is significant that a similar response was obtained for Costa Rica, which among the CAFTA-DR countries is the only economy besides Guatemala to have a managed floated exchange regime. Therefore, similar results would be expected when forecasting the Costa Rican Colon vis-à-vis the US dollar exchange through the methodology used in this study.

[14] The total number of combinations that can be obtained with six elements is 31. Therefore, there are 30 different specifications besides the original one.

[15] Taking into account that we were dealing with quarterly data, the values used for λ were: 100, 600, 1100, 1600, 2100, 2600, and 3100, where 1600 is the default value established by Hodrick and Prescott (1980). Additional values for λ were also tried, but results remained similar to those shown in Figure 1. Therefore, our sensitivity exercise consisted of comparing, for each period-ahead forecast, the original forecast (where all cyclical component variables were obtained through a Hodrick Prescott filter with a value of λ equal to 100) with each of the 216 (= 31*7 -1) forecasts obtained through the 31 model specifications, for which forecasts for each model specification were performed based on cyclical variables calculated through each of the 7 different values of λ employed in the analysis.

Figure 1. BEER model: sensitivity analysis using MSE criterion

P-value percentage differential between baseline and alternative exchange rate forecasts



Hodrick-Prescott's smoothing coefficient, λ, for each of the 30 possible alternative variable combinations.

The sensitivity analysis for the MSE forecast comparison criterion is shown in Figure 1. This figure is divided into two panels. For one-period-ahead forecasts the left panel presents the percentage difference between the MSE p-value from the original exchange rate specification forecast and the MSE p-value from forecasts performed through all alternative specifications. There are seven groups of bars (each group corresponding to a different value of λ used to calculate the cyclical component of each fundamental variable), each containing thirty-one results (one for each model specification). The right panel presents similar results for two-period-ahead forecasts.[16] For any of the seven groups, a positive value implies that the MSE p-value from the alternative specification is greater than the MSE p-value from the original specification. Hence, the latter forecast is significantly better. Likewise, a negative value would imply that the alternative specification outperforms the original one (equation 6). The numerical results illustrated in Figure 1 are shown in Table A1 in the online appendix. With regard to one-

[16] We only show results for the initial two-period-ahead forecasts since those were the only periods in which the BEER model forecasts significantly outperformed those from the random walk specification.

period-ahead forecasts, 92.2% of the results are positive.[17] Hence, the base model outperforms most of the remaining model specifications at different smoothing parameter values. Interestingly, the higher the value of λ used in alternative specifications, the greater the base model outperformance, which implies that exchange rate forecasts from BEER models using variables in gap-form calculated through Hodrick-Prescott filters based on low smoothing parameters tend to outperform equally specified models whose variables in gap-form are calculated through higher values for λ. Results for two-period-ahead forecasts are surprisingly different. As shown in Table A1, just 38.7% of forecasts performed through the base model outperform those from alternative specifications. The remaining 61.3% of forecasts represent an improvement on the base model. Nevertheless, such an improvement is marginal, no greater than 0.013. Interestingly, most specifications that outperform the original two-period-ahead forecast are those that exclude the lagged nominal exchange rate gap component, $\hat{s}_{t-1}$. In other words, $\hat{s}^{f}_{t+2}$ (where the superscript *f* stands for forecasts) required us to estimate $\hat{s}^{f}_{t+1}$ before in some model specifications. Hence, forecast error was being carried into $\hat{s}^{f}_{t+2}$, so it slightly diminished the significance of the second period forecasted regarding model specifications that did not require such a component to perform a same period forecast. We conclude from this part of the analysis that equation (6) is a robust exchange rate specification that provides one-period-ahead forecasts consistently superior to all other specifications. However, the significance of the forecast slightly diminishes when forecasting the quetzal-dollar exchange rate over two periods ahead.[18]

The sensitivity analysis for the direction of change forecast comparison criterion is presented in Figure 2, which has the same structure as the previous figure. As observed, one- and two-period-ahead forecasts performed through the base model specification outperform forecasts produced by all other alternative specifications, according to this criterion.[19] The numerical results are presented in Table A2 in the online appendix. It is significant that results are independent of the value of λ used, particularly for the one-period-ahead forecasts.

In summary, the sensitivity analysis performed in this section demonstrates the robustness and goodness of fit of quetzal-dollar exchange rate forecasts obtained

[17] Although there is a small fraction of negative results (7.8%), their value is near zero. In fact it is equal to zero at three decimal approximations.

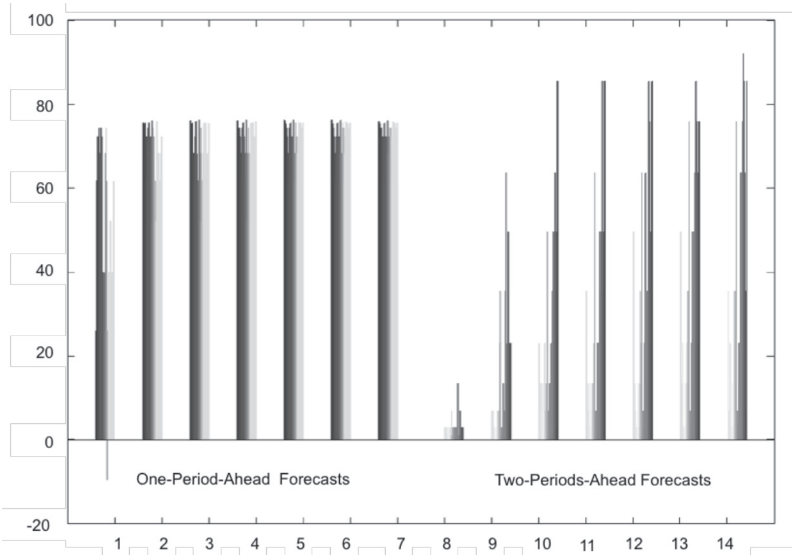
[18] We repeated the exercise excluding the variables mentioned to determine whether these model specifications could outperform random walk forecasts from three to eight periods ahead, but we did not get significant results.

[19] There is only one exception in the left panel which corresponds to combination 20 of Table A2, in the online appendix, when using a value of λ equal to 100.

through the BEER specification, equation (6), in which these model forecasts significantly outperform, in the very short run, those obtained through the random walk model.

Figure 2. BEER model: sensitivity analysis using direction of change criterion

P-value differential between baseline and alternative exchange rate forecasts



Hodrick-Prescott's smoothing coefficient, λ, for each of the 30 possible alternative variable combinations.

V. Conclusions

In this document we followed the empirical approaches of Meese and Rogoff (1983), and Cheung, Chinn and García-Pascual (2004) to compare nominal exchange rate forecasts for the quetzal vis à vis the U.S. dollar produced by several theoretical exchange rate models with those generated by a random walk specification. The models used in the analysis are the purchasing power parity, the uncovered interest rate parity, the monetary model in its flexible and sticky-price versions, the portfolio balance, and a behavioral empirical exchange rate (BEER) model. We generated the forecasts based on two alternative model specifications. First, we employed an innovative trend-gap approach in which all series were separated into their trend and gap components. Therefore, the theoretical models were expressed in a gap form, while the exchange rate trend component followed an ARIMA model. The second model was an error-correction specification.

Forecast comparisons were performed with regard to the random walk specification and with regard to all other model forecasts. To compare forecasts we employed three different forecast comparison criteria: i) the loss differential criteria constructed through the mean squared error statistic; ii) the direction of change criteria based on observed data; and iii) the cointegration criteria between each forecast and the observed series. We found that most models provide better forecasts than the random walk in the very short run: up to two periods (quarters) ahead. Among the different forecasts, the BEER and the PPP models estimated through the trend-gap specification were found to provide the most precise short run forecasts for $t+1$ and $t+2$, respectively, and the BEER was found to provide the better direction of change forecast up to eight-period-ahead forecasts. Therefore, according to the latter specification, the quetzal-dollar short run fundamentals are: i) the domestic money supply; ii) the US GDP; iii) family remittances; and, iv) the unit price of sugar exports.

Although forecasts for longer horizons do not provide a huge improvement over those generated through the random walk model, most forecasts were found to be cointegrated with observed exchange rate series even for a longer forecast horizon. According to these results, even though forecast precision weakens for longer horizons, their long run trend follows observed data quite well. Although further work is needed to improve forecast precision in the long run, quetzal-dollar short run fundamentals were identified.

Finally, a sensitivity analysis provided strong support for the robustness of BEER model forecasts as compared to alternative specifications using multiple combinations of the initial equation. This is mainly the case for one- and two-period-ahead forecasts.

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