Exchange Rate Forecastability: Divisia, the User Cost Price, and the Euro

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Motivation

- Divisia monetary aggregates have been shown to be an improvement on the simple-sum monetary aggregates.
- They have helped solve some of the difficult problems in the profession.
- One such problem is forecasting exchange rates.
- Meese and Rogoff (1983) convincingly argued that no model could outperform a driftless random walk in predicting exchange rates.
- Many studies have tried to find a model that improves on the random walk but results have been mixed.
- The use of Divisia monetary aggregates and User Cost Prices can help in this matter as well.

Research Question

- *What we want to know*: Does the inclusion of Divisia monetary aggregates and User Cost Prices in traditional structural models improve their predictive power for exchange rates?

- This study includes the User Cost Price and Divisia monetary aggregates as variables in the Flexible Price Monetary model (FP), Sticky Price (SP) and Hooper Morton (HM) models, plus Uncovered Interest-rate Parity (UIP) to see if forecasting power improves on the random walk when the aforementioned variables replace the interest rate and simple sum monetary aggregates (respectively). Specifically, this study looks at the USD/EUR exchange rate.

- *This study* Finds that UIP with User Cost Prices (UIPUC) improves on random walk forecasts in every forecasting period and that the improvement becomes statistically significant starting in the fourth period.

- Purchasing Power Parity (PPP) and UIP analyses and discussions can be found as far back as the sixties (see, for instance, Balassa (1964)). Dornbusch (1976) proposed a Sticky Price (SP) model based on monetary fundamentals and Frankel (1979) further developed this framework by emphasizing the role of expectations. Hooper and Morton (1982) extended this model to include current account balances.
- However, Meese and Rogoff (1983) wrote a seminal study in which they convincingly argued that no exchange rate model can outperform a driftless random walk in out-of-sample forecasting. Since then, Mark (1995) proposed that at longer horizons a monetary fundamentals model could provide with better out-of-sample forecasts. This model has been subject to criticism by Killian (1999) and Faust et al (2003) where they argue that improvements occur only with a two-year window and disappear afterwards.

- More recent attempts which have shown more promising results. Lothian and Wu (2011) show that UIP has remarkable forecasting power in longer time horizons. Wright (2008) shows that Bayesian Model Averaging outperforms the random walk in shorter time horizons. Lace et al. (2015) argue that the EUR/USD exchange rate can be determined by government yields in the short-run.
- Barnett and Kwag's (2006) were able to show that the use of Divisia monetary aggregates and the User Cost Price dramatically improve the forecasting power of structural models. In a similar vein, Ghosh and Bhadury (2018) show that Divisia Monetary aggregates are powerful indicators of exchange rate movements for several economies.

- The User Cost Price and Divisia Monetary aggregates were derived by Barnett (1978, 1980). Some of the most important works in the literature have been collected in Barnett and Serletis (2000) and Barnett and Binner (2004).
- Reimers et al. (2002) found that Divisia aggregates for several countries in Europe have better out-sample-predicting power for the GDP deflator in the Euro area. Schunk (2001) showed that using Divisia aggregates improves the accuracy of US real GDP and GDP deflator predictions.
- Binner (2005) finds there are strong indications that Divisia outperforms simple-sum aggregates in a non-linear framework when forecasting inflation for the euro.

- Methodology: Generalities
- This study compares out-of-sample exchange forecasts produced by eight structural models. The first four are HM, FP, SP, and UIP. Divisia monetary aggregates then replace simple-sum aggregates (where applicable) and the User Cost Price replaces short-term interest rates. They are respectively refered to as HMD, FPD, SPD and UIPUC. Their performances are compared to forecasts produced by a random walk under three criteria: RMSE, DoC, and the Diebold-Mariano Statistic (DM).
- What follows is a more detailed explanation of the methodology.

- Methodology: Divisia
- We know that the capital stock of money in a given time period is not equal to the monetary service flow (as capital goods do not fully depreciate in a period).
- The price of these monetary service flows is the opportunity cost, or user cost, of holding a particular monetary asset for that period.
- The User Cost Price then is the present value of however much interest an agent is not receiving because they are holding an asset, given that there exists a pure investment asset which provides a higher return and no monetary services.

- Methodology: Divisia
- The User Cost Price is calculated thusly:

$$\pi_{it} = (R_t - \gamma_{it})/(1 + R_t) \tag{1}$$

- where γ_{it} is the return on asset i and R_t is the return on the pure investment, or benchmark, asset.

- Methodology: Divisia
- With the User Cost Price precisely defined, an aggregate for the monetary service flows can be elaborated which will track these flows correctly. For this purpose a Divisia index is used. For the construction of Divisia indexes, let:

$$s_{it} = \pi_{it} m_{it} / \sum \pi_{jt} m_{jt} \qquad (2)$$

- where m_{it} is the nominal monetary asset i at time t.

- Methodology: Divisia
- The Divisia monetary index is:

$$\ln M_t - \ln M_{t-1} = \sum_{t=1}^{n} s_{it}(\ln m_{it} - \ln m_{it-1}) \qquad (3)$$

- Here M_t is the quantity index and s_{it} is defined as $s_{it} = 1/2(s_{it} + s_{it-1})$. From the above equation, one can see that the growth rate of the index is a weighted sum of each monetary asset i. Each i has a share in the User Cost and this is precisely its corresponding weight in the Divisia index.

- Methodology: Divisia
- Finally, the accompanying User Cost Price index Π is defined as:

$$\ln \Pi_t - \ln \Pi_{t-1} = \sum_{t=1}^{n} s_{it}(\ln \pi_{it} - \ln \pi_{it-1}) \qquad (4)$$

- The idea here is that agents substitute toward holding the monetary assets which have the lowest relative user costs whenever there is a change in the own interest rate of another component monetary asset. This reflects how agents take into account opportunity costs in their decision process.

- Methodology: The Models
- Hooper and Morton (1982) developed an exchange rate forecasting model which was based on previous models such as Dornbusch's (1976) Sticky Price model and the Flexible Price Monetary model by Frenkel (1976) .
- The HM model includes the Current Account (CA) as an explanatory variable (its principal innovation).

- Methodology: The Models
- Thus, we have the following:

$$
\begin{aligned}
e_t = {} & \beta_0 + \beta_1(m_t - m_t^*) + \beta_2(y_t - y_t^*) \\
& + \beta_3(i_t - it^*) + \beta_4(p_t - p_t^*) + \beta_5 ca_t + \beta_6 cat^* + \nu_t
\end{aligned} \tag{5}
$$

- where e_t is the exchane rate and m_t and m_t^*, y_t and y_t^*, i_t and i_t^*, p_t and p_t^*, ca_t and ca_t^* are, respectively, domestic and foreign money supply, domestic and foreign output, domestic and foreign interest rates, domestic and foreign current long-run expected rates of inflation, and domestic and foreign current account balances at time t.

- Methodology: The Models
- The model specification involves an error-correction and the equation becomes the following:

$$\begin{aligned} lne_{t+h} - lne_t = \; & \alpha_0 + \alpha_1 (lne_t - \beta_0 \\ & - \beta_1 ln\tilde{m}_t - \beta_2 ln\tilde{y}_t - \beta_3 ln\tilde{i}_t - \beta_4 ln\tilde{p}_t \\ & - \beta_5 ca_t - \beta_6 ca^*_t) + \epsilon_t \end{aligned} \tag{6}$$

Here $\tilde{m}_t$, $\tilde{y}_t$, $\tilde{i}_t$, and $\tilde{p}_t$ are domestic to foreign relative money supply, output and short-term interest rates, respectively, and h is the forecasting horizon. I should note that I have replaced long-run expected rates of inflation with with the corresponding CPI indexes.

- Methodology: The Models
- Notice that by setting $\beta_5 = \beta_6$=0, the model is reduced to the Sticky Price model; $\beta_4 = \beta_5 = \beta_6$=0 results in the Flexible Price Monetary model; and, $\beta_1 = \beta_2 = \beta_4 = \beta_5 = \beta_6$=0 is Uncovered Interest-Rate Parity.
- Every one of the above models will be estimated twice: once with the variables as they have just been presented, and a second time with $\tilde{m}_t$ replaced by the Divisia index and $\tilde{i}_t$ replaced the User Cost Price index. There are then a total of eight models whose forecasting performance will be evaluated.

- Methodology: Evaluation
- In this study I use rolling regressions in order to produce the predicted forecasts.
- I asses the out-of-sample performance of each model 1 through 8 quarters ahead by comparing each one to a benchmark model which in this case is the driftless random-walk.
- I use Root Mean Square Error (RMSE), Direction of Change (DoC) and the Diebold-Mariano (DM) statistic as criteria.

- Methodology: Out-of-sample performance evaluation
- In order to evaluate how well each model is performing I have compared each one to a benchmark model which in this case is the driftless random-walk given by

$$\ln e_{t+h} - \ln e_t = \epsilon_t \tag{7}$$

- Following Meese and Rogoff's methodology, I take the expectation of the random walk so that it becomes a martingale, i.e. the predictor of the exchange rate h periods ahead is whatever the exchange rate is at time t.

- Methodology: Out-of-sample performance evaluation
- First, I use the RMSE of each of the four models and divide it by the RMSE of the random-walk. A ratio of less than one indicates that the model is performing better than the random-walk and viceversa.

- Methodology: Out-of-sample performance evaluation
- The second method of evaluation is the Direction of Change (DoC) ratio where I measure the proportion of times each model correctly predicts whether the actual exchange rate increases or decreases. Assuming that the expected value of random walk predicting the right DoC is 0.5, values above 0.5 indicate that a model is outperforming the random walk. The higher the proportion is, the better the model is performing.

- Methodology: Out-of-sample performance evaluation
- The third method is the statistic produced by Diebold & Mariano (1995), which allows for the comparison of forecasts in terms of whether the difference between two forecasts for the same forecasting period is statistically significant and whether the improvement is statistically significant (and thus, one forecast is "better" than another).

- Methodology: Out-of-sample performance evaluation
- If $g(e_{it})$ is the loss function of a forecast error, the loss differential function is defined as $d_t = g(e_{1t}) - g(e_{2t})$. If d_t is zero, then the forecasts under examination are equally accurate. Under the null, the expected value of d_t is zero. The DM statistic itself takes the form

$$DM = \bar{d}/\sqrt{2\pi \hat{f}_{d(0)}/T} \tag{8}$$

- where $\bar{d}$ is the sample mean of the loss differential function and $\hat{f}_{d(0)}$ is a consistent estimate of the spectral density. Under the null, $DM \to N(0,1)$. The null is rejected if $|DM| > z_{\alpha/2}$.

- Data
- For this paper, the data are quarterly series of the different variables in the models starting in January, 2001 through January, 2017 for the USD/EUR exchange rate.
- Data for Divisia aggregates are only available starting in January, 2001 at the Bruegel Institute and so the series begins at that particular date.
- The in-sample period goes from that date until the first quarter of 2009 and the out-of-sample period starts in the second quarter of 2009.

- Data
- For US data, I use 3-month Treasury Bill rates for the short-term interest rates, quarterly US GDP for output, US CPI as the price level, and the Current Account Balance. All of them were retrieved from the St. Louis Fed Federal Reserve Economic Data (FRED).
- The simple-sum M3 monetary aggregate comes from the Organization for Economic Co-operation and Development's (OECD) database. The User Cost Price and the Divisia M3 Monetary Aggregates for the US were taken from the Center for Financial Stability's website.

- Data
- As for the Euro, interest rates on Euro Area government bonds, Euro area GDP, Euro area CPI were taken from the FRED website. The Euro simple-sum M3 monetary aggregate also comes from the OECD database.
- The Current Account Balance was taken from the European Central Bank (ECB) database. The User Cost Price and Euro Divisia M3 monetary aggregates were taken from the Bruegel Institute database.

- Results: RMSE
- Table 1 displays the RMSE ratios of the HM model and the HM model with Divisia and User Cost Prices (HMD) for every forecasting period.
- Similarly, tables 2, 3, and 4 display the RMSE ratios for the SP model and SP with Divisia and the User Cost Price (SPD), the FP model and FP with Divisia and the User Cost Price (FPD), and UIP and UIP with the User Cost Price (UIPUC), respectively.

- Results: RMSE
- In tables 1 to 3 results are quite similar: models which include the Divisia index and the User Cost Price have a greater forecasting power than the models which use simple-sum aggregates and short-term interest rates.
- But none of these models outperform the random walk in any period (except for SP and FP in the first forecasting period). Table 4, though, shows a completely different story.
- Here UIPUC not only improves on the forecasting power of UIP but also outperforms the random walk in every forecasting period.

Exchange Rate Forecastability: Divisia, User Cost Price, and the Euro

Table 2.1: Ratio of HM RMSE over Random Walk RMSE

	HM	HMD
1 quarter	1.00687	1.00371
2 quarters	1.06588	1.04105
3 quarters	1.12969	1.02284
4 quarters	1.20447	1.07642
5 quarters	1.23153	1.07526
6 quarters	1.29829	1.17720
7 quarters	1.31225	1.16461
8 quarters	1.35662	1.21225

Figure: USD/EUR exchange rate.

Exchange Rate Forecastability: Divisia, User Cost Price, and the Euro

Table 2.2: Ratio of SP RMSE over Random Walk RMSE

	SP	SPD
1 quarter	0.99828	1.00619
2 quarters	1.03722	1.03001
3 quarters	1.10472	1.03480
4 quarters	1.18508	1.06516
5 quarters	1.22500	1.06074
6 quarters	1.29515	1.15276
7 quarters	1.31373	1.14679
8 quarters	1.35479	1.17359

Figure: USD/EUR exchange rate.

Table 2.3: Ratio of FP RMSE over Random Walk RMSE

	FP	FPD
1 quarter	0.99828	1.00619
2 quarters	1.03722	1.03001
3 quarters	1.10472	1.03480
4 quarters	1.18508	1.06516
5 quarters	1.22500	1.06074
6 quarters	1.29515	1.15276
7 quarters	1.31373	1.14679
8 quarters	1.35479	1.17359

Figure: USD/EUR exchange rate.

Table 2.4: Ratio of UIP RMSE over Random Walk RMSE

	UIP	UIPUC
1 quarter	1.02207	0.98906
2 quarters	1.05736	0.98553
3 quarters	1.08836	0.96603
4 quarters	1.13401	0.94735
5 quarters	1.19455	0.94440
6 quarters	1.27315	0.97313
7 quarters	1.29771	0.97732
8 quarters	1.30771	0.96407

Figure: USD/EUR exchange rate.

- Results: DoC
- Under the DoC criterion results are much more mixed and rather uninformative.
- Examining tables 5 to 8, proportions are not consistent for any of the forecasting dates.
- All four models outperform the random walk exceeding 0.5 threshold for some dates but fall dramatically below it for others.
- Here I include table 9 simply in order to show that even the actual forecasts from the random walk also fail to perform as expected (only in the second forecasting period is the proportion 0.5).

Exchange Rate Forecastability: Divisia, User Cost Price, and the Euro

Table 2.5: Ratio of Direction of Change HM vs. HMD

	HM	HMD
1 quarter	0.45161	0.41935
2 quarters	0.46667	0.40000
3 quarters	0.48276	0.55172
4 quarters	0.32143	0.32143
5 quarters	0.55556	0.55556
6 quarters	0.61538	0.50000
7 quarters	0.64000	0.44000
8 quarters	0.54167	0.50000

Figure: USD/EUR exchange rate.

Exchange Rate Forecastability: Divisia, User Cost Price, and the Euro

Table 2.6: Ratio of Direction of Change SP vs. SPD

	SP	SPD
1 quarter	0.41935	0.41935
2 quarters	0.53333	0.53333
3 quarters	0.51724	0.48276
4 quarters	0.35714	0.39286
5 quarters	0.44444	0.55556
6 quarters	0.61538	0.73077
7 quarters	0.60000	0.48000
8 quarters	0.54167	0.58333

Figure: USD/EUR exchange rate.

Table 2.7: Ratio of Direction of Change FP vs. FPD

	FP	FPD
1 quarter	0.41935	0.41935
2 quarters	0.50000	0.46667
3 quarters	0.48276	0.41379
4 quarters	0.32143	0.46429
5 quarters	0.51852	0.48148
6 quarters	0.69231	0.65385
7 quarters	0.52000	0.60000
8 quarters	0.58333	0.45833

Figure: USD/EUR exchange rate.

Table 2.8: Ratio of Direction of Change UIP vs. UIPUC

	UIP	UIPUC
1 quarter	0.45161	0.45161
2 quarters	0.53333	0.53333
3 quarters	0.48276	0.48276
4 quarters	0.39286	0.35714
5 quarters	0.37037	0.44444
6 quarters	0.65385	0.73077
7 quarters	0.40000	0.44000
8 quarters	0.62500	0.58333

Figure: USD/EUR exchange rate.

Table 2.9: Ratio of Direction of Change RW

	RW
1 quarter	0.41935
2 quarters	0.50000
3 quarters	0.51724
4 quarters	0.39286
5 quarters	0.44444
6 quarters	0.61538
7 quarters	0.44000
8 quarters	0.58333

Figure: USD/EUR exchange rate.

- Results: DM
- The DM statistic provides supporting evidence for the results found under the RMSE criterion. When comparing the forecasts produced by the models and those produced by the random walk, all models except UIPUC behave similarly to UIP as presented in table 10.
- What this means is that DM statistics are all large and positive and p-values quickly converge to 1 (in the case of models without Divisia and User Cost Price) or get very close to one (in the case of models with Divisia and User Cost Price) as the forecasting horizons increase.

- Results: DM
- UIPUC, though, is different. First, in every forecasting horizon, the DM statistic is negative and increasingly so.
- Second, p-values decrease in every period except for a small rise in the second period.
- Notice that by the third quarter, the p-value is barely above the 10% level.
- From quarters 4 to 6 p-values are below the 10% significance level; and in quarters 7 and 8, they are below the 5% significance level.

Table 2.10: Diebold-Mariano Statistic UIP vs. UIPUC

	DM UIP	p-value UIP	DM UIPUC	p-value UIPUC
1 quarter	0.64684	0.74110	−1.01440	0.15520
2 quarters	1.02390	0.84710	−0.91968	0.17890
3 quarters	1.21990	0.88870	−1.24240	0.10700
4 quarters	1.72250	0.95750	−1.53070	0.06292
5 quarters	2.30420	0.98940	−1.38790	0.08259
6 quarters	3.93230	1	−1.43680	0.07538
7 quarters	5.47870	1	−1.94320	0.02600
8 quarters	6.48360	1	−2.23270	0.01278

Figure: USD/EUR exchange rate.

- Discussion
- The truly interesting results appear where the models are evaluated under the RMSE and DM criteria.
- There, it is remarkable to see that the UIPUC model "beats" the random walk in every forecasting period and that the improvement becomes statistically significant as the forecasting horizons extend into the future.

- Discussion
- What this would seem to indicate is that, on the one hand, agents are not just monitoring short-term interest rates but the returns available on a variety of assets in different time periods; on the other hand, agents take into account the opportunity cost of holding assets - the foregone return.
- These results are also consistent with previous work showing that interest rates are good exchange rate predictors.
- As mentioned before, under the DoC criterion there is no strong evidence for or against the use of any one particular model (including the benchmark model). In some periods, some models produce results which are above the 0.5 reference and in some they do not.

- Forecasting exchange rates is not a lost cause.
- Interest rates seem to have become the driving variable for exchange rates.
- No single model is best. This is not a one-size-fits-all situation (yet).
- The use of Divisia monetary aggregates and the User Cost Price improves forecasts.

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