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Do Divisia monetary aggregates help forecast exchange rates in a negative interest rate environment?

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ABSTRACT

This paper contributes to the literature as the first work of its kind to examine the role and importance of Divisia monetary aggregates and concomitant User Cost Price indices as superior monetary policy forecasting tools in a negative interest rate environment. We compare the performance of Divisia monetary aggregates with traditional simple-sum aggregates in several theoretical models and in a Bayesian VAR to forecast the exchange rates between the euro, the dollar and yuan at various horizons using quarterly data. We evaluate their performance against that of a random walk using two criteria: Root Mean Square Error ratios and the Clark-West statistic. We find that, under a free-floating exchange regime, superior Divisia monetary aggregates outperform their simple sum counterparts and the benchmark random walk in a negative interest rate environment, consistently.

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Forecasting; exchange rates; Bayesian vector autoregression; uncovered interest rate; sticky price

1. Introduction

Forecasting exchange rates is very difficult. Although many economists have written studies on the matter and have found positive results, most of these have later been refuted or at least called into question. There is no one model that works in all circumstances and several authors have argued that none work. In particular, Meese and Rogoff (1983) presented compelling evidence that no model outperforms a driftless random walk in forecasting exchange rates. Since then, researchers have had a hard time finding a convincing alternative. One such example is Lothian and Wu (2011) which shows that Uncovered Interest Parity (UIP) has remarkable forecasting power in longer time horizons; another is Wright (2008) where the author argues that Bayesian Model Averaging outperforms the random walk in shorter time horizons. Even so, in 2019 Cheung et al. (2019) produced results that reinforced the idea that no model can consistently beat a random walk. None of the aforementioned studies, however, has adopted the approach found in Barnett and Kwag (2006) where they use Divisia monetary aggregates and the User Cost Price within a structural model framework with great success in forecasting the US dollar/British pound exchange rate.

Our objective in this paper is to extend the Barnett and Kwag (2006) experiment by applying it to the Euro/US dollar, US dollar/Yuan, and Euro/Yuan exchange rates (henceforth, EUR/USD, USD/CNY, EUR/CNY) in a negative interest rate environment. We should point out that the USD/CNY exchange rate is included for the sake of generality, as it is not affected directly by negative interest rates. In order to see the usefulness of Divisia aggregates and the User Cost Price, we split our data into pre-negative rates data and the complete data set (which includes negative interest rates). For the case of the USD/CNY, we change in-sample and out-of-sample periods in order to reflect changes in China's exchange rate policy. Just as in Barnett and Kwag's study, we employ Divisia Monetary aggregates (Barnett 1978, 1980) and the User Cost Prices calculated for the Euro zone, the US and China in several structural models and a Bayesian VAR (BVAR) model (for contrast, as it is a non-theoretical

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model). In particular, Divisia monetary aggregates replace simple-sum monetary aggregates and the User Cost Price replaces interest rates in each model. We start by evaluating the performance of the Hooper-Morton (HM) model and then proceed to the Flexible Price Monetary model (FP), the Sticky Price (SP) model, Uncovered Interest-rate Parity (UIP), and BVAR. The inclusion of UIP and BVAR in this paper is another innovation with respect to the Barnett and Kwag study. We evaluate the performance of each model using the Root Mean Square Error (RMSE) ratio and the Clark-West (CW) statistic and compare each model's performance to that of the random walk, as per standard practice in the literature. Each of the aforementioned models becomes HMD, FPD, SPD, and BVARD when it includes Divisia monetary aggregates and the User Cost Price, except UIP which becomes UIPUC, as it includes the User Cost Price but does not include Divisia aggregates. Finally, we include two models that underscore the particular behavior of the USD/CNY exchange rate: a model with international reserves (Res) as its only explanatory variable, and a model with the statistically significant variables from HM and HMD plus reserves (which is also statistically significant). These latter models are referred to as CIR and CIRD[1] when they include interest rates and User Cost Prices and the Divisia index, respectively.

This paper contributes to the literature as the first work of its kind to examine the role and importance of Divisia monetary aggregates and concomitant User Cost Price indices as superior monetary policy forecasting tools in a negative interest rate environment. We use quarterly data and the forecasting periods are 1 through 12 quarters ahead. We run the regression for each model twice for each data set: once with the original variables and once with Divisia aggregates and the User Cost Price. We find that, under the RMSE criterion, using Divisia monetary aggregates helps produce forecasts for the EUR/USD that consistently out-perform simple-sum aggregates and the random-walk in negative and non-negative rates environments using UIPUC and BVARD; for the EUR/CNY exchange rates, consistency is observed using the BVARD; no such consistency is found for the USD/CNY but the Res and CIR models outperform the random walk consistently but only for the short-run. We believe the latter result has to do with China's foreign exchange policies. Using the CW statistic, results are largely consistent with those under RMSE.

The rest of the paper proceeds as follows: in Section 2, we discuss the previous literature related to exchange rate forecasting and Divisia Monetary aggregates; in Section 3, we define and describe the User Cost Price and Divisia monetary aggregates; in Section 4, we refer to the evolution of China's foreign exchange policy; in Section 5, we discuss negative interest rates as a policy instrument; in Section 6, we present the models; in Section 7, we describe the data and their sources; in Section 8, we present the results, briefly discussing them; Section 9 concludes.

2. Literature review

Forecasting models for exchange rates have existed for decades. PPP and UIP analyses and discussions can be found as far back as the sixties and as recently as 2013 (see, for instance, Balassa 1964 and Lothian and Wu 2011). Dornbusch (1976) proposed the 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. But almost immediately after that paper was published, 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 better out-of-sample forecasts. This model has been subject to criticism by Faust, Rogers, and Wright (2003). There have been, however, more recent attempts which have shown more promising results: Wright (2008) and the aforementioned Lothian and Wu (2011) are two such cases. Molodtsova and Papell (2009) find that a model including Taylor rule fundamentals succeed at one-month predictions under the CW criterion; Lace, Mačerinskienė, and Balčiūnas (2015) argue that EUR/USD exchange rate can be determined by government yields in the short-run. More recently, Chang and Matsuki (2022) also finds that Taylor rule fundamentals help improve exchange rate forecasting under the RMSE and CW criteria.

BVAR was used in forecasting as far back as Litterman (1986). Sarantis (2006) showed that a BVAR model outperforms a random walk in forecasting daily exchange rates. Bańbura, Giannone, and Reichlin (2010) used BVAR for forecasting employment, the Consumer Price Index (CPI) and the Fed Funds Rate with positive results for first-quarter predictions. In a similar fashion, Edge, Kiley, and Laforte (2010) use several BVAR specifications in order to forecast macroeconomic variables within a DSGE framework, while comparing the accuracy of the forecasts produced by their model to a benchmark model (the FRB/US model). Recently, Schüssler et al. (2018) have used VAR-based models with Bayesian estimation methods for exchange rate forecasting with some success.

More germane to the present study is, of course, Barnett and Kwag (2006) where the authors 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 movements for several economies.The User Cost Price and Divisia Monetary aggregates were derived by Barnett (1978, 1980) which resulted in many volumes of work on monetary aggregation theory and the practical application of these concepts to different areas of economic research. Some of the most important works in the literature (but by no means all of it) has been collected in Barnett and Serletis (2000) and Barnett and Binner (2004). Reimers (2002) found that Divisia aggregates for several countries in Europe have better out-of-sample-predicting power for the GDP deflator in the Euro area. Similarly, Schunk (2001) showed that using Divisia aggregates improves the accuracy of US real GDP and GDP deflator predictions. Also, Binner et al. (2005) finds there are strong indications that Divisia outperforms simple-sum aggregates in a non-linear framework when forecasting inflation for the euro area, whilst the predictive power of the User Cost Price spread for economic recessions in both China and the USA has been investigated recently by Chang, Mattson, and Tang (2019). Belongia and Ireland (2015) show that Divisia monetary aggregates contain useful information for central bankers that help better describe the behavior of macroeconomic variables and Belongia and Ireland (2016) provide evidence of correlation between pro-cyclical movements in the money stock and output, especially when using Divisia monetary aggregates. Following the latter work, Dery and Serletis (2021) compute the correlations of the cyclical components in Divisia monetary aggregates and industrial production. Liu, Dery, and Serletis (2020) find that credit card-augmented Divisia monetary aggregates are helpful in predicting economic activity. In a similar vein, Liu and Serletis (2020) argue that unlike Divisia M4 aggregates, credit card-augmented Divisia M4 volatility negatively impacts economic activity. Barnett and Park (2021) use credit card-augmented Divisia monetary aggregates and credit card-augmented inside Divisia aggregates to forecast inflation.

3. Divisia monetary aggregates

From the path-breaking work of Barnett (1978, 1980) on microeconomic theory and aggregation theory, 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 foregoing because they are holding an asset, given that there exists a pure investment asset which provides a higher return and no monetary services. The User Cost Price is calculated thus:

$$\pi_{i,t} = (R_t - \gamma_{i,t})/(1 + R_t) \tag{1}$$

where $\gamma_{i,t}$ is the return on asset i and R_t return on the pure investment or benchmark asset. A key feature of the User Cost Price is that it can never be negative as a benchmark interest rate is added to compute each component weight, and the higher this benchmark rate is compared with other interest rates, the more equal all the relative weights become. In order to avoid negative weights, a simple solution is to add an arbitrary constant to the benchmark rate to obtain positive weights throughout, and this is particularly relevant for our results (see Section 7).

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 monetary index is used. For the construction of Divisia monetary indexes, let the share weight for each individual asset i over time, t, $s_{i,t}$, be defined as

$$s_{i,t} = \pi_{i,t}\mu_{i,t} \Big/ \sum_{j=1}^{n} \pi_{j,t}\mu_{j,t} \tag{2}$$

where $\mu_{i,t}$ is the nominal monetary asset i at time t, multiplied by its corresponding User Cost Price and divided by the weighted sum of all nominal monetary assets $\mu_{j,t}$. And so, the Divisia monetary index is

$$\ln M_t - \ln M_{t-1} = \sum_{i=1}^{n} s^*_{i,t}(\ln \mu_{i,t} - \ln \mu_{i,t-1}) \tag{3}$$

Here M_t is the quantity index and $s^*_{i,t}$ is defined as $s^*_{i,t} = (s_{i,t} + s_{i,t-1})/2$. 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 Price and this is precisely its corresponding weight in the Divisia monetary index. Finally, the accompanying User Cost Price index Π is defined as

$$\ln \Pi_t - \ln \Pi_{t-1} = \sum_{i=1}^{n} s^*_{i,t}(\ln \pi_{i,t} - \ln \pi_{i,t-1}) \tag{4}$$

The idea here is that agents substitute toward holding the monetary assets which have the lowest relative User Costs Prices 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. The Divisia monetary aggregates and associated User Cost Price indices internalize the liquidity preferences of the asset holders in the construction of the index via the share weights, $s^*_{i,t}$, of the assets held.

4. China's financial markets

Financial markets are eager for any signal of monetary policy from the People's Bank of China (PBC) and the importance of effective monetary policy communication will only increase as China continues to liberalize its financial system and open its economy. The implementation of 'China's trade liberalization policy (i.e. Open Door Policy)' has achieved rapid economic growth for three decades, please see Bohnet, Hong, and Müller (1993) for details. The capital inflow through foreign direct investment, together with an abundance of cheap labor together helped China and the whole world enjoy low price goods for over twenty years. Prior to 1994, China applied a dual-core pegged foreign exchange rate domestically and internationally in order to protect its fragile financial system. Since 1994, the Chinese yuan has operated with a currency peg in order to keep its value low compared to other countries. The effect on trade is that Chinese exports are cheaper and, therefore, more attractive when compared to those of other nations. This policy encourages the global marketplace to buy its goods to ensure economic prosperity.

More recently, China's exchange rate regime has undergone gradual reform. After announcing the move away from a fixed exchange rate in July 2005, China began taking regular steps towards a more flexible currency, while exchange rate stability continued to play an important role. The PBC announced that China was 'moving into a managed floating exchange rate regime based on market supply and demand with reference to a basket of currencies.' The basket of currencies was not specified, however, and the regime in operation was one with a continued tight link to the US dollar. Specifically, there would be a daily rate (the central parity rate, or the fix) announced before the start of the trading day that would form the midpoint of the band within which the USD/CNY rate could fluctuate on that day. The yuan has therefore become more flexible over time but is still carefully managed, and depth and liquidity in the onshore FX market is relatively low compared to other countries with de jure floating currencies. Allowing a greater role for market forces within the existing regime by making central parity formation for the daily trading band (the fix) mechanical and transparent is critical for greater two-way flexibility of the exchange rate. The use of FX intervention should be guided by the need to limit excessive volatility; and capital flow management measures (CFMs) should not be modulated to help manage the exchange rate.

Going forwards, further steps to develop the FX market, improve FX risk management, and the development of an alternate monetary policy anchor by continuing to modernize the monetary policy framework are recommended. An overview of the evolution of China's exchange rate regime from 2005 onward, including details of the unique constraints faced by China on its path to a floating exchange rate is provided by Das (2019). China's unique institutional setup and the impact of the PBCs main communication channels on financial markets is provided by McMahon, Schipke, and Li (2018). This detailed analysis of China's monetary policy framework recommends that providing timely information in one place (in Chinese and English), expanding PBC forecasting resources and capacity, and holding regular press conferences would not only be helpful for monetary policy, but also increase the attractiveness of China's capital markets and advance yuan internationalization.

In order to understand how China's exchange rate policy operates, we have included the Res, CIR and CIRD models. As mentioned in the introduction, the Res model includes only Chinese international reserves as its single explanatory variable; CIR and CIRD include only the statistically significant variables from the HM model plus reserves, which are the current account balance, the reference interest rate (User Cost Price for CIRD), international reserves, and the Divisia index for CIRD. Section 7 describes the results these particular models produce. As mentioned in Section 1, they are the only models that improve on the random walk more consistently for USD/CNY. These results are auxiliary to our research but help our understanding of the behavior exhibited by this exchange rate.

5. Negative interest rates

Negative interest rate policy (NIRP) has become a standard instrument in the ECBs toolkit over time but remains controversial, both in central banking circles and academia. Central banks impose the drastic measure when they fear their national economies are slipping into a deflationary spiral, in which there is no spending, and hence, dropping prices, no profits, and no growth. Most central banks that adopted NIRP were primarily motivated by the stabilization of inflation expectations as NIRP aims to increase the supply of credit by taxing banks excess reserves at the central bank and thereby support growth, Jobst and Lin (2016). NIRP complements asset purchases and forward guidance that has been implemented since the Global Financial Crisis to ensure that the economy is sufficiently stimulated. In spite of these positive effects on the operation of monetary policy, NIRP has often been criticized for its potential side effects, particularly on the banking sector. A theoretical model that explains how policy rates transmit to banks supply of credit, is provided by Bittner et al. (2020). A useful summary of existing work on the impact of negative rates on banks lending and securities portfolios, and the consequences for the real economy are provided in Heider, Saidi, and Schepens (2019).

Sweden's central bank was the first to deploy negative interest rates in July 2009 when the Riksbank cut its overnight deposit rate to −0.25%. The European Central Bank (ECB) followed suit in June 2014 when it lowered its deposit rate to −0.1%. As experience with negative interest rates was scant, the ECB proceeded cautiously over time, lowering the deposit facility rate (DFR) in small increments of 10 basis points, until it reached −0.5% in September 2019. The ECB turned to negative interest rates to lower the value of the euro. Low or negative yields on European debt will deter foreign investors, thus weakening demand for the euro. Empirical evidence regarding the impact of NIRP on exchange rates is scant, although a survey on recent developments in the monetary policy transmission mechanism in NIRP adopted countries by Ball et al. (2016) concludes that exchange rate appreciation pressures are generally reduced and that the policy has been associated with an improvement in overall financial conditions along with a modest expansion of credit in the euro area. Arteta et al. (2016) suggest that the impact of NIRP on exchange rates has been more varied with currencies depreciating on average against the US dollar and on trade-weighted-terms, except for the Japanese yen and the Swiss franc. Altavilla et al. (2021) studies how firms affected by banks that charge negative interest rates actually increase investments.

The theoretical challenge is to integrate the role of liquid assets into a model of bank lending. Holding liquid assets and trading them in interbank markets is essential for lending because it allows banks to measure and manage asset liquidity. As stated in Section 3 above, a sophisticated Divisia index measure, under fairly general assumptions, represents the ideal aggregate measure of 'liquidity services' available in the economy and is therefore potentially of great interest to monetary policymakers aiming at understanding the effects of monetary policy on the aggregate economy, Keating et al. (2019). We follow Chang, Mattson, and Tang (2019) and take the view that the Divisia method of pricing incorporates the segmented markets hypothesis by treating assets of different degrees of liquidity and different maturities as imperfect substitutes. Indeed, one of the main contributions of the Divisia monetary aggregate literature is to uncover and acknowledge the failings of the simple-sum approach that treats all monetary assets as perfect substitutes. Furthermore, the expectations of the interest rates in this case can be put aside as all constituent component assets are treated as imperfect substitutes based on their liquidity and store of value pricing at the present time period, although a more complex expectations hypothesis could be developed as demonstrated in the monetary asset case in Barnett and Wu (2005). The gains in predictive accuracy by incorporating a User Cost Price index in macro forecasting models, including exchange rate forecasting models, is clear; User Cost Price indices provide a unique interpretation of the link between the yield spread and recessions.

6. The models

Hooper and Morton (1982) developed an exchange rate forecasting model which was based on previous models such as the Dornbusch (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). Thus, we have the following,

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

where e_t is the exchange rate and m_t and m_t^*, y_t and y_t^*, i_t and i_t^*, and p_t, 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.

The model specification involves an error-correction restriction in order to avoid short-run dynamics. What this means is that the variation from the exchange rate is a correction of the deviation from a long-run equilibrium in the previous period. Taking the natural logarithms of all variables except the current account variable, the equation becomes the following,

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

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. We should note that we have replaced long-run expected rates of inflation with the only proxy available, relative prices.

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. The Res, CIR and CIRD models follow the same process. The first only includes the *res* variable, which is the log of international reserves in China, and the latter two include reserves plus the variables which are statistically significant for the HM model. These include the reference interest rate (or User Cost Price), ca_t, and the Divisia monetary aggregate for CIRD. *res* is statistically significant in the three cases.

The BVAR model with a Minnesota prior was introduced in the aforementioned Litterman (1986) and, as previously described, has been widely used in forecasting. If the model is as follows

$$e = (I_m \otimes X)\alpha + \epsilon, \quad \epsilon \sim (0, \Sigma_\epsilon \otimes I_T) \tag{7}$$

then e and ϵ are $mT \times 1$ vectors of exchange rates and errors, respectively, and where m is the number of variables and T, the time periods. I_m is the identity matrix, X is the matrix of independent variables and α is a $ml \times 1$ vector where l is the number of lags. More specifically, $\alpha = \bar{\alpha} + \xi_\alpha$ with $\xi_\alpha \sim N(0, \Sigma_\alpha)$, where in the Minnesota prior $\bar{\alpha} = 0$ except $\bar{\alpha}_{1a} = 1, a = 1, \ldots, m$, Σ_α is diagonal and each element $\sigma_{ab,l}$ (equation a, variable b, and lag l) is as follows

$$\sigma_{ab,l} = \phi_0/h(l), \quad a = b \tag{8}$$

If b is endogenous, then

$$\sigma_{ab,l} = \phi_0 \times \phi_1/h(l) \times (\sigma_b/\sigma_a)^2, \quad a \neq b \tag{9}$$

And if b is exogenous, then

$$\sigma_{ab,l} = \phi_0 \times \phi_2 \tag{10}$$

In this case $\phi_0, \phi_1, \phi_2, (\sigma_b/\sigma_a)^2$ and $h(l)$ are, respectively, hyperparameters, a scaling factor, and a function of lags l. Note that ϕ_0 measures the tightness of the first lag's variance, ϕ_1 is the relative tightness of any other variables, and ϕ_2 is the relative tightness of exogenous variables. Finally, $h(l)$ is a measure of the relative tightness of the variance of the lags.

The error correction model follows a similar process to the one laid out for the SP model, using the same variables. The number of lags is 5 for the EUR/USD and USD/CNY and 6 from the EUR/CNY, the averages of three information criteria.

Every one of the above models will be estimated twice: once with their standard variables, and a second time with M3 monetary aggregates replaced by the Divisia index and the reference interest rate replaced by the User Cost Price – except for the Res model which includes neither. The use of the User Cost instead of the interest rate follows Barnett, Offenbacher, and Spindt (1984). There are a total of thirteen models whose forecasting performance will be evaluated. All data are in logs, except interest rates and the User Cost Prices.

6.1. Performance evaluation

In this study we use a rolling regression in order to produce the predicted forecasts. We first pick an in-sample period for which the models are first estimated and then exchange rates are forecast for the out-of-sample period. The sample is then updated to the following period until there are no more out-of-sample observations. In order to pick the in-sample and out-of-sample periods for the whole sample (including negative rates), we chose the date at which interest rates become negative, i.e. June 2014, for the exchange rates involving the euro. For the USD/CNY, we picked January, 2015 as the start of the out-of-sample period, as that signified the end of the 2005–2015 period of exchange rate regime reform. For the pre-negative rates data, the out-of-sample period begins after the end of the Great Recession and for the USD/CNY, the out-of-sample period goes through the end of 2018. We must point out, however, that we do this only to test whether a change in the in-sample and out-of-sample periods affects the forecasting performance of the model (it does), since USD/CNY is not affected directly by the negative interest rate policy: neither the Fed nor the People's Bank of China have such a policy.

The performance of each model is evaluated by comparing each one to a benchmark model which in this case is the driftless random walk. For the first evaluation method we use the RMSE of each of the 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 vice-versa. This is also known as the Theil's U statistic. The second method is the statistic produced by Clark and West (2006) and Clark and West (2007), which allows for the comparison of forecasts produced by nested models in terms of whether the difference between two forecasts for the same forecasting period is statistically significant and whether or not the improvement is statistically significant (one forecast being 'better' than another).

7. Data

The data we utilize are quarterly series of the different variables in the models from 2002Q1 to 2018Q4. We obtained Divisia M3 monetary aggregates and User Cost Prices for the Euro Area (including the first 12 member countries), US, and China from the Bruegel Institute[2], Center for Financial Stability[3] and The Center for Financial Development and Stability[4] websites, respectively. As for the other variables, we use 3-month Treasury bill rates for the short-term interest rates, quarterly GDP for output, CPI as the price level, and the current account balances. We use traditional M3 monetary aggregates to compare with our theoretically superior Divisia monetary aggregates. All of these were retrieved from the Federal Reserve Economic Data bank available from the Federal Reserve Bank of St. Louis' website [5].

8. Results and discussion

8.1. Figures

Figures 1 and 2 in the annex show the forecasts of the BVARD and UIPUC models against the random walk forecasts and the actual exchange rates for the out of sample period 3, 6, 9, 12 months ahead in order to illustrate their behavior.

8.2. Root mean square error ratios

Tables 1–4 display the RMSE ratios of the different models under consideration without Divisia and with Divisia and the User Cost Price for every forecasting period, the full sample and the sample without negative rates, respectively. In the case of the USD/CNY, they show the samples with the different in-sample periods, one ending in the second quarter of 2009 and the other ending in the last quarter of 2014. What we notice is that, when we compare both tables, the only two models that consistently beat the random walk are the UIPUC and BVARD[6] for the EUR/USD exchange rate. That is to say, all the other models' improvements are either sensitive to in-sample/out-of-sample period changes or show no improvements at all. The one exception is the BVARD for the EUR/CNY where the model with Divisia and the User Cost Price beats the random walk with and without negative rates, especially in the short-run. The more moderate forecasting results for EUR/CNY show an improvement over the models with reference interest rates and simple-sum aggregates but not the random walk. Our explanation is that negative interest rates applied in the Euro area have distortionary effects in the theoretical models, as they turn differentials into sums and, more importantly, do not take into account the fact that other available interest rates, other than the reference interest rate, are still positive. The User Cost Price, by construction, can never be negative and it takes into account other interest rates (returns) available to economic agents in its construction. Moreover, the User Cost Price fully reflects the substitution effect, which occurs when interest rates change and agents change their portfolio holdings of monetary assets. Through the UIP hypothesis, this is directly connected to exchange rate determination and prediction, especially when we use the broader definitions of money (M3 in this case). The User Cost Price index itself is a weighted basket of interest rates which operates in a similar fashion. The results obtained for the USD/CNY can be explained by the 'managed float' regime for the Chinese yuan through monetary policy during the foreign exchange market regime reform. To illustrate this point, we include Tables 9 and 10. These tables show the RMSE ratios for the CIR model[7], where we can see that the inclusion of reserves and the exclusive use of statistically significant variables helps the CIR model improve over the random walk consistently in the short-run, even if we change the in-sample/out-of-sample periods. We find similar results in the case of the Res model. This casts a light on the operation of exchange rate policy in China and its relation to its international reserves and underscores how important the latter are for the same policy. In other words, the improvements over the random walk appear only in the context of a floating exchange rate regime. It is also worth noting that UIPUC performs so well because the difference in this model is not between two reference rates but between a weighted basket of returns. It is this weighted basket of interest rates that are used to weight monetary aggregates. The sophisticated Divisia aggregates encapsulate the response of economic agents to changes in the interest rates, potentially pushing the exchange rate slightly in one direction or another in the same period as the money supply increases or decreases, in part, also, as a consequence of China's build-up of reserves. The EUR/CNY is not constrained by the mechanisms implemented in the case of the USD/CNY and the EUR/CNY is affected by the negative interest rate policy. In the case of UIP with negative rates, the difference will actually become a sum (of two positive or negative numbers) – the opposite of what happens when we use the User Cost Price which is constructed using an arbitrary benchmark rate to ensure it is non-negative by construction. Another point we should mention is that the BVAR with Divisia

Table 1. Annex. RMSE Ratios (Full Sample).

	Panel A. Hooper-Morton Model RMSE over Random Walk RMSE					
	Quarterly EUR/USD Ratio		Quarterly EUR/CNY Ratio		Quarterly USD/CNY Ratio	
Time Horizon	HM	HMD	HM	HMD	HM	HMD
1 quarter	1.155	1.182	1.055	1.071	0.983	1.005
2 quarters	1.188	1.217	1.090	1.114	0.985	1.025
3 quarters	1.211	1.217	1.065	1.091	0.989	1.062
4 quarters	1.214	1.227	1.027	1.081	0.993	1.116
6 quarters	1.277	1.305	0.985	1.003	1.077	1.265
8 quarters	1.279	1.374	0.976	0.972	1.189	1.471
12 quarters	1.012	1.052	0.706	0.795	1.616	1.862
	Panel B. Sticky Price Monetary Model RMSE over Random Walk RMSE					
	Quarterly EUR/USD Ratio		Quarterly EUR/CNY Ratio		Quarterly USD/CNY Ratio	
Time Horizon	SP	SPD	SP	SPD	SP	SPD
1 quarter	1.149	1.201	1.020	1.087	1.027	1.017
2 quarters	1.185	1.258	1.003	1.143	1.045	1.031
3 quarters	1.210	1.292	0.923	1.084	1.058	1.048
4 quarters	1.203	1.334	0.863	1.036	1.073	1.102
6 quarters	1.273	1.414	0.832	0.900	1.177	1.253
8 quarters	1.314	1.505	0.748	0.743	1.358	1.506
12 quarters	1.012	1.089	0.656	0.491	2.139	2.126
	Panel C. Flexible Price Monetary Model RMSE over Random Walk RMSE					
	Quarterly EUR/USD Ratio		Quarterly EUR/CNY Ratio		Quarterly USD/CNY Ratio	
Time Horizon	FP	FPD	FP	FPD	FP	FPD
1 quarter	1.090	1.141	1.053	1.135	1.023	1.012
2 quarters	1.100	1.185	1.040	1.188	1.049	1.033
3 quarters	1.100	1.183	0.937	1.096	1.073	1.065
4 quarters	1.071	1.199	0.865	1.033	1.101	1.133
6 quarters	1.114	1.215	0.822	0.906	1.224	1.294
8 quarters	1.129	1.251	0.673	0.715	1.425	1.541
12 quarters	0.857	0.968	0.557	0.414	2.134	2.099

is the model that behaves as one would expect, considering the literature on Bayesian methods: it has strong forecasting power in the short-run and becomes weaker as we move towards the long run.

8.3. Clark-west statistics

The CW statistics in Tables 5–8 provide supporting evidence for the results found under the RMSE criterion, i.e. the User Cost Price helps improve forecasting power for UIPUC and its inclusion and that of Divisia monetary aggregates also increases the forecasting power of BVARD[8] in the short-run. The samples are split in the same way as in Tables 1– 4. When comparing the forecasts produced by the models and those produced by the random walk, all models behave similarly to how they performed under the RMSE criterion. In Tables 6 and 8, for UIPUC for the EUR/USD in the longer forecasting horizons, the CW increases and p-values usually decrease in every period and by the 2-year horizon, the p-value approaches or reaches the 10% significance level. At the 2 and 3-year horizons it is usually below that threshold. This gives supporting evidence to illustrate the greater predictive power of the User Cost Price, since the improvements it produces are statistically significant. The opposite happens with the BVARD for the EUR/USD and the EUR/CNY. This implies that, again, in these cases, models which include the User Cost Price and Divisia monetary aggregates produce forecasts that provide statistically significant improvements on the random walk forecasts and the standard models' forecasts. Also, as mentioned in the previous section, these improvements can only be observed in the exchange rates affected by negative interest rates in the context of free floating regimes. Otherwise, models (with or without Divisia) do not

Table 2. Annex. RMSE Ratios (Continued).

	Panel D. Uncovered Interest Parity Model RMSE over Random Walk RMSE					
	Quarterly EUR/USD Ratio		Quarterly EUR/CNY Ratio		Quarterly USD/CNY Ratio	
Time Horizon	UIP	UIPUC	UIP	UIPUC	UIP	UIPUC
1 quarter	1.065	0.996	1.095	1.062	1.049	1.045
2 quarters	1.066	0.954	1.158	1.124	1.084	1.059
3 quarters	1.047	0.919	1.147	1.117	1.164	1.097
4 quarters	1.033	0.907	1.124	1.098	1.231	1.125
6 quarters	1.033	0.900	0.948	0.960	1.338	1.158
8 quarters	1.032	0.828	0.836	0.853	1.441	1.193
12 quarters	0.808	0.648	0.526	0.708	1.612	1.188
	Panel E. Bayesian Vector Autoregression RMSE over Random Walk RMSE					
	Quarterly EUR/USD Ratio		Quarterly EUR/CNY Ratio		Quarterly USD/CNY Ratio	
Time Horizon	BVAR	BVARD	BVAR	BVARD	BVAR	BVARD
1 quarter	1.044	0.549	1.089	0.988	1.030	1.042
2 quarters	1.074	0.937	1.128	0.990	1.049	1.057
3 quarters	1.054	0.985	1.082	0.990	1.059	1.061
4 quarters	1.014	1.024	1.040	0.993	0.942	0.964
6 quarters	0.925	1.037	1.107	0.760	0.746	0.825
8 quarters	1.013	1.029	0.982	1.038	1.056	1.206
12 quarters	1.008	1.018	1.163	1.099	0.838	1.863

Table 3. Annex. RMSE Ratios (W/out Negative Rates).

	Panel A. Hooper-Morton Model RMSE over Random Walk RMSE					
	Quarterly EUR/USD Ratio		Quarterly EUR/CNY Ratio		Quarterly USD/CNY Ratio	
Time Horizon	HM	HMD	HM	HMD	HM	HMD
1 quarter	0.924	0.999	1.121	1.128	0.728	0.741
2 quarters	0.805	1.052	1.191	1.297	0.605	0.641
3 quarters	0.728	1.111	1.230	1.386	0.547	0.616
4 quarters	0.618	1.112	1.319	1.526	0.442	0.531
6 quarters	0.696	1.594	1.418	1.711	0.311	0.429
8 quarters	0.722	1.861	1.514	1.786	0.214	0.305
12 quarters	1.089	1.845	1.231	1.326	0.144	0.200
	Panel B. Sticky Price Monetary Model RMSE over Random Walk RMSE					
	Quarterly EUR/USD Ratio		Quarterly EUR/CNY Ratio		Quarterly USD/CNY Ratio	
Time Horizon	SP	SPD	SP	SPD	SP	SPD
1 quarter	0.926	1.060	1.233	1.266	0.677	0.681
2 quarters	0.838	1.148	1.392	1.481	0.565	0.572
3 quarters	0.798	1.235	1.432	1.542	0.499	0.507
4 quarters	0.657	1.257	1.492	1.686	0.418	0.437
6 quarters	0.720	1.837	1.601	1.861	0.298	0.350
8 quarters	0.838	2.076	1.635	1.862	0.211	0.259
12 quarters	1.246	1.981	1.297	1.373	0.081	0.218
	Panel C. Flexible Price Monetary Model RMSE over Random Walk RMSE					
	Quarterly EUR/USD Ratio		Quarterly EUR/CNY Ratio		Quarterly USD/CNY Ratio	
Time Horizon	FP	FPD	FP	FPD	FP	FPD
1 quarter	0.920	1.121	1.195	1.212	0.701	0.693
2 quarters	0.814	1.255	1.368	1.450	0.578	0.569
3 quarters	0.773	1.397	1.452	1.552	0.495	0.495
4 quarters	0.599	1.474	1.520	1.708	0.406	0.393
6 quarters	0.643	2.262	1.618	1.890	0.262	0.261
8 quarters	0.877	2.586	1.646	1.880	0.158	0.197
12 quarters	1.247	2.455	1.301	1.395	0.216	0.278

Table 4. Annex. RMSE Ratios (Continued).

	Panel D. Uncovered Interest Parity Model RMSE over Random Walk RMSE					
	Quarterly EUR/USD Ratio		Quarterly EUR/CNY Ratio		Quarterly USD/CNY Ratio	
Time Horizon	UIP	UIPUC	UIP	UIPUC	UIP	UIPUC
1 quarter	0.892	0.890	1.211	1.165	0.897	0.773
2 quarters	0.824	0.867	1.343	1.248	0.830	0.637
3 quarters	0.757	0.862	1.432	1.311	0.782	0.545
4 quarters	0.685	0.792	1.541	1.429	0.711	0.455
6 quarters	0.741	0.9065	1.673	1.563	0.611	0.344
8 quarters	0.625	0.745	1.604	1.414	0.554	0.271
12 quarters	0.672	0.890	1.239	1.015	0.303	0.126
	Panel E. Bayesian Vector Autoregression RMSE over Random Walk RMSE					
	Quarterly EUR/USD Ratio		Quarterly EUR/CNY Ratio		Quarterly USD/CNY Ratio	
Time Horizon	BVAR	BVARD	BVAR	BVARD	BVAR	BVARD
1 quarter	1.005	0.533	1.009	0.896	0.873	0.796
2 quarters	1.116	0.951	1.130	0.960	0.701	0.680
3 quarters	1.126	1.080	1.201	1.010	0.597	0.637
4 quarters	1.109	1.194	1.231	1.039	0.512	0.604
6 quarters	1.283	1.486	1.006	1.128	0.256	0.380
8 quarters	1.601	1.625	1.132	0.998	0.214	0.227
12 quarters	1.614	1.978	0.973	0.842	0.103	0.116

improve consistently or under-perform consistently, which we can observe in Tables 5 and 7. Generally speaking, the CW statistics reveal that, when the sample includes negative interest rates, Divisia indexes and the User Cost Price improve the prediction of exchange rates in the longer run. Moreover, we observe that the p-values for CW statistic for the Res, CIR, and CIRD models are below the 10% significance level for several horizons for the first sample (in-sample ending in 2009 Q2) although p-values do not quite reach this significance level for the second sample (in-sample ending in 2014 Q4). Again, this underscores the importance of international reserves in the operation of China's exchange rate policy and their 'Managed float' (more details in annex available upon request to the corresonding author).

9. Conclusion

This paper is based on solid theoretical foundations and contributes to the literature as the first work of its kind to examine the role and importance of Divisia monetary aggregates and concomitant User Cost Price indices as superior monetary policy forecasting tools in a negative interest rate environment. We echo Belongia (2006) that the use of User Cost Price duals appear to be worthy of further investigation. In particular, the sensitivity of inference to changes in measurement alone goes to the core of empirical monetary research. Conventional practice in empirical work and policy discussions have been to knowingly use index numbers that cannot possibly be meaningful representations of either the aggregate quantity of money or its price. Results presented here provide the first available evidence that Divisia monetary aggregates and their concomitant User Cost Price indices provide superior information about future forecasts of exchange rates in a negative interest rate environment. This result is important for monetary policymakers and academic researchers around the world, particularly given that until recently monetary policymakers operated in a negative interest rate environment (and could do so again in a recession that became severe enough). The Divisia monetary aggregates and associated User Cost Price indices internalize the liquidity preferences of the asset holders in the construction of the index via the share weights of the assets held. A final inference to draw is that resources directed towards the construction and dissemination of monetary statistics that meet the same standards applied to other economic aggregates are likely to yield a high return in our understanding of exchange rate forecasting in particular and economic activity more generally. Future work will consider further innovations in the construction of the Divisia index to incorporate more sophisticated measures of the riskiness of the assets, building upon (Binner et al. 2018;

Table 5. Annex. Clark and West Test (Full Sample).

Panel A. Hooper Morton vs. Hooper Morton with Divisia

	Quarterly EUR/USD Ratio				Quarterly EUR/CNY Ratio				Quarterly USD/CNY Ratio			
Time Horizon	HM CW stat	HM p-val	HMD CW stat	HMD p-val	HM CW stat	HM p-val	HMD CW stat	HMD p-val	HM CW stat	HM p-val	HMD CW stat	HMD p-val
1 quarter	−0.273	0.606	−0.235	0.592	−1.081	0.853	−0.873	0.803	0.492	0.314	0.442	0.332
2 quarters	−0.232	0.590	−0.145	0.557	−0.458	0.674	−0.144	0.556	0.274	0.394	0.084	0.467
3 quarters	0.143	0.444	0.275	0.393	0.515	0.307	0.655	0.261	−0.201	0.578	−0.427	0.662
4 quarters	0.545	0.297	0.581	0.285	1.109	0.142	1.009	0.164	−0.760	0.770	−0.819	0.787
6 quarters	0.687	0.252	0.793	0.221	1.293	0.109	1.311	0.106	−2.444	0.985	−1.823	0.954
8 quarters	1.170	0.133	1.155	0.136	1.828	0.047	2.078	0.031	−3.434	0.997	−3.501	0.997
12 quarters	1.899	0.050	2.082	0.038	2.833	0.013	2.692	0.015	−5.595	0.999	−5.672	0.999

Panel B. Sticky Price vs. Sticky Price Divisia

	Quarterly EUR/USD Ratio				Quarterly EUR/CNY Ratio				Quarterly USD/CNY Ratio			
Time Horizon	SP CW stat	SP p-val	SPD CW stat	SPD p-val	SP CW stat	SP p-val	SPD CW stat	SPD p-val	SP CW stat	SP p-val	SPD CW stat	SPD p-val
1 quarter	−0.113	0.544	−0.041	0.516	−0.352	0.635	−0.648	0.738	0.110	0.457	0.207	0.419
2 quarters	−0.102	0.540	−0.144	0.556	0.577	0.286	−0.065	0.526	−0.299	0.616	−0.118	0.546
3 quarters	0.213	0.417	0.101	0.460	1.462	0.082	1.087	0.146	−0.528	0.697	−0.357	0.637
4 quarters	0.638	0.267	0.358	0.363	1.704	0.054	1.573	0.068	−0.992	0.831	−0.753	0.768
6 quarters	0.826	0.212	0.780	0.225	1.671	0.059	2.209	0.023	−2.522	0.987	−1.698	0.943
8 quarters	1.138	0.140	1.006	0.168	2.342	0.019	3.091	0.005	−3.504	0.997	−3.602	0.998
12 quarters	1.672	0.069	1.528	0.085	2.589	0.018	4.297	0.002	−6.192	1.000	−6.168	1.000

Panel C. Flexible Price vs. Flexible Price Divisia

	Quarterly EUR/USD Ratio				Quarterly EUR/CNY Ratio				Quarterly USD/CNY Ratio			
Time Horizon	FP CW stat	FP p-val	FPD CW stat	FPD p-val	FP CW stat	FP p-val	FPD CW stat	FPD p-val	FP CW stat	FP p-val	FPD CW stat	FPD p-val
1 quarter	0.430	0.336	0.191	0.425	−0.256	0.600	−0.626	0.730	−0.121	0.547	0.061	0.476
2 quarters	0.699	0.247	0.303	0.383	0.443	0.331	−0.224	0.587	−0.609	0.724	−0.295	0.614
3 quarters	1.240	0.116	0.720	0.241	1.561	0.069	0.944	0.179	−0.890	0.807	−0.519	0.695
4 quarters	1.581	0.067	0.814	0.214	1.818	0.044	1.460	0.082	−1.311	0.895	−0.853	0.796
6 quarters	1.760	0.051	1.238	0.119	1.869	0.042	2.234	0.022	−2.570	0.988	−1.706	0.944
8 quarters	2.301	0.021	1.539	0.076	2.453	0.016	2.913	0.007	−3.501	0.997	−3.594	0.998
12 quarters	2.221	0.031	2.271	0.029	3.051	0.009	4.491	0.001	−6.283	1.000	−6.225	1.000

Table 6. Annex. Clark and West Test (Continued).

	Panel D. Uncovered Interest Parity vs. Uncovered Interest Parity w/User Costs											
	Quarterly EUR/USD Ratio				Quarterly EUR/CNY Ratio				Quarterly USD/CNY Ratio			
Time Horizon	UIP CW stat	UIP p-val	UIPUC CW stat	UIPUC p-val	UIP CW stat	UIP p-val	UIPUC CW stat	UIPUC p-val	UIP CW stat	UIP p-val	UIPUC CW stat	UIPUC p-val
1 quarter	0.451	0.329	1.161	0.130	0.050	0.480	−0.151	0.559	−0.800	0.783	−1.056	0.848
2 quarters	0.782	0.222	1.850	0.041	0.297	0.385	−0.198	0.577	−1.168	0.871	−1.220	0.880
3 quarters	1.305	0.105	2.092	0.026	0.685	0.251	−0.121	0.547	−1.821	0.956	−1.548	0.929
4 quarters	1.548	0.071	2.147	0.024	1.106	0.143	0.075	0.471	−2.177	0.977	−1.700	0.945
6 quarters	2.168	0.025	2.534	0.012	2.824	0.007	1.481	0.081	−2.865	0.993	−2.366	0.983
8 quarters	2.623	0.012	3.260	0.004	2.903	0.007	2.101	0.030	−3.631	0.998	−3.631	0.998
12 quarters	2.894	0.012	3.108	0.009	3.659	0.004	3.835	0.003	−4.945	0.999	−4.194	0.998
	Panel E. Bayesian Vector Autoregression vs. Bayesian Vector Autoregression w/Divisia											
	Quarterly EUR/USD Ratio				Quarterly EUR/CNY Ratio				Quarterly USD/CNY Ratio			
Time Horizon	BVAR DM stat	BVAR p-val	BVARD DM stat	BVARD p-val	BVAR DM stat	BVAR p-val	BVARD DM stat	BVARD p-val	BVAR DM stat	BVAR p-val	BVARD DM stat	BVARD p-val
1 quarter	−0.879	0.805	2.361	0.015	−1.062	0.849	0.043	0.483	−0.267	0.604	−0.575	0.714
2 quarters	−1.428	0.914	1.606	0.063	−1.999	0.969	−0.006	0.502	−0.300	0.616	−0.540	0.702
3 quarters	−1.2980	0.894	0.861	0.201	−1.757	0.951	−0.054	0.521	−0.112	0.544	−0.230	0.589
4 quarters	−0.171	0.567	−0.490	0.684	−1.037	0.842	−1.215	0.878	0.903	0.190	0.726	0.239
6 quarters	2.154	0.025	−0.740	0.764	2.416	0.015	0.253	0.402	1.977	0.035	1.330	0.103
8 quarters	−0.286	0.610	−0.610	0.723	0.783	0.225	−0.337	0.629	−0.012	0.505	−2.006	0.965
12 quarters	−0.255	0.597	−0.060	0.523	−0.955	0.814	−0.632	0.726	−0.933	0.809	−4.504	0.999

Table 7. Annex. Clark and West Test (W/out Negative Rates).

	Panel A. Hooper Morton vs. Hooper Morton with Divisia											
	Quarterly EUR/USD Ratio				Quarterly EUR/CNY Ratio				Quarterly USD/CNY Ratio			
Time Horizon	HM CW stat	HM p-val	HMD CW stat	HMD p-val	HM CW stat	HM p-val	HMD CW stat	HMD p-val	HM CW stat	HM p-val	HMD CW stat	HMD p-val
1 quarter	1.221	0.119	0.661	0.258	0.092	0.464	0.309	0.380	3.965	0.001	3.958	0.001
2 quarters	2.442	0.013	0.693	0.249	0.016	0.494	−0.154	0.560	5.091	0.001	5.127	0.001
3 quarters	2.325	0.017	0.412	0.343	−0.238	0.593	−0.783	0.777	5.625	0.001	5.455	0.001
4 quarters	2.657	0.009	0.469	0.323	−0.750	0.768	−1.297	0.893	6.471	0.001	5.999	0.001
6 quarters	2.861	0.007	0.223	0.413	−1.557	0.928	−3.062	0.995	8.774	0.001	7.469	0.001
8 quarters	2.472	0.015	−0.553	0.704	−1.869	0.956	−2.956	0.993	10.365	0.001	8.674	0.001
12 quarters	0.303	0.385	−1.141	0.854	−2.211	0.969	−4.526	0.999	9.914	0.001	10.742	0.001
	Panel B. Sticky Price vs. Sticky Price Divisia											
	Quarterly EUR/USD Ratio				Quarterly EUR/CNY Ratio				Quarterly USD/CNY Ratio			
Time Horizon	SP CW stat	SP p-val	SPD CW stat	SPD p-val	SP CW stat	SP p-val	SPD CW stat	SPD p-val	SP CW stat	SP p-val	SPD CW stat	SPD p-val
1 quarter	1.346	0.097	0.368	0.358	0.238	0.407	0.078	0.469	3.925	0.001	3.950	0.001
2 quarter	2.566	0.010	0.103	0.460	−0.243	0.594	−0.417	0.659	5.200	0.001	5.207	0.001
3 quarter	1.871	0.040	−0.006	0.502	−1.267	0.888	−1.067	0.849	6.002	0.001	5.782	0.001
4 quarter	1.718	0.053	0.161	0.437	−1.866	0.959	−1.458	0.917	7.058	0.001	6.670	0.001
6 quarter	2.036	0.031	−0.015	0.506	−3.183	0.996	−2.963	0.994	10.006	0.001	9.201	0.001
8 quarter	2.535	0.014	−0.919	0.811	−3.377	0.997	−3.170	0.995	11.866	0.001	10.722	0.001
12 quarter	−0.829	0.783	−1.368	0.893	−3.991	0.997	−4.600	0.999	14.034	0.001	16.439	0.001
	Panel C. Flexible Price vs. Flexible Price Divisia											
	Quarterly EUR/USD Ratio				Quarterly EUR/CNY Ratio				Quarterly USD/CNY Ratio			
Time Horizon	FP DM stat	FP p-val	FPD DM stat	FPD p-val	FP DM stat	FP p-val	FPD DM stat	FPD p-val	FP DM stat	FP p-val	FPD DM stat	FPD p-val
1 quarter	1.414	0.087	0.374	0.356	0.143	0.444	0.065	0.474	3.939	0.001	3.970	0.001
2 quarter	2.320	0.016	0.285	0.390	−0.172	0.567	−0.375	0.644	5.164	0.001	5.172	0.001
3 quarter	2.136	0.024	0.207	0.419	−1.268	0.888	−1.037	0.842	5.853	0.001	5.653	0.001
4 quarter	1.863	0.041	0.375	0.357	−1.811	0.955	−1.404	0.910	6.854	0.001	6.511	0.001
6 quarter	2.151	0.025	0.077	0.470	−3.530	0.998	−2.933	0.994	9.717	0.001	9.033	0.001
8 quarter	1.931	0.040	−0.953	0.820	−3.820	0.999	−3.214	0.996	11.773	0.001	10.646	0.001
12 quarter	−0.834	0.784	−1.257	0.875	−3.553	0.995	−4.430	0.998	14.248	0.001	17.543	0.001

Table 8. Annex. Clark and West Test (Continued).

	Panel D. Uncovered Interest Parity vs. Uncovered Interest Parity w/User Costs											
	Quarterly EUR/USD Ratio				Quarterly EUR/CNY Ratio				Quarterly USD/CNY Ratio			
Time Horizon	UIP CW stat	UIP p-val	UIPUC CW stat	UIPUC p-val	UIP CW stat	UIP p-val	UIPUC CW stat	UIPUC p-val	UIP CW stat	UIP p-val	UIPUC CW stat	UIPUC p-val
1 quarter	2.275	0.018	2.337	0.016	0.016	0.493	0.152	0.440	3.977	0.001	3.976	0.001
2 quarter	2.902	0.005	2.471	0.012	−0.003	0.501	0.551	0.294	5.156	0.001	5.178	0.001
3 quarter	2.598	0.010	1.754	0.049	−0.781	0.777	0.432	0.336	6.029	0.001	6.030	0.001
4 quarter	2.758	0.007	1.547	0.071	−1.404	0.910	−0.011	0.504	7.236	0.001	7.221	0.001
6 quarter	2.651	0.010	1.449	0.085	−3.150	0.996	−1.344	0.899	11.582	0.001	10.463	0.001
8 quarter	2.884	0.007	3.268	0.004	−4.089	0.999	−1.505	0.920	16.003	0.001	13.582	0.001
12 quarter	2.357	0.025	0.695	0.255	−2.645	0.983	0.589	0.287	22.321	0.001	15.892	0.001
	Panel E. Bayesian Vector Autoregression vs. Bayesian Vector Autoregression w/Divisia											
	Quarterly EUR/USD Ratio				Quarterly EUR/CNY Ratio				Quarterly USD/CNY Ratio			
Time Horizon	BVAR CW stat	BVAR p-val	BVARD CW stat	BVARD p-val	BVAR CW stat	BVAR p-val	BVARD CW stat	BVARD p-val	BVAR CW stat	BVAR p-val	BVARD CW stat	BVARD p-val
1 quarter	0.756	0.229	3.460	0.001	0.874	0.197	2.124	0.024	2.989	0.004	3.256	0.002
2 quarter	−0.385	0.648	1.485	0.078	−0.224	0.587	1.825	0.043	4.260	0.001	4.874	0.001
3 quarter	−0.456	0.673	−0.235	0.591	−1.454	0.917	0.608	0.276	5.058	0.001	5.835	0.001
4 quarter	−0.498	0.687	−0.744	0.766	−2.224	0.979	0.243	0.405	6.160	0.001	7.663	0.001
6 quarter	−0.241	0.593	−0.974	0.826	0.001	0.499	−1.182	0.871	8.579	0.001	13.409	0.001
8 quarter	−1.544	0.924	−1.699	0.941	−1.373	0.901	0.397	0.349	13.801	0.001	15.061	0.001
12 quarter	−1.560	0.919	−2.241	0.970	0.344	0.370	1.953	0.046	17.154	0.001	17.038	0.001

Table 9. Quarterly USD/CNY Ratio of CIRD RMSE over Random Walk RMSE 2009.

	CIR	CIRD
1 quarter	0.981	0.990
2 quarters	0.956	0.983
3 quarters	0.975	1.025
4 quarters	0.996	1.064
6 quarters	1.037	1.161
2 years	1.084	1.243
3 years	1.063	1.292

Table 10. Quarterly USD/CNY Ratio of CIRD RMSE over Random Walk RMSE 2015.

	CIR	CIRD
1 quarter	0.999	1.007
2 quarters	0.985	1.009
3 quarters	1.031	1.075
4 quarters	1.087	1.151
6 quarters	1.214	1.355
2 years	1.450	1.685
3 years	1.587	2.047

Barnett and Liu 2019) while further work to understand the information channel of monetary policy following monetary policy shocks is recommended, Hoesch, Rossi, and Sekhposyan (2020).

10. Annex: actual vs forecasted values, for 3 months, 6 months 9 months and 12 months ahead

10.1. Figure 1

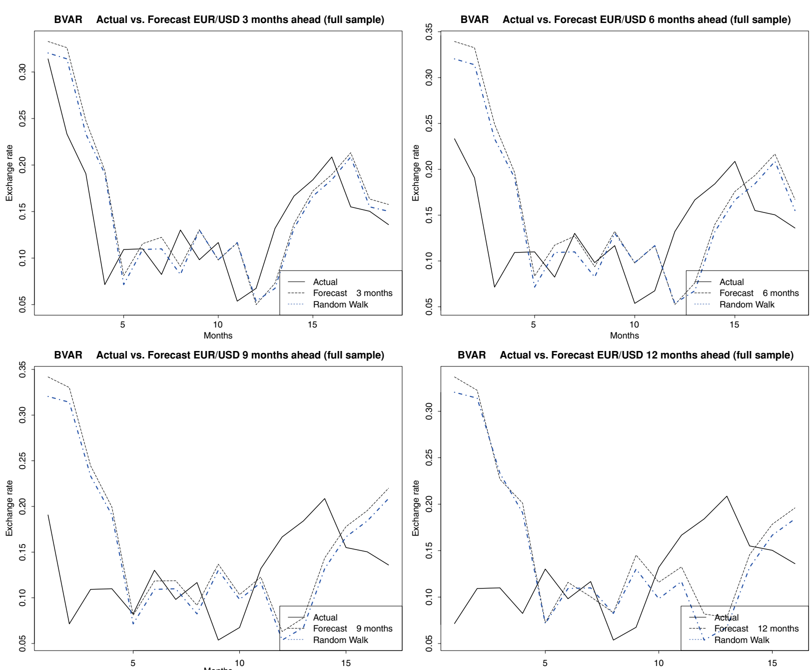

Figure 1.

10.2. Figure 2

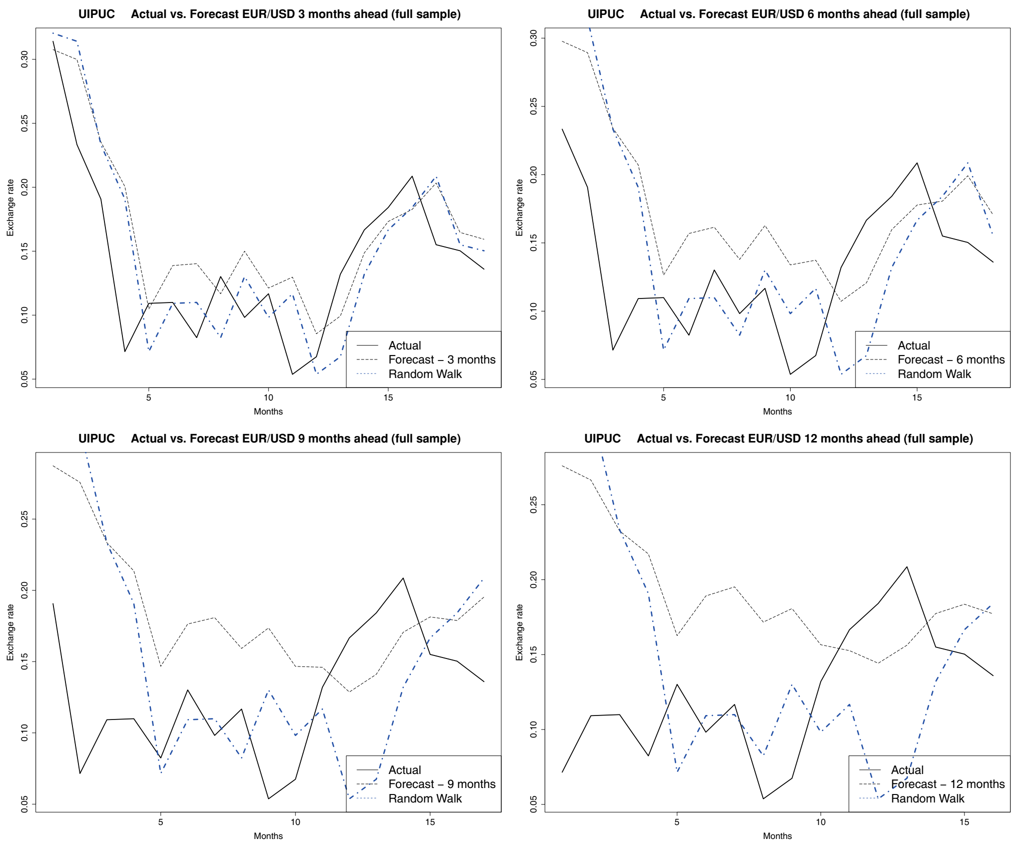

Figure 2.

Notes

1. The letters reflect the statistically significant variables: Chinese current account balance, interest rates (or User Cost Price), reserves, and Divisia monetary aggregates.
2. https://www.bruegel.org/publications/datasets/divisia-monetary-aggregates-for-the-euro-area/.
3. http://www.centerforfinancialstability.org/.
4. http://cfds.henuecon.education/index.php/data/chinese-divisa-data.
5. fred.stlouisfed.org.
6. Given the sample size, we have also calculated RMSE ratios for BVAR and BVARD on monthly frequencies and found that results do not vary greatly. For brevity, we have not included them in the text but they are available as an appendix upon request.
7. The CW statistics for the CIR and CIRD models, as well as the RMSE ratios and CW statistics for the Res model are included in an Appendix that can be made available upon request.
8. Given the sample size, we have also calculated CW statistics for BVAR and BVARD on monthly frequencies and found that results do not vary greatly. For brevity, we have not included them in the text but they are available as an appendix upon request.

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No potential conflict of interest was reported by the author(s).

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