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Short-term exchange rate predictability☆

Yu Ren[a], Qin Wang[*,c], Xiangyu Zhang[b]

[a] Wenlan School of Business, Zhongnan University of Economics and Law, Wuhan 430073, China
[b] Department of Economics, Simon Fraser University, Canada
[c] School of Finance, Zhongnan University of Economics and Law, Wuhan 430073, China

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ABSTRACT

In this paper, we revisit the monetary model in growth rates in explaining exchange rates. Different with the literature, we consider the cross-sectional dependence when using the panel data to predict exchange rates. By using quarterly and monthly data in 30 countries, we find that the monetary model in growth rates can outperform random walk with and without drift in the prediction.

1. Introduction

The difficulty in predicting exchange rates has been a longstanding problem in international economics and finance. Among many prediction models, monetary models emphasize the role of money and other assets in determining the balance of payments when the exchange rate is pegged, and in determining the exchange rate when it is flexible. They try to explore whether there are enduring instances where economic models can explain and predict future movements in exchange rates. The monetary models build a bridge between economic fundamentals and exchange rates. However, it is widely recognized that the current monetary models do poorly on prediction of post-Bretton Woods data.

For the out-of-sample prediction of exchange rates, (Meese and Rogoff, 1983a) and (Meese and Rogoff, 1983b) found that the random walk performs better than the monetary model. (Chinn and Meese, 1995) confirmed the same results for relatively short horizon (one-month- to twelve-month-ahead) forecasts. (Mark, 1995) concluded that the monetary model has strong and statistically significant predictive power at long forecast horizons of three to four years. However, (Cheung et al., 2005) found that the monetary model does not predict well at forecast horizons of one, four as well as twenty quarters, and the same result was confirmed by the (Alquist and Chinn, 2008). (Molodtsova and Papell, 2009) again confirmed limited predictive power for the monetary model at horizon of one month. (Cerra and Saxena, 2010) revealed that the monetary model can significantly beat the random walk at forecast horizon of one year and five years by using panel estimation and allowing for fixed country effects. As (Rossi, 2013) summarizes, the random walk provides the toughest benchmark, and panel monetary models display some forecasting ability at long horizons.

In financial markets, risk hedgers, speculators, traders and other investors have relatively short horizons. Therefore, forecasts of exchange rates for short horizons are more important to practitioners. This paper focuses on the short-term predictability of exchange rates. Particularly, we predict exchange rates one month and one quarter ahead. In a recent comprehensive investigation of the out-

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* Corresponding author.
E-mail address: qinwang188@gmail.com (Q. Wang).

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of-sample forecasting performance of a large number of exchange rate models, (Cheung et al., 2005) concluded that no model consistently outperforms a random walk at short horizons, thus confirming the general conclusion of Meese and Rogoff (1983a) and (Meese and Rogoff, 1983b) that random walk forecasts of the exchange rates generally outperform alternative models extracted from economic theories, especially at short horizons.

In this paper, based on the monetary model in growth rates, we consider the cross-sectional dependence and use the common correlated effects (CCE) estimation proposed in Pesaran (2006) to do estimation and prediction. Cross-sectional dependence does not raise the attention in exchange rate prediction. However, it appears that the international capital flows and trades are prominently integrated and so the foreign exchange markets. The explanatory variables in the conventional monetary models cannot capture all the factors that determine exchange rates. Once a factor is ignored by the model, we can observe the cross-sectional dependence in the estimation residuals. In order to improve the prediction performance, cross-sectional dependence should be taken into account.

Another advantage of using CCE estimation is that some macro variables, such as interest rates, expected inflations and trade balances data, are normally inaccessible or inaccurate for developing countries. When these variables are not included the model, they can be treated as latent factors in our model. This feature alleviates the problem of potential model misspecification, and hence provides better predictions.

Empirically, we use monthly and quarterly data from 30 countries and areas, and find that, in one period ahead forecasting, our model can provide significantly smaller mean square prediction error, compared with random walk with/without drift. Moreover, our results are robust to different sample periods.

The closest work to our paper are (Guo and Savickas, 2005), (Sarantis, 2006) and (Cerra and Saxena, 2010). (Guo and Savickas, 2005) showed that the inclusion of U.S. idiosyncratic stock market volatility yields one-step-ahead forecasts of exchange rate changes that outperform the random walk. However, the results are based on semi-annual data. When quarterly data are used, the results become insignificant. (Sarantis, 2006) used a Bayesian vector autoregressive model to examine daily predictability of exchange rates. While, our model is based on macroeconomic variables, and use economic fundamentals to predict exchange rates. (Cerra and Saxena, 2010) builded up panel monetary model, and find predictability of exchange rates for annual data. We apply the growth rate data into a panel monetary model that allow for cross-sectional dependence, and extend predictability of exchange rates to monthly and quarterly level.

The rest of this paper is organized as follows. Section 2 shows the data we used. Section 3 provides the model. Section 4 illustrates the empirical results. Section 5 concludes.

2. Data

We use the data for 30 countries and areas including Australia, Brazil, Canada, Chile, Czech Republic, Euro Area, Hungary, Iceland, India, Indonesia, Israel, Japan, Mexico, New Zealand, Norway, Paraguay, Peru, Philippines, Poland, Russia, Singapore, South Africa, South Korea, Sweden, Switzerland, Thailand, Turkey, Ukraine, United Kingdom and Uruguay. Two sets of frequencies are collected here. The monthly data is from 2002M1 to 2016M9, and the quarterly data is from 1999Q1 to 2016Q3.[1] All the data come from the IMF's database and CEIC, measured as end-of-period values. We choose the U.S. dollar as the numeraire and the exchange rate is quoted as the price of the U.S. dollar in terms of the domestic currency (domestic currency units per U.S. dollar). The nominal money supplies are the sum of money and quasi-money. We use the nominal GDP and the industry production index to measure quarterly and monthly economic activities, respectively. We use m to denote the log of the relative money supply to the numeraire country (U.S.), y the log of the relative economic activities. Following the early literature, we investigate the predictability of the log of the nominal exchange rates s.[2]

3. Model

3.1. The monetary model with cross-sectional dependence

We follow (Cerra and Saxena, 2010), and treat m and y as the explanatory variables to the nominal exchange rates. These variables are also the core variables in both flexible price (Frenkel–Bilson) and sticky price (Dornbusch–Frankel) monetary models.[3] Additional variables could include interest rates, expected inflation, and trade balances. Due to data availability, these variables may not be used as explanatory variables in the model.

As explained in Hendry and Mizon (2001), in the presence of structural breaks and policy-regime shifts, a differenced model can have a smaller bias than a model in levels. Therefore, we opt to use the monetary model in growth rates, which is specified as:

$$s_{i,t+1} - s_{i,t} = \alpha_i' d_{t+1} + \beta_i^m (m_{i,t+1} - m_{i,t}) + \beta_i^y (y_{i,t+1} - y_{i,t}) + v_{i,t+1}, \quad t = 1, 2, \ldots, T \tag{1}$$

where d_{t+1} is a vector of observed common effects including intercept and three seasonal dummies.

For the simplicity of notation, it can be written as

[1] Due to data availability, the monthly data starts from January 2002.

[2] In the literature, exchange rates have been pointed out to have potential seasonality. Here, we do not seasonally adjust exchange rates. Instead, we add seasonal dummies in our model to remove seasonality.

[3] See (Frenkel, 1976), (Frankel, 1979), (Bilson, 1978), (Bilson, 1979), (Dornbusch, 1976).

$$\Delta s_{i,t+1} = \alpha_i' d_{t+1} + \beta_i^m \Delta m_{i,t+1} + \beta_i^y \Delta y_{i,t+1} + v_{i,t+1}, \quad t = 1, 2, \ldots, T \tag{2}$$

where $\Delta s_{i,t+1} = s_{i,t+1} - s_{i,t}$, $\Delta m_{i,t+1} = m_{i,t+1} - m_{i,t}$ and $\Delta y_{i,t+1} = y_{i,t+1} - y_{i,t}$. The first order difference specification emphasizes the effects of changes of the monetary fundamentals on exchange rates.

We consider both the cross-sectional dependence and the heterogeneity in the panel data in Eq. (2). We allow both the intercept and coefficients to be heterogeneous across countries, and assume that the error terms $v_{i,t}$ have the following multifactor structure

$$v_{i,t} = \gamma_i' f_t + \epsilon_{i,t} \tag{3}$$

in which f_t is an $m \times 1$ vector of unobserved common factors, and $\epsilon_{i,t}$ is the individual-specific error which is assumed to be distributed independently of $s_{i,t}$ and f_t. Here, f_t can be regarded as any macro variables that may affect exchange rates but not in the model explicitly, for example, the growth rates of interest rates, expected inflations and trade balances.

Following (Pesaran, 2006), we allow $\epsilon_{i,t}$ to be weakly dependent across cross-sectional units and serially correlated over time. The pattern of serial correlation in $\epsilon_{i,t}$ can vary across cross-sectional units. Besides, the common factors f_t can be serially correlated and correlated with $\Delta s_{i,t}$, $\Delta m_{i,t}$ and $\Delta y_{i,t}$.

3.2. A cross-sectional dependence test

According to (Pesaran, 2004), the cross-sectional dependence test statistic based on the pair-wise correlation coefficients is defined as

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \right) \overset{a}{\sim} N(0, 1) \tag{4}$$

in which $\hat{\rho}_{ij}$ is the sample estimate of pair-wise correlation of variable series or residuals. Specifically,

$$\hat{\rho}_{ij} = \hat{\rho}_{ji} = \frac{\sum_{t=1}^{T} \hat{v}_{it} \hat{v}_{jt}}{\left(\sum_{t=1}^{T} \hat{v}_{it}^2\right)^{1/2} \left(\sum_{t=1}^{T} \hat{v}_{jt}^2\right)^{1/2}}, \tag{5}$$

where $\hat{v}_{it}$ is the estimate of v_{it} obtained by estimating Eq. (2). The null hypothesis of CD test is that there is no cross-sectional dependence with the alternative that there is.

3.3. Forecasting

We use the CCE estimation to obtain α_i, β_i^m and β_i^y.[4] Then the forecast of $s_{i,t+1}$ is

$$\hat{s}_{i,t+1} = s_{i,t} + \hat{\alpha}_i' d_{t+1} + \hat{\beta}_i^m \Delta m_{i,t+1} + \hat{\beta}_i^y \Delta y_{i,t+1} + \hat{\gamma}_i' \hat{f}_{t+1} \tag{6}$$

in which $\hat{\alpha}_i$, $\hat{\beta}_i^y$, $\hat{\beta}_i^m$ and $\hat{\gamma}_i$ are CCE estimators, and $\hat{f}_{t+1}$ is the forecast of the unobserved common factors. Following (Cheung et al., 2005) and (Cerra and Saxena, 2010), we use the future values of $m_{i,t+1}$ and $y_{i,t+1}$ in prediction.

The future values of $m_{i,t+1}$ and $y_{i,t+1}$ can be observed in the data, while, the forecast $\hat{f}_{t+1}$ cannot. In order to make Eq. (6) valid, we need to provide a prediction of $\hat{f}_{t+1}$ first. We follow the two-step procedure in Bernoth and Pick (2011) to solve this problem.

First, we estimate the unobserved common factors using the CCE estimation and collect the residuals. The residuals are

$$\hat{v}_{i,t} = \Delta s_{i,t} - \hat{\alpha}_i' d_t - \hat{\beta}_i^m \Delta m_{i,t} - \hat{\beta}_i^y \Delta y_{i,t}, \tag{7}$$

in which $\hat{\alpha}_i$, $\hat{\beta}_i^m$ and $\hat{\beta}_i^y$ are the CCE estimators.

Then, we apply the principal component analysis (PCA) to extract the first component as an unobserved factor f_t. We regress the residuals, $\hat{v}_{i,t}$, on f_t without a constant by the OLS to obtain the estimator of $\hat{\gamma}_i$.

$$\hat{v}_{i,t} = \gamma_i' f_t + \epsilon_{i,t}. \tag{8}$$

Then, we use an AR(1) process to fit f_t and forecast $\hat{f}_{t+1}$.[5] Hence, we calculate the forecast of $s_{i,t+1}$ based on the Eq. (6).

4. Empirical results

4.1. Model evaluation

We compare the out-of-sample forecasting performance of our model with random walk with/without drift and the monetary model in growth rates in Cerra and Saxena (2010).

Specifically, we consider the following four models:

[4] Estimation details are in (Pesaran, 2006).
[5] AR(1) is selected based on AIC.

Table 1
Out-of-sample forecasting.

	Quarterly data			Monthly data		
Forecasting periods:	2013Q1–2016Q3	2013Q3–2016Q3	2014Q1–2016Q3	2013M1–2016M9	2013M7–2016M9	2014M1–2016M9
Panel A: v.s. Random walk **without** drift						
Theil ratio	0.86	0.85	0.84	0.95	0.94	0.94
DM statistic	−2.16	−2.16	−2.13	−1.88	−1.91	−1.88
p-value	0.03	0.03	0.03	0.06	0.06	0.06
Direction	0.57/N.A.	0.56 /N.A.	0.58/N.A.	0.58/N.A.	0.57 / N.A.	0.5758/N.A.
Panel B: v.s. Random walk **with** drift						
Theil ratio	0.88	0.87	0.86	0.95	0.95	0.94
DM statistic	−2.08	−2.05	−2.06	−1.96	−2.00	−1.96
p-value	0.04	0.04	0.04	0.05	0.05	0.05
Direction	0.57/0.53	0.56 /0.54	0.58 / 0.52	0.58/0.46	0.57 / 0.47	0.58/0.46
Panel C: v.s. Fixed effect model						
Theil ratio	0.93	0.93	0.92	0.95	0.95	0.95
DM statistic	−1.85	−1.79	−1.83	−2.22	−2.26	−2.23
p-value	0.06	0.07	0.07	0.03	0.02	0.03
Direction	0.57/ 0.54	0.56 /0.55	0.58/0.56	0.58/0.48	0.57/0.48	0.58/0.48

This table reports the out-of-sample performances of our model. The benchmark models are the random walk with and without drift and the fixed effect model. Theil ratio is defined as the root mean squared forecast error ratio of the model with respect to the benchmark. The DM statistics are reported based on the DM test of the statistical significance of the Theil ratio, followed by the corresponding *p*-values. 'Direction' denotes the proportion of forecasts that correctly predict the direction of change of the exchange rates. The two numbers are our model and the benchmark model, separated by a slash.

(I) Random walk without drift:

$$\hat{s}_{i,t+1} = s_{i,t} \tag{9}$$

(II) Random walk with drift:

$$\hat{s}_{i,t+1} = s_{i,t} + \hat{\varsigma}_i \tag{10}$$

(III) Monetary model in growth rates (Cerra and Saxena, 2010 Model E):

$$\hat{s}_{i,t+1} = s_{i,t} + \hat{\alpha}_i' d_{t+1} + \hat{\beta}_i^m \Delta m_{i,t+1} + \hat{\beta}_i^y \Delta y_{i,t+1} \tag{11}$$

For Model III, we follow (Cerra and Saxena, 2010) and pool the coefficients on the explanatory variables while allowing for country fixed effects for the intercepts.

(IV) Our monetary model in growth rates

$$\hat{s}_{i,t+1} = s_{i,t} + \hat{\alpha}_i' d_{t+1} + \hat{\beta}_i^m \Delta m_{i,t+1} + \hat{\beta}_i^y \Delta y_{i,t+1} + \hat{\gamma}_i' \hat{f}_{t+1}. \tag{12}$$

To evaluate the forecasting performances, we use the Theil's U statistics, which is defined as the root mean squared forecast error (RMSFE) ratio of the structural models with respect to a benchmark. If this ratio is less than one, it means that model performs better than the benchmark. Following the literature, we also use the Diebold–Mariano test (Diebold and Mariano, 1995) to test the null hypothesis that two forecasting models have equal predictive accuracy. Moreover, we also evaluate model based on the proportion of forecasts that correctly predict the direction of change of the exchange rates.

4.2. Forecasting results

We divide the data into two parts. We estimate each model over the first part, make forecasts, and then recursively increase the estimation period until the end of the second part. In addition, before we estimate our model (Model IV), we collect the residuals delivered by Model III and test the cross-sectional dependence.[6] It turns out that all the tests are rejected at the level of 10%.

We set random walk with/without drift and Model III (the fixed effect panel model) as the benchmark models. Then, we calculate the Theil's U-statistics (the RMSFE ratio), the Diebold–Mariano statistics (DM) with the corresponding *p*-values and the proportion of forecasts that correctly predict the direction of change of the exchange rates. In order to check the robustness of our results, we also report the forecasting results for different samples at quarterly and monthly frequencies. Table 1 summarizes the results.

In Panel A of Table 1, the benchmark model is the random walk without drift. We can see that the Theil ratios of our model are all less than 1, which means that it delivers smaller squared forecast errors than the random walk without drift. In addition, the DM test shows that the superiority of our model for it is statistically significant as all the *p*-values are less than 10%. The results are quite

[6] Due to space limit, we do not report the CD test statistics here.

robust to six forecasting samples. Panel B reports the results as the benchmark is the random walk with drift. For the Theil ratios and the DM statistics, we observe similar patterns as in Panel A. In Panel C, the benchmark model is the fixed effect model. We observe that the Theil ratios are little bit higher than the values in Panel A and B, while, still less than 1. This means that although the fixed effect model is worst to our model, it is better than the random walk. This finding extends the results in Cerra and Saxena (2010), which only discussed the predictability of annual data.

Table 1 also reports the predictability of direction change for three models. Since the random walk without drift provides no information on the direction change, we use 'N.A.' in Panel A. Two numbers are shown in the last columns of Panel B and Panel C. They are the proportions of forecasts that correctly predict the direction of change of the exchange rates for our model and the benchmark model, respectively. As we can see, our model always delivers higher proportion rate than the alternative one, no matter which forecasting sample is considered.

5. Conclusion

In this paper, we propose to use CCE method to estimate the monetary model in growth rates, and to predict exchange rates in short terms. The monetary model in growth rates has been discussed in the literature, but the cross-sectional dependence in the model has not yet noted. We find that, after handling the cross-sectional dependence properly, the monetary model in growth rates can outperform the random walk with and without drift in one month or one quarter ahead forecasting. This result is robust to different estimation and prediction samples.

The success of short-term prediction of exchange rates in our model provides an empirical connection between economic fundamentals and exchange rates. Moreover, it sheds some light on solving the longstanding problem in the international economics and finance.

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