Predicting RMB exchange rate out-of-sample: Can offshore markets beat random walk?

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Abstract: This study evaluates the in-sample and out-of-sample RMB exchange rate forecasting with a predictor of CNH-CNY pricing differential. Despite significant evidence of in-sample fit of conditional models at short horizons, we find that RMB exchange rate forecasts based on CNH-CNY spreads do not work well out-of-sample. While the poor performance in predicting CNH is mainly driven by the PBC announcement on improving quotation of the central parity of RMB in Aug. 11, 2015, the out-of-sample performance of CNY predictions was consistently worse than its unconditional counterpart before 2015. Finally, we show that predictive regressions using CNH-CNY spreads can beat random walk even in the CNY market, as long as we impose restrictions on the signs of slope coefficients to rule out implausible forecasts, or removing noises from the predictor based on moving threshold values. We discuss implications of our forecasting results for pricing power and capital restrictions as well.

Key words: RMB Exchange rate, Out-of-sample predictability, Onshore and offshore Markets
JEL Classification Code: C53, F31, G15

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1. Introduction

It is widely accepted that exchange rates are difficult to predict, at least starting with the seminal work of Meese and Rogoff (1983a, 1983b), in which they show the failure of both structural and time-series exchange rate models in generating better results than the random walk. Since then, a large number of studies have used various method to examine the predictability of currencies with a list of predictors, such as interest rate, price, and output differentials, Taylor rule, net foreign asset positions, and microstructure variables (e.g., Rossi, 2005; Cheung et al, 2005; Molodtsova & Papell, 2009; Rime et al, 2010; Dick et al, 2015). Frankel & Ross (1995), Della Corte & Tsiakas (2012) and Rossi (2013) provide reviews of earlier and recent contributions in this literature, respectively. The results seem to be mixed, depending on the choice of predictor, model specification, country, data type, sample period, forecast horizon, and so on. Since the evidence for the predictive models to beat random walk is still limited, debates on the Meese-Rogoff puzzle continue to exist, especially over short horizons.

However, few studies have payed attentions to investigate the predictability of RMB exchange rates. It is mainly due to the facts that the RMB was not freely floating and convertible to major currencies, and China's capital account was strictly controlled. But, things have changed since 2005, when the Chinese authority launched

a series of reforms to overhaul the RMB's exchange rate regime, and to liberalize its capital account. This process is further accelerated by the implementation of RMB internationalization strategy around 2009. By now, the RMB is widely used and traded in international markets, and expected to develop as a major reserve currency. The RMB is also set to join the U.S. Dollar, the Euro, the British Pound and the Japanese Yen, as the fifth component of the International Monetary Fund's Special Drawing Rights (SDR) currency basket in the near future. Meanwhile, China's share of global products and trades is also increasing rapidly over the last decade. Studies focused on the predictability of RMB exchange rates thus should be of great interest to both the finance community and policy makers.

Earlier studies on RMB exchange rate forecasting were focused on the evaluation of RMB misalignment based on price and output differentials, government intervention, behavioral equilibrium models, flow equilibrium models, and so on (e.g., Chang and Qin, 2004; Zhang and Pan, 2004; Wang et al, 2007; Cheung et al, 2007, 2009, 2010). Following the reform of RMB exchange rate regime to enhance the RMB's flexibility since 2005, recent studies gradually become to be interested in forecasting RMB exchange rate changes.

Among all the economic forces that may influence RMB exchange rates, the existence of offshore RMB market come under the spotlight, since it is expected to be able to provide useful information to forecast future movement of RMB change rates. Although there is only one currency in China (called RMB), the onshore and offshore environments for trading RMB are largely insulated one from another, causing the emergence of two distinct markets for RMB transactions. Both academics and practitioners therefore tend to use a wedge between onshore markets and offshore markets to gauge the future movement of RMB exchange rate. Since the offshore RMB exchange rates are largely determined by market forces without regulations comparing with the constrained onshore RMB markets, the onshore RMB exchange rate is expected to depreciate (or appreciate) more than it does on average when there is a positive (negative) and large spread between offshore and onshore markets.

Traditionally, the US Dollar settled non-deliverable forward (thereafter, also called "NDF") rate was showed to be a useful indicator of expectations of future RMB movement (e.g., Mackel et al, 2011; McCauley, 2011). A recent work of Tong et al (2015) also find some out-of-sample predictive power of NDF on CNY exchange rate at short maturity before 2013. However, as the establishment of deliverable offshore RMB market (thereafter, also called "CNH" market), the deviations between NDF rates and the onshore market (thereafter, also called "CNY" market) spot rates quickly lose its predictive power for future RMB exchange rate changes, since the NDF follows the CNH DF to become an interest rate market due to increasing ability for interest rate arbitrage.

Therefore, in this study, we look instead at a wedge between the newly established

offshore CNH rates and onshore CNY rates, and explore whether or not it can provide information useful in predicting future RMB exchange rate changes. In this sense, our work is more related to the work of Cheung and Rime (2014) who find significant interactions between the CNY and CNH markets. There are, however, important conceptual differences. While they also find that the CNH rather than CNY adjusts more to deviations between them on average, their focus is on the comparisons of out-of-sample performance of CNY, CNH and order flows in predicting central parity rate. In contrast, we focus on the out-of-sample performance of deviations between CNH and CNY rates in predicting both of the CNY and CNH rate changes. Although the primary variable of interest in this work is similar to those of Funke et al (2015), their objective is, however, to assess the impact of fundamental and policy factors in driving the CNH-CNY spreads.

Other studies, on the other hand, evaluate whether RMB exchange rates are forecastable using time-series econometric methods. For example, Cai et al (2012) compare alternative time-series models of RMB exchange rate forecasting. They proposed a functional coefficient model with GARCH effects for CNY exchange rates forecasting. Unlike these studies that rely on the past RMB exchange rate changes as the main explanatory variable, this study focus on the predictive information content of deviations between onshore and offshore markets for future RMB changes.

In short, this study adds to the literature by exploring the information content of CNH-CNY spreads in predicting RMB exchange rates using both the in-sample fit and out-of-sample evaluation. The in-sample fit examines the explanatory power of CNH-CNY spreads. On the other hand, the out-of-sample evidence focuses on its predictive power. While it is unclear about how much we should place weight on out-of-sample forecasts (e.g., Inoue & Kilian, 2005), we take up the Meese & Rogoff (1983a, 1983b) challenge to ask whether deviations between onshore and offshore markets could have been exploited by investors in real time to forecast future RMB exchange rate changes. To be more concrete, we compare the conditional predictive models with the CNH-CNY spreads using up-to-date information, with an unconditional model of random walk with no predictability. We use recursive least square regressions of an error-correction type model to construct forecasts conditioning on the CNH-CNY spreads. To test the out-of-sample predictability, we follow Goyal & Welch (2003, 2008) to examine the cumulative relative out-of-sample sum-squared error performance and the out-of-sample R^2 statistics. We find little evidence that RMB exchange rates are predictable by conditioning on information in offshore markets compared with an unconditional model of random walk.

Then, our diagnostic results suggest that the primary source of poor out-of-sample performance seems to come from coefficients instability. Our results further reveal that the out-of-sample performance in predicting both CNH and CNY rate changes are impacted greatly by an unexpected event: the PBC announcement on improving quotation of the central parity of RMB in Aug. 11, 2015. Upon this event, the

predictability of CNY increased while the CNH's forecastability decreased significantly. However, as long as we drop the one-month period following this reform, the predictive regressions using CNH-CNY spreads can beat random walk consistently in the CNH market. On the other hand, the conditional model of CNH-CNY spreads appeared to fail to outperform the random walk most of the time by any of the metrics in the CNY market.

Finally, we explore the impact of imposing restrictions suggested by economic theory on the predictive relationship between RMB exchange rate changes and CNH-CNY spreads in the CNY prediction exercise. First, we show that the predictive ability using CNH-CNY spreads can be improved greatly, as long as we impose restrictions on the signs of slope coefficients to rule out implausible forecasts. Second, we show that the predictive power of CNH-CNY spreads can beat random walk in the CNY markets by a large margin, once we remove trend from the predictor based on moving threshold values.

The rest of this article is organized as follows. Section 2 provides a background information for onshore and offshore RMB markets, and introduces the CNH-CNY spread as our main predictor for future RMB movement. Section 3 describes our data. Section 4 presents the results of in-sample fit, as well as the out-of-sample forecasting exercise by comparing it with the prevailing random walk view. Section 5 concludes.

2. CNH-CNY spread as a predictor for future RMB movement

2.1 Onshore and offshore RMB markets

There is only one currency in China but exists two distinct onshore and offshore markets with different market participants, trading scheme, and regulatory environment. Table (1) provides a brief summary of sensible features of both onshore and offshore markets for RMB currency. Among them, the onshore market, known as the CNY market in the mainland China, is characterized as a constrained market in the forms of central bank's intervention, the stipulation of a daily trading band, and the setting of central parity rates, despite recent efforts by the authority to increase its flexibility. Only onshore participants and permitted offshore investors, such as QFII schemes and trade settlements, can participate in this market.

Table 1: Key facts of the onshore and offshore markets

Label	Trading	Regulation	Participants	Establishment
CNY	Onshore RMB; CFETS trading.	Regulated by PBC: daily floating band; central rate parity; direct intervention.	Onshore and permitted offshore investor	Reformed in 2005.7; Restart the reform since 2010.6

CNH	Offshore deliverable RMB; OTC trading	Mostly liberalized, Under supervision of HKMA with PBC	Offshore investor	Since 2010.7
NDF	Offshore USD settled Non-deliverable RMB OTC, fix on CNY	Unregulated	Offshore investor	Long before CNH

By contrast, there is no presence of a central bank in the price formation process or in setting trading range limits in the offshore RMB foreign exchange market. In fact, there are essentially two offshore markets in operation for RMB transactions. The first one is the long-lasted US Dollar settled non-deliverable forward market, known as the NDF market. This is the traditional market for investors to gain RMB exposure offshore. This is not only a free market without any regulations, but also truly an offshore market with onshore players restricted from participating on it. An important link between the NDF market and CNY market is that the offshore NDF rates fix off the onshore CNY market. Therefore, the deviation between NDF and CNY rates is often regarded both by academics and practitioners as an indicator of expectations of future RMB movement.

The other one is the newly established deliverable RMB offshore market, also known as the CNH market that first appeared in Hong Kong in 2010. In comparison with the traditional NDF market, the CNH market for RMB was intentionally designed by the Chinese authority following the RMB Internationalization strategy. Although there exists some kinds of management at the macro level by HKMA in cooperation with PBC, transactions in this market are fairly liberal without interventions to manage the CNH exchange rate. Since the CNH market is exposing to the universe of international players with few restrictions, it has a different set of participants from the onshore CNY market.

Moreover, the CNH market is also a real deliverable market compared to the traditional NDF market. Due to the development of CNH market, investors now are migrating from NDF markets to the CNH forward markets so rapidly that the CNH market is already a dominant offshore RMB market, measured in terms of daily turnover. As the CNH forward market becomes an efficient interest rate market due to increasing ability for interest rate arbitrage, it is now acting more like a standard foreign exchange forward curve reflecting interest rate differentials, and dragging the NDF curve with it.

In sum, expectations of RMB exchange rate changes were the dominant driver of the NDF curve before the inception of the CNH market. Nevertheless, after the establishment of the CNH market as well as its regulatory reform, interest differential now is the primary determinant for both the CNH DF and NDF curves. Moreover, the NDF market is also expected to become less liquid and more volatile, as it is gradually taken over by the CNH market. Therefore, in what follows, we would not

look at the ability of NDF curve in predicting future RMB exchange rate. Instead, we would focus our attention on the ability of the newly established CNH market, and explore whether or not it can provide information useful in predicting future RMB exchange rate changes.

2.2 CNH-CNY spread

The main predictor examined in this study is the deviation between onshore RMB spot rates and the RMB spot rates in the newly created deliverable offshore market since 2010. Generally, the price for the same assets at the same time would be equal across different markets abstract from transaction costs, provided there are no restrictions on capital flows between the two markets. As we have stated earlier, the RMB has two distinct deliverable markets located onshore and offshore, respectively. The RMB in offshore markets is also a valid tender offer in mainland China as long as it can be transferred back through any kind of channels. Since the onshore RMB (CNY) and the offshore RMB (CNH) are essentially the same asset, according to the law of one price, we would be expecting that the price is the same for both the CNY onshore CNY RMB and offshore CNH RMB.

However, the two markets are largely segmented from each other due to the limited channels through which RMB can flow into and out of Mainland China. Moreover, as Table (1) shows, while the RMB exchange rate in the CNH market is determined by market forces without restrictions, the CNY exchange rate is still under strict regulation of PBC through means of daily trading band, the setting of central parity rates, and direct interventions in the market. As a result, each market has its own supply and demand conditions. There have been persistent and unnegligible deviations between the CNY and CNH rates. The deviations between the two markets arise because different market participants in different market conditions and environments can respond differentially to the same fundamentals and policies. Craig et al (2013) and Funke et al (2015) suggest that fluctuations in liquidity conditions and risk sentiments are the main forces in driving the deviations between the CNH and CNY rates.

If the deviations between CNY and CNH markets are large enough, it would induce arbitrage transactions to narrow down the gap between them. Of course, CNY and CNH rate would converge in the end as long as the restrictions on cross-border transfer channels are abandoned. However, given the relative difficulty of cross-border transfer of RMB due to the time and cost you need to incur to benefit from arbitrage transactions, we can observe persistent deviations between CNY and CNH exchange rates. Large and persistent difference in the value of RMB between the two markets could therefore be informative in the direction of RMB exchange rate movement in the future.

In particular, the CNH exchange rate could be viewed as an implied

free-market-trading determined RMB rate in the offshore market for the onshore RMB exchange rate. If the CNH rate is higher relative to CNY rate, we can hypothesize that the CNY rate is under depreciation pressure, since the CNY rate would be higher under a free-market trading system. However, as we stated earlier, the CNY RMB is traded in a constrained market that may be subject to interventions from the central bank. If the monetary authority steps in to anchor the CNY market without moving close to the market-trading implied RMB rate, it would leave the CNH instead of CNY rate that will be adjusting more to the discrepancy due to arbitrage transactions. Thus, we hypothesize that a positive deviation of CNH relative to CNY rate can predict CNY exchange rate depreciation or/and CNH exchange rate appreciation in the future, and vice versa.

Moreover, our conditional predictive regressions are appropriate since the CNH-CNY spread is stationary (see Table (2) below), so that the CNH and CNY rates are co-integrated (Campbell and Shiller, 1987; Engle and Granger, 1987). In the context of co-integration, our predictive regressions for changes in CNH and CNY market could be viewed as a form of error-correction model which is especially useful in the study of short-run dynamics. If the CNY rate is higher than the CNH rate, then the error-correction term of CNH-CNY spread would work to push the CNY rate back toward the market-trading implied CNH rate. If the Chinese authority intervene with the CNY market, the positive spread between CNH and CNY rates can also pull the CNH rate up close to the CNY rate. Of course, the ability of CNH-CNY spread to forecast future movement of CNH or/and CNY changes is also dependent on its own persistence. In sum, we hypothesize that a positive spread between CNH and CNY rates is associated with future depreciation of onshore CNY rates and/or appreciation of offshore CNH rates.

3. Data

All of our RMB exchange rate data used in this study are quotes from the dataset of the WM/Reuters Historic Rate Data, complied by WM/Reuters, disseminated by Datastream. This dataset are at the daily frequency, covering a large number of RMB related exchange rates including both spot rates series and forward rates series among the CNY onshore markets, CNH offshore markets, and NDF offshore markets. Each exchange rate is quoted as RMB units per US Dollar.

In addition to the original daily data series, we also convert the daily data into weekly (monthly) data by sampling the data on the last trading day of each week (month). Offer and bid rates as well as mid rates are available. The bid (ask) exchange rate is the rate at which participants in the inter-bank market can sell (buy) US Dollar using RMB from a currency dealer. The benchmark results in this study are, however, based on mid rates without bid/ask spreads. It is not only because the no-arbitrage condition alone that underlies the our offshore related predictors does not recognize them, but also due to the fact that the main concern of this study lies in the

predictability issue.

Among all the RMB exchange rates, the CNY series of RMB against US Dollar can date back as far as to 1994. However, the newly created CNH series included in Datastream for spot rates of RMB against US Dollar starts only at February 28, 2011. Since our focus in this study is to evaluate the out-of-sample forecasting power of predictors constructed from deviations between the onshore and offshore markets, we therefore report the baseline results based on the sample period since March, 2011, to the up-to-date available data of October, 2015.
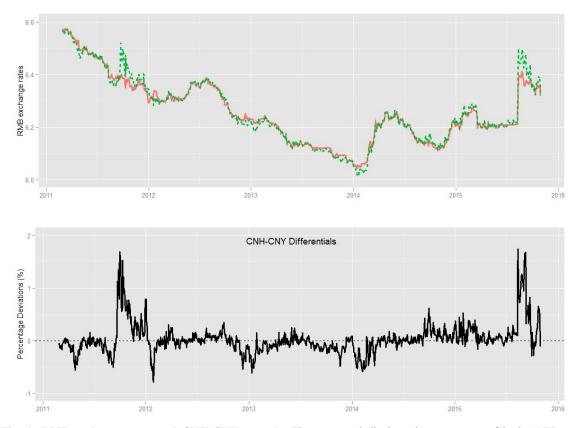

Fig. 1: RMB exchange rates and CNH-CNY spreads. The top panel displays the movement of both CNH (dotted line) and CNY (solid line) RMB exchange rate over the sample period from March 2011 to October 2015. The bottom panel shows the CNH-CNY spread over the same period.

Table 2: Descriptive Statistics

	Mean	Stdev	Median	Min	Max	Skew	Kurt
ΔCNY	-0.0036	0.1245	-0.0048	-0.6091	1.8097	3.0929	46.055
ΔCNH	-0.0006	0.1816	-0.0149	-1.0418	3.0142	5.0938	77.238
CNH-CNY	0.0003	0.0028	0.0000	-0.0062	0.0203	2.4049	10.243
spread		w/o	w/		Daily	Weekly	Monthly
	Unit-root tests	-7.15	-7.20	AR(1) Persistence	0.90	0.65	0.56

Note: Unit-root tests are the Augmented Dickey-Fuller test for the absence of a unit root. An ADF value of -3.5 rejects the presence of a unit root at the 1% level. "w/o" and "w/" represent ADF tests without and with a constant term, respectively. AR(1) Persistence is the first-order autoregressive coefficients.

The top panel of Figure (1) displays the movement of both CNH (dotted line) and CNY (solid line) RMB spot rates over the sample period from March 2011 to October 2015. The bottom panel shows the CNH-CNY spreads over the same period. Two sensible features can be observed from this figure. First, the RMB exchange rates seem to be trending down till the early 2014, when it turned to depreciate to some extent and showed more fluctuations since then. Second, the CNH-CNY spreads appeared to be positive when the RMB was during depreciation, and vice versa. Table (1) provides the descriptive statistics for changes in CNH and CNY rates, as well as the series of CNH-CNY spreads. We also report the results of unit-root tests and AR(1) persistence for the CNH-CNY spreads.

4. Empirical results

4.1 In-sample fit

The benchmark in-sample fit results in this study is based on the following predictive regressions.

$$\Delta s_{t+k} = s_{t+k} - s_t = \alpha + \beta z_t + \varepsilon_{t+k},$$ (1)

where s_t denotes the natural log of nominal RMB exchange rate against US dollar at time t, measured as the RMB price of US dollar, so that an increase in the exchange rate is a depreciation of the RMB. z_t represents the CNH-CNY spread predictor constructed from the deviations of onshore and offshore RMB markets. k usually takes the values of one. Since we are using data at the daily, weekly, and monthly frequency, $k = 1$ means that the forecasting horizon is one-day, one-week, and one-month, respectively. k can also take the value of 12 when we are using monthly overlapping observations for annual analysis. ε_{t+k} is the forecasting error.

Table (3) reports the predictive regression results of RMB exchange rate changes using the CNH-CNY deviations as the sole predictor over the full sample period. Panel (A) shows the results for CNY prediction, while Panel (B) presents results for CNH forecasting. Our results show that the CNH-CNY deviations seem to have significant forecasting power at the high frequency prediction exercise. The unadjusted OLS t-statistic and the heteroscedasticity autocorrelation robust t-statistic for CNY prediction are calculated as 2.42 and 1.64, respectively. Both of them appear to be statistically significant at conventional levels. It implies that our hypothesis holds true that positive spread of CNH over CNY exchange rate is indeed associated with depreciation in the next day, and vice versa. We can observe even striking results for CNH prediction exercise. The estimated forecasting coefficient for full sample is

about -7.2. The magnitude is more than twice as high as the one obtained in CNY prediction, but with a negative sign. The slope coefficient is also highly significant in the statistical sense even after correcting for heteroscedasticity and autocorrelations.

Table 3: In-sample forecasts using the CNH-CNY spread

CNH-CNY	Intercept	Slope	R^2	s.e.	N
Panel A: Forecasting CNY changes					
Daily	-0.004	**3.233**	0.53	0.124	1105
	(-1.18)	**(2.42)**			
	[-1.23]	**[1.64]**			
Weekly	-0.017	2.635	0.08	0.294	243
	(-0.89)	(0.44)			
	[-0.92]	[0.58]			
Monthly	-0.057	-11.571	0.25	0.546	55
	(-0.773)	(-0.36)			
	[-0.774]	[-0.39]			
Annually	-0.770	-84.633	0.64	2.136	44
	(-2.384)	(-0.518)			
	[-0.050]	[-0.522]			
Panel B: Forecasting CNH changes					
Daily	-0.001	**-7.173**	1.4	0.178	1105
	(-0.15)	**(-4.14)**			
	[-0.16]	**[-2.03]**			
Weekly	-0.004	**-32.29**	6.7	0.387	243
	(-0.16)	**(-4.14)**			
	[-0.16]	**[-4.27]**			
Monthly	-0.041	-50.555	3.3	0.648	55
	(-0.476)	(-1.34)			
	[-0.488]	[-1.37]			
Annually	-0.746	-175.367	2.4	2.28	44
	(-2.167)	(-1.008)			
	[-0.119)	[-0.203]			

Note: This table presents the in-sample predicting results of RMB exchange rate changes using the CNH-CNY deviations as the sole predictor. We report results at both daily, weekly, monthly, and annual horizons. The first row of each predicting exercise is the coefficients; the second row is the corresponding OLS t-statistic; the third row is the heteroscedasticity-autocorrelation robust t-statistic. Since we are using monthly overlapping observations of annual data, we report the Newey-West adjusted t-statistic with 12 lags for annual horizons. The s.e. is the standard error of the regression residuals, and N is the number of observations. The sample period is from March 2011 to October 2015, and refers to the dependent variables in daily frequency analysis.

However, the in-sample predictive ability of CNH-CNY spread for CNY changes declines dramatically, as we move to lower frequency forecasting exercises, such as at the weekly and monthly frequency. At the weekly horizon, the slope coefficient is reduced to 2.6 with a t-value no more than 0.6. Increasing to the monthly and annual

horizons, we can even observe negative slope coefficients for prediction regressions. At least, there are two potential explanations for this results. First, it is possibly because that the opportunities are already exploited within a day. Second, it could also be due to the fact that the monetary authority steps in and intervenes with the market.

But, the inability to find evidence for CNY predictability at longer horizons suggest that the CNH rates may display predictability at lower frequency, since the error-correction type predictive regressions are indeed a joint hypothesis of onshore and/or offshore predictability. As reported in Panel (B) of Table (3), the predictive exercise of CNH changes is still highly significant at the weekly horizon, both in the economic and statistical sense. The estimated forecasting coefficient is about -32, and associate with a t-value of more than 4 in absolute value. It implies that higher than usual CNH rates in excess of CNY are expected to revert greatly in the following week. Nevertheless, the forecasting power of CNH-CNY spread regressions for predicting CNH changes also declined significantly, if we move to the lower frequency of monthly and annually horizons.

The above results from CNY and CNH market combined seem to suggest that although there are evidence of arbitrage opportunities for both CNY and CNH market at the daily frequency, the opportunities would disappear away quickly in the CNY market. However, the adjustments could continue to exist in the CNH market for the following week. This seems to support our second conjecture that the Chinese monetary authority might be active in intervening with the CNY RMB market when there is deprecation or appreciation pressure, through means of manipulation of central rate parity or direct interventions. The effects are so strong that we can observe a phenomena at odds with our hypothesis: positive deviations between CNH and CNY are related to appreciation of RMB in the longer horizons.

In sum, our results show that the CNH-CNY deviation has strong predictive power for both the CNY and CNH market at the daily frequency. This finding is not only consistent with our hypothesis, but also implying profitable opportunities in the RMB market. However, it is worth of noting that even highly sophisticated institutional investors in financial markets could not have used the above in-sample predicting results to predict future exchange rate fluctuations. A trader in currency markets can only incorporate prevailing information into his dataset, not the entire sample period, to estimate a model of forming expectation of what the future spot exchange rate would be. In what follows, we would focus our attention on the out-of-sample predicting exercise using real-time available data. Our examination of out-of-sample forecasts would concentrate on the daily frequency, according to the in-sample results.

4.2 Out-of-sample forecasts

From now on, we focus on the use of only prevailing real-time data to carry on out-of-sample forecast exercise using the CNH-CNY spread as the sole predictor. In

particular, we follow the tradition of Meese and Rogoff (1983a, 1983b) to compare the relative out-of-sample performance of two RMB exchange rate changes forecasting strategies to diagnose the predictive ability of CNH-CNY spreads. The first one is to estimate a conditional model using then-available data by running recursive regressions in Equation (1') with the CNH-CNY spread as the predictor, in order to forecast RMB exchange rate changes next day:

$$\Delta s_{t+1} = s_{t+1} - s_t \ \alpha \ \beta \ z_t \ \varepsilon_{t+1} \tag{1'}$$

The other one is relying on the unconditional model of random walk with drift that uses prevailing up-to-date historical average of exchange rate changes to forecast the following day's changes[2]:

$$\Delta s_{t+1} = s_{t+1} - s_t = \alpha + \varepsilon_{t+1}, \tag{2}$$

4.2.1 Out-of-sample statistics

We evaluate the out-of-sample predictability of our models mainly using two sets of statistical tools. The first one is the Out-Of-Sample (OOS) R^2 statistic: R_{oos}^2. The R_{oos}^2 statistic is defined in a comparable way with in-sample R^2, and is computed as

$$R_{oos}^2 = 1 - \frac{\mathrm{MSE}(\Delta \hat{s}_t)}{\mathrm{MSE}(\Delta \overline{s}_t)} = 1 - \frac{\sum_{t=1}^{T}(\Delta s_t - \Delta \hat{s}_t)^2}{\sum_{t=1}^{T}(\Delta s_t - \Delta \overline{s}_t)^2}, \tag{3}$$

where $\Delta \hat{s}_t$ is the fitted value of RMB exchange rate changes derived from a conditional predictive model estimated through period $t-1$, and $\Delta \overline{s}_t$ is the historical average changes of RMB exchange rate obtained through the period $t-1$. The historical average changes is equivalent to the fitted value from the unconditional random walk with drift model. A positive R_{oos}^2 statistic implies that our conditional predictive model has lower mean-squared prediction errors (MSE) than the random walk model. In other words, the predictive models conditioned on the CNH-CNY spreads between offshore and onshore markets outperform the benchmark random walk model if R_{oos}^2 is positive.

The second set of tools to evaluate the out-of-sample performance of our CNH-CNY spread predictor, is the cumulative relative performance based on the

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[2] We use random walk with drift model instead of a pure random walk model for the following reasons. First, exploratory analyses in previous sections suggest a deterministic trend in changes in RMB exchange rates. Second, we remove only the predictive variable from the original conditioning model, since we are interested in the comparison between conditional and unconditional model. Third, echoing with Cheung and Dime (2014), we also find that a pure random walk without drift model yields even worse out-of-sample forecasting performance.

prediction errors of alternative models. We pay most of our attention to the difference between the cumulative sum-squared errors (SSE) from the unconditional model of random walk, and the cumulative sum-squared errors from a conditional model. Goyal and Welch (2003) suggest using a simple graphic diagnostic to compare the cumulative SSE statistics of alternative models. A positive value of the difference indicates that our predictors has superior information to help outperform the benchmark random walk model up to date. A positive slope of the figure, on the other hand, indicates that our conditional models using information from the wedge between onshore and offshore markets have lower prediction error than the unconditional random walk model in a given point of time. In addition to the cumulative relative performance of out-of-sample SSE, we also report relative performance of out-of-sample RMSE (Root Mean Squared Errors) and MAE (Mean Absolute Errors) for robust checks.

4.2.2 CNY forecasting results

Figure (2) plots the time-series of slope coefficients of CNY changes on CNH-CNY spreads when forecasting regressions are conducted with only up-to-date information. This figure shows that the impact of CNH-CNY spread on future CNY exchange rate movement are quite volatile before late 2011. At the beginning of CNH history, the spread between CNH and CNY rate has positive influence on the future RMB exchange rate changes. Nevertheless, the predictive coefficients of the spread tumbled about half-year later, and stabilized around the level of zero in late 2011. Since then, an investor based on the conditional model of CNH-CNY spread would gradually increase his estimate of the impact of the spread. It seems that the CNH-CNY spread can provide an observer reliably non-zero positive estimate of its influence through early 2014. The predictive coefficients of CNH-CNY spread fall into negative numbers again at that time. Fortunately, the CNH-CNY spread restores its predictive power quickly, and progressively increased its impact over time. The impact of the CNH-CNY spread on future CNY rate changes reached peak following the PBC announcement on improving quotation of the central parity of RMB in Aug. 11, 2015.

Although the choice in splitting the sample into estimation period and evaluation period is ad hoc in the end, we follow the criteria below. First, we need a long enough initial estimation period to obtain a reliable coefficient estimates to start the evaluation. Second, we need to retain a long enough evaluation period to be representative. Thus, we start our evaluation from 2012 and leave all the 2011 data for initial estimation, as a benchmark result. We also report results for a longer evaluation period starting from the 60th sample points in our sample period.

We are now ready to report out-of-sample statistics for the CNY predicting exercise. First, we calculate the cumulative sum of squared out-of-sample prediction errors for two strategies: conditional vs. unconditional. Then, we compute the difference between cumulative sum-squared errors (SSE) for the unconditional historical average

forecasts and the CNH-CNY spread forecasts over time. The result is plotted in Figure (3). A positive slope of the curve indicates that our conditional forecasting regression outperforms the historical average in a given year, while the opposite holds true if the slope is negative. A positive value of the difference indicates that the CNH-CNY spread outperforms the benchmark unconditional model of random walk up to date.
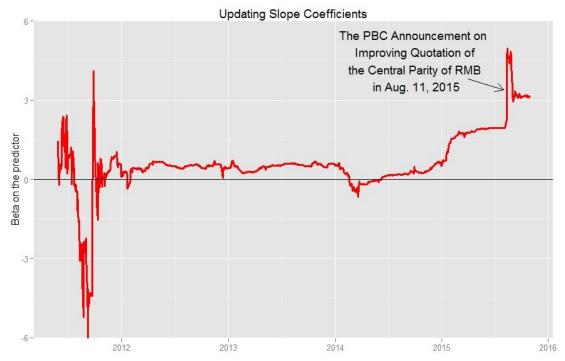

Fig 2: Updating slope coefficients of CNY prediction. This figure plots the recursive slope coefficient estimates in a predictive regression of CNY changes on CNH-CNY spreads using only up to date information.

Figure (3) shows that the conditional forecasting model of CNH-CNY spreads cannot outperform the unconditional model of simple historical average consistently over time. It is observed almost all the time that the CNH-CNY spread has higher predicting error than the prevailing historical average of RMB exchange rate changes. The predictive power of CNH-CNY spread seems to be particularly poor around the mid-September of 2011, when there is usually high positive spread between CNH-CNY rates, possibly due to the sudden worsening of the international financial markets and the betting on RMB depreciation at that time. From then on, the difference between cumulative sum-squared errors of alternative models seems to decline continually and steadily all the way with a negative slope. On the other hand, the forecasting power of CNH-CNY spread appears to strike back since the beginning of 2015 to deliver consistently a positive slope. Parallel with the changing predictive coefficients, the predictive ability of CNH-CNY spread seems to reach a mountain peak following the PBC announcement on improving quotation of the central parity of RMB in Aug. 11, 2015. At the last observation of our sample period, we have a relative SSE of -0.038 indicating that the conditional model of CNH-CNY spread has performed slightly worse than the prevailing historical average so far.
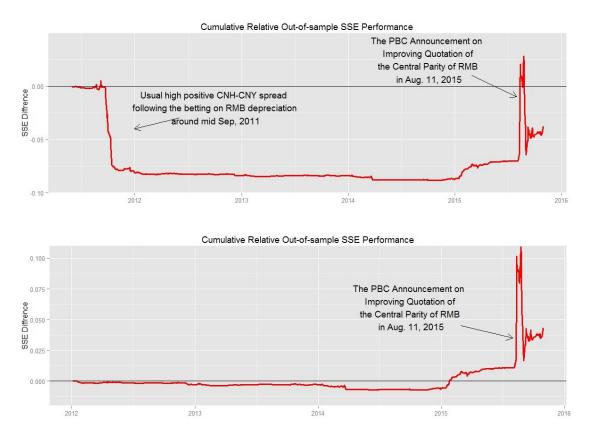
Fig 3: Cumulative relative out-of-sample sum-squared error performance of CNY prediction. The top panel plots the SSE performance using 60 data points as the initial estimation period, while the bottom panel plots the benchmark results that start evaluation from 2012.

To provide a cross-check for the graphic diagnostic, we also report out-of-sample statistics based on the prediction errors over the full sample period, when both the conditional model of CNH-CNY spread and the unconditional model of random walk with drift are estimated only with prevailing up-to-date data. The results are reported at the Panel (A) of Table (4). By contrast to the significant in-sample fit, the out-of-sample performance of CNH-CNY spread seems to be very poor as it delivers a negative out-of-sample R^2_{oos} statistic at the end of sample period.

Moreover, we obtained a root mean squared error (RMSE) of 0.1267 for the unconditional mean model, and 0.1268 for the CNH-CNY spread forecasting model. The slightly negative value of ΔRMSE confirms the relatively poor out-of-sample performance of forecasting regressions using the CNH-CNY spread as the sole predictor. We can find similar results using the statistic of MAE (0.0778 vs. 0.0789). In sum, Table (4) reveals the facts that the conditional model of CNH-CNY spread failed to outperform the unconditional mean model by any of the metrics.

Table 4: Out-of-sample statistics

	R_{oos}^2	RMSE			MAE		
		U	C	Δ	U	C	Δ
Panel A: CNY							
Plain (L)	**-0.0023**	0.1267	0.1268	-0.0001	0.0778	0.0781	-0.0003
Plain (B)	**0.0030**	0.1268	0.1266	0.0002	0.0757	0.0758	-0.0001
Panel B: CNH							
Plain (L)	**-0.0157**	0.1826	0.1840	-0.0014	0.1016	0.1004	0.012
Plain (B)	**0.0054**	0.1701	0.1697	0.0004	0.0948	0.0932	0.0015
Plain (EX)	**0.0212**	0.1614	0.1597	0.0017	0.0913	0.0895	0.0018

Note: This table reports the out-of-sample statistics (R_{oos}^2 , RMSE, and MAE) based on prediction errors from a null of unconditional model of random walk with drift, and an alternative conditional model of CNH-CNY spreads. Both models use only prevailing up-to-date data. The sample period is from March 2011 to October 2015. A positive (negative) number of R_{oos}^2 , ΔRMSE or ΔMAE indicate that our conditional model of CNH-CNY has better (worse) predictive power than the unconditional random walk model. "B" represents the benchmark case, "L" denotes the evaluation for a longer period; "EX" is a special case for CNH out-of-sample forecasting evaluation that exclude from the benchmark results the one-month data points starting at Aug. 12, 2015 following the PBC announcement on improving quotation of the central parity of RMB.

4.2.3 CNH forecasting results

Figure (4) plots the time-series of updating slope coefficient estimates of CNH changes on the predictor of CNH-CNY spreads. Similar to the case of CNY forecasting, the estimated coefficients of CNH-CNY spread was unstable during 2011. However, the predictive coefficients for CNH changes soon stabilized at a level close to -10, and kept almost unchanged throughout since late 2011, except for the period of PBC's reform on central parity quotations. At that time, the magnitude of predictive coefficients of CNH-CNY seemed to decline a little bit compared to normal times. As a whole, this figure shows that the CNH-CNY spread can provide a reliable and stable negative estimates of its influence almost all the time. The negative coefficients indicate that a positive spread of CNH in excess of CNY rates is associated with future appreciation of offshore CNH rates that is consistent with our hypothesis.

Panel (B) of Table (4) shows the out-of-sample statistics for the conditional model of CNH-CNY spreads as well as the unconditional random walk model in CNH forecasting. The R_{oos}^2 statistic is negative for longer evaluation period and slightly and barely above zero for the benchmark case. These result seems to suggest that the conditional model of CNH-CNY spreads cannot beat the random walk in the CNH market as well. However, we would better to take a look at the evolution of cumulative relative out-of-sample SSE performance between conditional and unconditional models, before we can draw any conclusions about the out-of-sample predictability of CNH-CNY spreads in the CNH market. It is plotted in Figure (4).
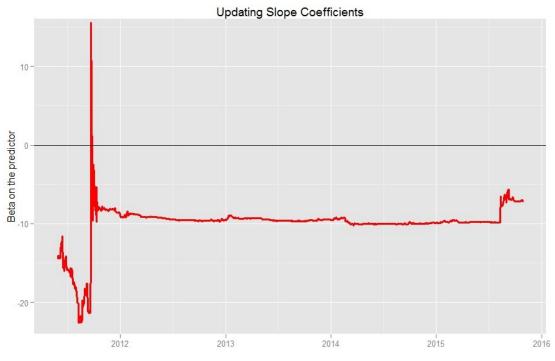
Fig 4: Updating slope coefficients of CNH prediction. This figure plots the recursive slope coefficient estimates in a predictive regression of CNH rate changes on CNH-CNY spreads using only up-to-date information.

Corresponding to the dynamics of recursive slope coefficient estimates in a predictive regression of CNH changes, Figure (5) shows that our conditional forecasting model of CNH-CNY spread can outperform the unconditional model of random walk consistently most of the time. It is observed from the benchmark results that the curve consistently has a positive value, except for the period following the PBC's announcement on improving quotation of the central parity of RMB in Aug. 11, 2015. It indicates that our CNH-CNY spread indeed has superior information to help outperform the benchmark random walk model up to date. In addition, the upward sloping curve seems to suggest that the predictive regressions conditioned on CNH-CNY spread have lower predicting error for future RMB changes in almost all the data points than the prevailing view of random walk in the literature of exchange rate changes.

If we exclude the one-month data points from the benchmark results (starting from Aug. 12, 2015 following the PBC announcement on improving quotation of the central parity of RMB). The cumulative relative out-of-sample SSE performance would be positive at all from the beginning, and keep moving upward throughout our sample period. In other words, our results reveal that the poor up-to-date performance in predicting CNH rate changes are almost entirely driven by one unexpected event: the PBC announcement on improving quotation of the central parity of RMB in Aug. 11, 2015. Moreover, similar to the case of CNY forecasting, the primary source of relatively poor out-of-sample performance for benchmark and longer samples seems to come also from coefficients instability and increasing persistence of the predictor.

Without periods of the unexpected reform on central parity, our results show that predictive regressions using CNH-CNY spreads can beat random walk consistently in the CNH markets.
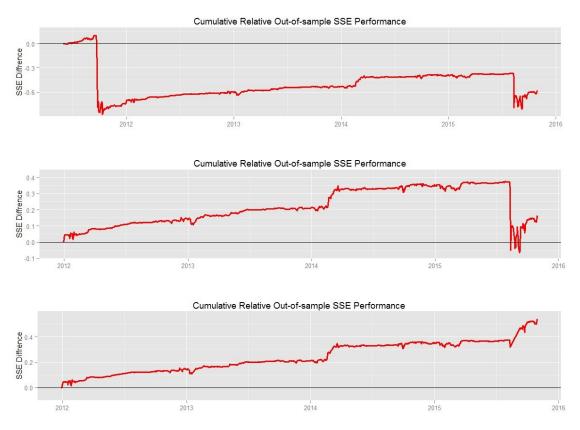

Fig 5: Cumulative relative out-of-sample sum-squared error performance of CNH prediction. The top panel plots the SSE performance using 60 data points as the initial estimation period. The middle panel plots the benchmark results that start evaluation from 2012. The bottom panel further exclude one-month sample from the benchmark results (starting from Aug. 12, 2015 following the PBC announcement on improving quotation of the central parity of RMB) in out-of-sample evaluation.

4.2.4 Improving CNY forecasts

(1) Imposing sign restrictions on predictive coefficients

The above results seem to suggest that the offshore CNH exchange rates are predictable with CNH-CNY spreads out-of-sample, while there is little evidence of out-of-sample predictability for the onshore CNY exchange rates. However, before we can draw any conclusions, we would like to ask whether the poor out-of-sample performance of CNY forecasting can be improved by imposing simple restrictions suggested by economic theory. In this section, we therefore explore the impact of imposing restrictions on the predictive relationship between RMB exchange rate and our forecasting variables on the CNY out-of-sample prediction exercise.

Specifically, we would do it through two ways. First, we can impose sensible

restrictions on the out-of-sample predictive regressions. This approach is similar to Campbell and Thomson (2008)'s exercise in predicting equity premium. In particular, we can set the fitted value of exchange rate changes to zero whenever the regression coefficients have the opposite sign with our hypothesis. Coefficient estimates of predictive regressions could be negative despite that our hypothesis suggest a positive relationship between CNH-CNY deviations and future CNY RMB exchange rate movement. Moreover, the forecasts of our prediction model could imply a depreciation in RMB exchange rates, while there is a positive deviation between CNH and CNY rates that would however suggest the CNY RMB is under appreciation pressure. Those unexpected "incorrect" coefficient estimates and forecasts can be severe especially in a short period of estimation sample. In practice, it is hardly to imagine that an investor would use the perverse coefficients or forecasts against what the no-arbitrage conditions would suggest. Imposing sign restrictions on coefficient estimates is therefore a tractable way to avoid such implausible forecasts in the CNY prediction exercise.

Table 5: Out-of-sample statistics of CNY forecasting with restrictions

	R^2_{oos}	RMSE			MAE		
		U	C	Δ	U	C	Δ
Panel A: Sing restrictions							
Slope constraints (L)	**0.0060**	0.1267	0.1262	0.0004	0.0778	0.0777	0.0001
Slope constraints (B)	**0.0073**	0.1268	0.1257	0.0010	0.0757	0.0749	0.0008
Panel B: Removing threshold value							
Threshold (L)	**0.0273**	0.1271	0.1253	0.0018	0.0781	0.0772	0.0008
Threshold (B)	**0.0363**	0.1272	0.1249	0.0023	0.0755	0.0743	0.0012

Note: This table reports the out-of-sample statistics (R^2_{oos}, RMSE, and MAE) of CNY forecasting with restrictions based on a null of unconditional model of random walk with drift, and an alternative conditional model of CNH-CNY spreads. Both models use only prevailing up-to-date data. The sample period is from March 2011 to October 2015. A positive (negative) number of R^2_{oos}, ΔRMSE or ΔMAE indicate that our conditional model of CNH-CNY has better (worse) predictive power than the unconditional random walk model. Panel (A) reports statistics by introducing the restriction that the coefficients on our predictor of CNH-CNY spreads must be of the "correct" sign, otherwise the slope coefficients are set to zero instead. Panel (B) reports results by removing trend calculated a as two-week moving average from the CNH-CNY spread. "B" represents the benchmark case, "L" denotes the evaluation for a longer period.

Panel (A) of Table (5) reports the out-of-sample statistics (R^2_{oos}, RMSE, and MAE) of CNY forecasting with sign restrictions on slope coefficient estimates for a null of unconditional model of random walk with drift, and an alternative conditional model of CNH-CNY spreads. In particular, we introduce the restriction that the slope coefficients on our predictor of CNH-CNY spreads must be of the "correct" sign, otherwise the slope coefficients are set to zero instead. Both models use only prevailing up-to-date data. As for the benchmark result, a positive number

of R^2_{oos} (0.73%), which is more than twice as high as the unrestricted case (0.3%), indicates that our conditional model of CNH-CNY has much better predictive power than the unconditional random walk model. Alternative statistics, such as RMSE, and MAE, display consistent results as well. Furthermore, we also plot the dynamics of out-of-sample SSE performance for the predictive regressions with sign restrictions in Figure (6). It shows that the conditional model of CNH-CNY spreads has performed no worse than the unconditional model of random walk in most of time, and its performance has become much better than that of random walk since 2014.
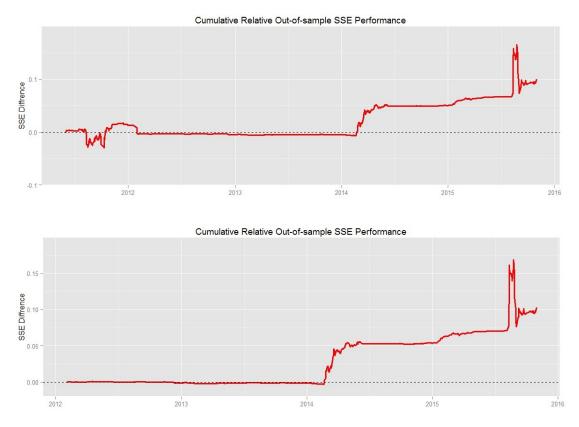

Fig 6: Cumulative relative out-of-sample sum-squared error performance of CNY prediction by imposing restrictions on predictive coefficients. The top panel plots the SSE performance using 60 data points as the initial estimation period, while the bottom panel plots the benchmark results that start evaluation from 2012.

(2) Removing trend from the predictor

In addition to imposing sign restrictions on predictive coefficients, we can also improve the predictability of CNH-CNY spreads by removing some trend from our predictor. There are at least two aspects suggesting that the CNH-CNY spread is a noise predictor. First, from an economic perspective, we implicitly assume that no-arbitrage conditions play a role in the predictive exercises. However, it cannot be guaranteed that any deviations would induce arbitrage transactions. Deviations between the onshore and offshore markets could be small relative to the trading difficulty or trading costs, so that arbitragers cannot profit from them. For example, arbitrage transactions would involve costs that would be higher when restrictions on

capital flows across markets is tight, or the market liquidity is low. Given the segmentation of the onshore and offshore RMB markets, there could be threshold deviations needed to induce enough arbitrage transactions for the CNH and CNY rates to converge. As a result, CNH-CNY deviations show strong persistence and can only serve as a noise predictor without removing threshold values.

In an effort to improve out-of-sample forecasting power of our conditional models by considering possible threshold effects on the predictor, a standard solution could be splitting sample into two parts: the inactive arbitrage band, and the active arbitrage band. As Hutchison, Pasricha and Singh (2012) suggested, we can estimate threshold values to define active and inactive arbitrage bands in which a threshold value of deviations serve as a measure of the effectiveness of capital controls and transaction costs. For example, they use self-excited threshold autoregressive methodology to estimate threshold values of capital controls and transaction costs for currency markets in China and India. However, this method suffers from the following two shortcomings. First, this method is backward in nature, because it involves the use of a whole sample to estimate threshold values ex post. By contrast, our focus is on the out-of-sample evaluation of the predictability CNH-CNY spreads using real-time available information. Second, the threshold values can be time-varying, as the trading environment, capital regulations and market liquidity can be changing over time. Thus, an alternative solution would be to use up-to-date moving averages as estimates of threshold value for CNH-CNY deviations[3].

Second, from an econometric perspective, because the CNH-CNY spread is a persistent variable, the predictive regressions would potentially be subject to bias. A common practice suggested by the literature (e.g., Campbell, 1991; Ang & Bekaert, 2006) is also to use a detrended predictor relative to its trailing moving average. In practice, we tried alternative windows of width for moving averages from one week to four weeks. But the results do not change materially. We report our results based on a two-week window in Panel (B) of Table (5). The top panel of Figure (6) displays the adjusted predictor by removing trend from CNH-CNY spreads, while the bottom panel shows the trend computed as the two-week moving averages. Measured as the absolute value of moving averages, the trading difficulty of exploiting the CNH-CNY spreads seemed to be trending down till the mid-2015, but grew strongly after the reform in Aug 11, 2015.

As for the benchmark case, our results show that the out-of-sample R^2_{oos} is

significantly improved from 0.3% in the unrestricted regressions with the "noise" predictor, to as high as 3.6% in the predictive regressions by removing moving averages from the predictor. Moreover, the cumulative relative out-of-sample SSE curve in Figure (7) is almost completely upward sloping. It suggests that the

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[3] To verify that there is indeed evidence of threshold effects in CNH-CNY deviations, we also employed the Lagrange Multiplier (LM) test of Hansen (1996) to confirm it ex post.

prevailing random walk view of exchange rate changes are overwhelmed by the predictive ability of CNH-CNY spreads.
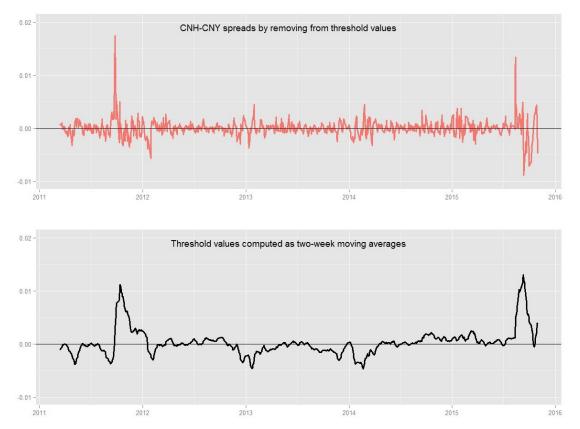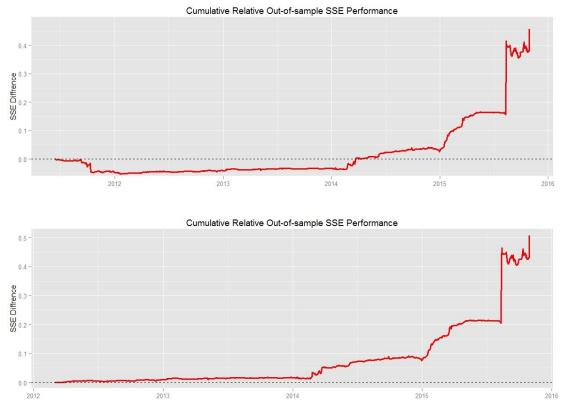

Fig 6: Removing trend from CNH-CNY spreads. The top panel displays the trend-removed CNH-CNY spreads; the bottom panel shows the trend computed as two-week moving averages.

Fig 7: Cumulative relative out-of-sample sum-squared error performance of CNY prediction by removing a moving average threshold from the predictor. The top panel plots the SSE performance using 60 data points as the initial estimation period, while the bottom panel plots the benchmark results that start evaluation from 2012.

4.3 Implications

In this section, we summarize both the in-sample and out-of-sample predicting results in Table (6). More importantly, this table shows how the predicting exercises would change in a response to policy events of RMB trading in both the onshore and offshore markets. In presenting our results, we also discuss related policy implications of our findings. In short, the main messages we can obtain from the results are as follows. **First**, the CNY rates are more close to a random walk that is hard to predict, while the CNH rates are the main forces in adjusting to the deviations between onshore and offshore markets. This fact implies that the onshore market has more pricing power than offshore markets in general. **Second**, the most important event that has significant impact on the predicting exercises both in onshore and offshore markets is the improvement of central parity quotation of RMB on 11 Aug 2015. After then, the CNH-CNY spread can predict both the onshore and offshore rates significantly, although the predictive ability of CNH rates decrease to some extent compared to the period before this event. This implies that the offshore market is getting more pricing power relative to the onshore market, as the quotation of central parity becomes more market oriented. By contrast, policy actions such as the widening of trading band in the onshore market have little impact on our predicting exercises. **Third**, both the CNH and CNY rates can be predicted out-of-sample using up-to-date information. It suggests that arbitrages by exploiting this information content of CNH-CNY deviations can potentially be profitable. **Forth**, the CNH-CNY spread can beat the prevailing view of random walk by a large margin in the onshore market only after removing trend from it. Since the trend is an indicator of trading difficulty or costs, it implies that arbitrages are incomplete, and capital restrictions can be effective in keeping the onshore market from following the pricing of CNH market. Thus, if the policy makers in China want to reserve more pricing power of RMB in the onshore market, it seems that they would continue to retain strict capital controls before the onshore market accomplishes the reform of exchange rate formation mechanism to. However, it is worth of noting that the out-of-sample performance of CNY prediction increased significantly after the "8.11" reform despite the enlargement of trading difficulty. It suggests that the CNH-CHY spreads can easily grow even larger relative to the trading difficulty, to overwhelm the effect of capital restrictions.

Table 6: How the policy events of RMB trading would impact the forecasting exercises

	CNY						CNH					
	Updating coefficients			Out-of-sample statistics			Updating coefficients			Out-of-sample statistics		
	Sign	Size	Significance	Slope	Level	R^2_{oos}	Sign	Size	Significance	Slope	Level	R^2_{oos}
• At the start of evaluation (from Mar 2011 until the 60th sample points)	+	1.5	non-significant	Negative			-	12	Significant	Positive		
• Full sample evaluation (from Mar 2011 to Oct 2015)	+	3.2	significant	Positive	Negative	Negative	-	7.2	Significant	Positive	Positive	Positive (w/o 8/11)
Onshore events:												
• Trading band expanded from ±0.5% to ±1% since 16 Apr 2012	Once negative, and revert back to the level of slight above zero.			Little impact.			Significantly negative with slightly increased magnitude.			Little impact		
• Trading band expanded from ±1% to ±2% since 17 Mar 2014	negative for a while, and gradually back to a slightly positive level			Little negative impact.			Significantly negative with slightly increased magnitude.			Little positive impact		
• **Quotation of the central parity of RMB improved since 11 Aug 2015**	**Increased substantially both in magnitude and significance.**			**Significant and positive impact.**			**Significantly negative with highly decreased magnitude.**			**Significant but negative impact.**		
Offshore events:												
• Hitting the quota celling set by PBC on 24 Sep 2011.	Once highly volatile, and revert back to a slightly positive level.			Significantly negative impact.			Once unusually volatile, and back to negative values			Significantly negative impact.		
• HKMA provides Liquidity support in offshore market Since 15 Jun 2012.	Remained low and stable since mid-year of 2012			Little impact.			Stabilized around -10 since early 2012 until Aug 2015.			Little impact		

Note: This table summarizes both the in-sample of out-of-sample predicting results using the CNH-CNY deviations as the sole predictor. We also describe how the policy events in onshore and offshore markets would impact the forecasting exercises.

5. Concluding remarks

This study evaluates the in-sample and out-of-sample RMB exchange rate forecasting with a predictor of CNH-CNY spreads. We find significant evidence of in-sample fit of conditional models with CNH-CNY spreads for both the CNY and CNH markets at short horizons. Moreover, we compare forecasts in which one estimates a conditional predictive regression with CNH-CNY spreads using up-to-date information, with forecasts using an unconditional model of random walk with drift in the same period. We fail to find evidence that RMB exchange rate forecasts based on CNH-CNY spreads can perform well out-of-sample.

Then, our results reveal that the poor performance in predicting CNH rate changes are almost entirely driven by an unexpected event: the PBC announcement on improving quotation of the central parity of RMB in Aug. 11, 2015. Without the period following the unexpected reform on central parity, our results show that predictive regressions using CNH-CNY spreads can beat random walk consistently in CNH exchange rate forecasting exercise. On the other hand, the out-of-sample performance of conditional CNY predictions was proved to be consistently worse than its unconditional counterpart before 2015. The primary source of poor out-of-sample performance seems to come from coefficients instability and increasing persistence of the predictor. However, we show that predictive regressions using CNH-CNY spreads can beat random walk even in the CNY markets, as long as we impose restrictions on the signs of slope coefficients to rule out implausible forecasts, or removing noises from the predictor based on moving threshold values.

In sum, this study shows that the error-correction type predictive regressions with CNH-CNY spreads can deliver better out-of-sample performance than random walk in predicting future RMB exchange rate changes at short horizons. Contrary to the error correction type predictive model with a correction term that capture the long-run disequilibrium between exchange rate and economic fundamentals (e.g., Mark, 1995.), our predictor is based on an arbitrage condition popular in finance. Thus, while the former is successful at long horizons, the later we use can be superior at short horizons.

Our results are not only relevant to the financial community for investment purpose, but also have important policy implications as well. As long as the coexistence of onshore and offshore markets and the restrictions on capital flows between them continue, the arbitrage transactions between them seem to prevail in the future. Moreover, the predictability of CNY rates seems to be improved following the PBC announcement on improving quotation of the central parity of RMB in Aug. 11, 2015, possibly because the authority reduces the degree of intervention in the onshore market. If the authority strikes back to continue to intervene much in the onshore CNY market, investors would, on the other hand, profit from arbitrage transactions in

the CNH market using the predictive ability of CNH-CNY spreads. In the end, the predictive information content of CNH-CNY spreads would disappear, only if the two rates converge following the removal of the restrictions on cross-border transfers.

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