Information Flow Between Forward and Spot Markets: Evidence From the Chinese Renminbi

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We apply a new model selection approach that allows for the joint determination of structural breaks and cointegration to examine the term structure of Chinese Renminbi (RMB)-U.S. dollar spot and forward exchange rates during the managed-floating period of 2005–2013. We find that the RMB market has exhibited different dynamic relationships between spot and forward exchange rates over time, apparently due to significant policy changes. Offshore forward rates with either shorter or longer maturities can substantially explain the in-sample variation of the onshore spot exchange rate at longer horizons, while only the offshore forward rate with a shorter maturity can significantly predict RMB onshore spot rate changes out-of-sample. © 2015 Wiley Periodicals, Inc. Jrl Fut Mark 36:695–718, 2016

1. INTRODUCTION

The importance of China as the second largest economy in the world is growing dramatically in the international monetary system and global financial markets. The exchange rate movement of the Chinese currency, Renminbi (RMB), has been of increasing interest, particularly given the controversy surrounding the impact of the RMB exchange rate on trade balance between China and its major trade partners (e.g., the U.S.) and the accelerated internationalization of the RMB since summer 2009. According to BIS's 2013 Triennial Central Bank Survey of foreign exchange turnover, RMB has become one of the top ten most traded currencies. In 2013, the RMB/$US trade constitutes 2.1% of global currency trade, rising from 0.8% in 2010. More recently,

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according to the data from the Society for Worldwide Interbank Financial Telecommunication (SWIFT), 2.2 percent of the world's payments were conducted using the Chinese currency in December 2014, rendering it the top five most-used global payment currencies.

On July 21, 2005, China announced the abolition of its decade-long fixed nominal exchange rate to the U.S. dollar, and the RMB moved into a managed floating regime against a basket of currencies of China's main trading partners. China initially introduced a trading band that allowed the RMB (onshore) spot exchange rate (i.e., CNY) to move up or down daily by 0.3% in bilateral exchange rates. It was later widened to 0.5% (on June 21, 2010), 1% (on April 16, 2012), and most recently to 2% (on March 17, 2014). Meanwhile, the recent development of the offshore RMB market (i.e., CNH) (Cheung and Rime, 2014; Ding, Tse, & Williams, 2014) is another major step of RMB internationalization.

The internationalization of the RMB clearly has led to more market-based RMB exchange rates and calls for better understanding of RMB exchange rates under the new regime. A crucial question concerns the forward unbiasedness hypothesis of the RMB market, that is, the forward rate is the unbiased predictor of the future spot rate. The forward unbiasedness hypothesis is one of the most researched and yet controversial hypotheses in the international finance literature (Nikolaou & Sarno, 2006, p. 628). Under some assumptions (e.g., risk neutral investors or no risk premium), earlier studies (e.g., Cornell, 1977) argue that the forward unbiasedness hypothesis might shed light on the efficiency of a foreign exchange market. By contrast, the more recent literature (e.g., Bansal & Dahlquist, 2000; Daniel, Hodrick, & Lu, 2014) shows that the existence of forward rate bias (and the violation of the uncovered interest rate parity) can be accounted for by time-varying currency risk premia and thus might not relate to market efficiency. Previous studies based on developed market currencies provide mixed evidence (e.g., Cornell, 1977; Clarida & Taylor, 1997; Clarida et al., 2003; Hansen & Hodrick, 1980; Meese & Rogoff, 1983), often concluding that the forward rate is a biased predictor of the future spot rate. Frankel and Poonawala (2010) further document that such a bias is smaller for a sample of 14 emerging market currencies (not including RMB) than for developed market currencies.[1]

Nevertheless, regardless of the existence of the bias or the controversy over its implication for market efficiency, it is of much interest in itself to explore whether the RMB forward exchange rate contains useful information about the future path of the spot exchange rate (Clarida & Taylor, 1997). The dynamic interaction between the spot and forward markets of a currency as informationally linked markets should be useful for better modelling and forecasting of both spot and forward exchange rates, which are crucial to international trade and finance decision making. Such a point is extremely relevant for the case of RMB (and particularly for the RMB-dollar exchange rate), as China already became the world's biggest trading nation in 2013 (measured by the sum of exports and imports of goods).[2]

This paper comprehensively investigates the dynamic relationship among RMB-dollar (onshore) spot and (offshore) non-deliverable forward (NDF) exchange rates during the

[1]de Zwart et al. (2009) examine currencies of 21 emerging markets with floating exchange rates, but do not include RMB either, perhaps due to the fact RMB had a rather short history under a managed floating regime when their study was conducted.

[2]The RMB/$US exchange rate under study is obviously important, as it involves the two largest economies in the world. In 2012, China was the second largest trading partner to the U.S. (after Canada) in terms of total trade of goods, the largest import market, and the largest source of trade deficits to the US.

managed-floating period of 2005–2013.[3] The paper contributes in the following ways. First, we more thoroughly examine the dynamics on the RMB-dollar market by more adequately allowing for potentially multiple structural breaks due to significant foreign exchange policy changes in China since 2005. While cointegration analysis is now a standard framework in analyzing the relationship between currency spot and forward rates, and the literature has recognized the potential for multiple structural breaks between RMB spot and (non-deliverable) forward rates (e.g., Ding et al., 2014; Zhao, de Haan, Scholtens, & Yang, 2013), we propose and apply a new approach to jointly determine structural breaks and cointegration via the model selection approach. Extending the literature (e.g., Zhao et al., 2013), the new approach simultaneously allows for potential multiple structural breaks in parameters of both cointegration space and short-run dynamics (i.e., the first-differenced VAR coefficients) among RMB spot and forward rates.[4] We find that RMB spot and four forward rates can be still characterized as containing four cointegrating relationships as theory predicts, although unlike Clarida and Taylor (1997) the long-run relationships do not exactly correspond to each of the four forward premia during the sample.[5]

Second, extending previous studies which only focus on only one RMB NDF contract with a short maturity (i.e., 1-month or 3-month maturity) (e.g., Ding et al., 2014; Gu and McNelis, 2013; Zhao et al., 2013),[6] we exploit the term structure of RMB NDF forward rates up to 12-month maturity and document the importance of additional information from longer maturity (i.e., 6-month and 12-month) forward rates in driving the spot rate movement. Specifically, the shocks to 6-month and 12-month (1-month and 3-month) forecast error variance decomposition together can on average explain at least 20% (about 43%) of the spot rate variation at the short horizon of 1-week and about 35–40% (about 44%) at the longer horizons of half a year to a year. Thus, the findings provide stronger evidence for the informational role of the RMB forward rates, as reported in the earlier literature (e.g., Ding et al., 2014; Gu and McNelis, 2013). Furthermore, extending Ding et al. (2014), the rolling forecast error variance decomposition shows that the information flow from forward rates of different maturities to the spot rate is dramatically different over time.

Finally, we more thoroughly investigate out-of-sample predictability of the (onshore) RMB spot rate using its (offshore) forward rates, and report new evidence that the one-

[3]See Fung et al. (2004) for the early discussion on the offshore RMB NDF market, which has been of main interest in the literature. There are also an onshore RMB deliverable forward market in China which is still under much government control, and very recently an offshore RMB deliverable forward market primarily in Hong Kong, which is still in its infancy. Noteworthy, a NDF market is essentially an analogue to the futures market for nonstorable commodities, where the nondelivery of the underlying asset against the forward/futures contract is due to capital control for the former and perishability of physical goods for the latter. Relevant to this study, Yang, Bessler, and Leatham (2001) show that there is a (more pronounced) bias for futures prices as a predictor of future cash prices in the cases of nonstorable commodities compared with storable commodities, because the storage, through which the cash-and-carry arbitrage may work effectively, is lacking for nonstorable commodities. By implication, (holding other things constant) a deliverable forward market probably would have a smaller bias than a NDF market for the same currency.

[4]Obviously, the new approach may also be useful for studying many issues on major currencies and other asset prices. For example, as demonstrated by Choi and Zivot (2007), forward discounts of G7 currencies exhibit multiple structural breaks, which should be accounted for before further analysis and inference.

[5]We also apply a relatively new unit root test with potential multiple structural breaks to provide more robust evidence on nonstationarity of RMB exchange rates under the managed floating regime and to better address the possibility that a potentially stationary RMB data generating process plus some trend breaks could be mistaken as a nonstationary RMB process (e.g., Melvin & Zhou, 1989; Yang & Leatham, 2001).

[6]The observation of focusing on a single forward rate rather than term structure of forward rates applies to studies on other emerging currencies. See Wang et al. (2014) for an example. The (forecast error variance decomposition) results from this study suggest that much information from forward rates with different maturities could be mistakenly ignored.

month NDF forward rate and forward premium carries useful information for forecasting future changes of the RMB spot rate during the sample period. The informational content of the 1-month forward rate remains whether it is used in the traditional simple univariate regression or used in the more complex vector error correction model. While our evidence is generally consistent with Gu and McNelis (2013), which as a notable exception to the literature also presents evidence for the RMB spot rate out-of-sample predictability, the model specifications under consideration are generally different from theirs (because the main interest of this paper is also different from theirs).[7]

The remainder of the paper proceeds as follows. We describe research methodology and the data in Sections 2 and 3, respectively. We present the empirical results in Section 4. Section 5 discusses and summarizes the main findings.

2. ECOMETRIC METHODOLOGY

The empirical framework used in this study is a cointegrated vector autoregression (VAR) model. Let Y_t denote a vector which includes m nonstationary spot and forward exchange rates. Assuming the existence of cointegration, the data generating process of Y_t can be written as an standard vector error correction model (VECM) with $(p-1)$ lags:

$$\Delta Y_t = \alpha\beta' Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-i} + \mu + \varepsilon_t (t = 1, \ldots, T), \tag{1}$$

where Δ is the difference operator ($\Delta Y_t = Y_t - Y_{t-1}$), α and β are both $(m \times r)$ matrices of parameters $(r < m)$ with β describing r long-run equilibriums among the m endogenous variables, Γ_i is a $(m \times m)$ matrix of coefficients describing short-run dynamics, and μ is a $(m \times 1)$ vector of constants, and ε_t is IIDN(0, Ω), with Ω being a positive definite matrix. We apply Johansen's (1991) maximum likelihood estimation procedure to estimate the VECM and to carry out the cointegration tests.

We consider the vector error correction model (1) for two purposes. First, we use it to study both short-run dynamics and, especially, the long run relationship in the RMB-dollar exchange market. The model is flexible in the sense that various theoretical restrictions can be imposed in the cointegration space ($\beta' Y_{t-1}$). For example, if $r = 0$, then there is no long run equilibrium relationship between forward rates and the spot rate and only short-run dynamics are important. The unbiasedness hypothesis that the forward rate is an unbiased predictor of the future spot rate can be easily imposed in the cointegration space (more on this later in the empirical results section). Second, we are interested in whether the more complex multivariate system provides a better description for the spot rate than a simple random walk. As pointed out by Clarida and Taylor (1997), the vector error correction model is able to "accommodate rejection of the simple efficiency hypothesis while still allowing forward premiums to contain information pertinent to future spot rate changes" (p. 353).

We further explore the out-of-sample evidence, as most previous studies focus on the in-sample evidence for the informational content of RMB forward rates. The out-of-sample evidence is important in itself and complements the in-sample evidence. In practice, many

[7]Gu and McNelis (2013) only examine the 3-month NDF forward rate, while we examine forward rates of four different maturities and document positive evidence for the 1-month forward rate. Also, differences in the inference between out-of sample forecasting and forecast error variance decomposition in this study can largely be attributed to different perspectives of the analysis. In particular, the forecast error variance decomposition focuses on strength or economic (rather than statistical) significance of the relationship between spot and forward rates as it is primarily based on the magnitude of coefficient estimates, and thus by construction less sensitive to potential structural breaks (Sims, 1980, p.20; Abdullah & Rangazas, 1988, p. 682).

variables could have little or negligible out-of-sample forecasting ability despite their enormous in-sample predictive power. Thus, the in-sample evidence focuses on explanatory power of these variables while the out-of-sample evidence bears more directly on their predictive power.

Determining whether there exists a (statistically) significant difference in forecasting accuracy between the two competing models is an important aspect of evaluating models through their out-of-sample performance. It is possible that, although two sets of forecasts are visually different from each other, they may not differ statistically. In this study, following Clarida et al. (2003), we apply a testing procedure proposed by Diebold and Mariano (1995). For a pair of h-step-ahead forecast errors ($\hat{e}_{A,t}$and $\hat{e}_{B,t}$, $t = 1, \ldots, T$), the forecast accuracy can be judged using some specific function $g(.)$ of the forecast error. The null hypothesis of equal forecast performance is:

$$E[g(\hat{e}_{A,t}) - g(\hat{e}_{B,t})] = 0,$$

where we use the popular square loss function $g(\hat{e}_t) = \hat{e}_t^2$. Define d_t by

$$d_t = g(\hat{e}_{A,t}) - g(\hat{e}_{B,t}).$$

The Diebold–Mariano test statistic is then

$$\mathrm{DM} = [\widehat{V}(d)]^{-0.5} d, \tag{2}$$

where d is the sample mean of d_t, $V\hat{}\,(d^-\,)$ is the Newey-West heteroskedasticity-and-autocorrelation consistent estimator of the sample variance of d. The DM statistic is asymptotically normally distributed under some regular conditions (we also compute modified DM test of Harvey, Leybourne, and Newbold (1997), and the main inference is qualitatively the same).

To move beyond the equality tests of forecast performance, a more stringent requirement would be that the competing forecasts embody no useful information absent in the preferred forecasts (Granger & Newbold, 1973). To test if model A captures useful information not captured in model B, we run the following regression:

$$\hat{e}_{B,t} = \lambda(\hat{e}_{B,t} - \hat{e}_{A,t}).$$

The null hypothesis is $\lambda = 0$, that is, forecasts of model B encompass forecasts of model A. In the case of one model nesting the other, we apply Clark and McCracken (2001)'s encompassing test (ENC-NEW test), which is defined by

$$\mathrm{ENC-NEW} = P \frac{P^{-1} \sum_{t=(R+1)}^{T} \left(\hat{\varepsilon}_{0,t}^2 - \hat{\varepsilon}_{0,t} \hat{\varepsilon}_{A,t} \right)^2}{P^{-1} \sum_{t=(R+1)}^{T} \hat{\varepsilon}_{A,t}} \to_d \Gamma_1, \tag{3}$$

where $\Gamma_1 = \int_\theta^1 s^{-1} B'(.), \theta = (1+\pi)^{-1}$, π is the limit of P/R, the ratio of the out-of-sample size over the in-sample size, and $B(.)$ is a vector Brownian motion whose dimension is determined by the number of predictive variables. Clark and McCracken (2001) also provide simulated critical values for the above nonstandard distribution.

3. DATA

The sample of the RMB/$ exchange rate covers the period from July 21, 2005 to December 15, 2013. The exchange rates were fixed until 07/20/2005 with the value of the RMB was pegged to the U.S dollar before that date. Following the literature (e.g., Clarida & Taylor, 1997; Gu &

McNelis, 2013), we use weekly observations (Wednesdays) to mitigate the potential autocorrelation problem, yielding a total of 438 weekly observations. The data are obtained from Datastream. We also convert all data into natural logarithms. Similar to Clarida and Taylor (1997) and Clarida et al. (2003), in our benchmark model we include five exchange rates: the spot rate (SPOT), the 1-month forward rate (F1M), the 3-month forward rate (F3M), the 6-month forward rate (F6M), and the 12-month forward rate (F12M)). The latter four amount to 4-, 13-, 26-, and 52-week forward rates.[8] Throughout the paper the RMB/$ exchange rate refers to the amount of RMB that can be exchanged with one U.S. dollar.

Figure 1, Panel A plots the spot rate and the four forward rates in levels and Panel B plots them in differences. Two features of the data immediately stand out. First, all five series move together and trend downward over the sample period, except during the two-year period of August 2008 through August 2010. Second, the weekly change in the 12-month forward rate displays considerable variability from the third quarter of 2007 to the first quarter of 2009. Panel C of Figure 1 plots the four forward premiums, which also show significant variation over the sample period. The premiums are generally negative from the beginning of the sample until December of 2011 with a noticeable exception when the RMB sells at premiums especially for the 6- and 12-month maturity from around September 2008 to March 2009. However, departing from the long time trend of the currency selling at discount, the premiums changed signs in mid-December 2011 and have since remained positive.

We first test the order of integration of the exchange rates using the augmented Dickey-Fuller test. The null hypothesis is that the exchange rate contains a unit root. The results are summarized in Table I. The null hypothesis cannot be rejected for all five rates at any conventional significance levels. We then proceed to test for the nonstationarity of the first differences of the exchange rates. The unit root hypothesis can now be rejected for all five first-differenced exchange rates. These results suggest that the spot rate and the four forward rates can be characterized as I(1) variables. We also test the nonstationarity of 1-, 3-, 6-, and 12-month forward premiums. The lower half of Table I shows that we fail to reject the unit root hypothesis at the 5% level for all four measures of the forward premiums.

An issue that oftentimes arises in using times series data is that the underlying data generating processes experience structural breaks (changes). Empirical results that fail to allow for structural breaks in modeling and testing may not be robust. To address this issue, we also test the nonstationarity of the spot rates, forward rates and forward premiums allowing up to two breaks in the data. The test procedure proposed by Carrion-i-Silvestre, Kim, and Perron (2009) is employed to allow multiple structural breaks under both the null and the alternative hypotheses. As shown in Table AI, we again fail to reject the unit root hypothesis for all five exchange rates assuming two breaks in the variables.[9] The evidence is somewhat mixed for the forward premium series. The unit root hypothesis cannot be rejected for the 6- and 12-month premiums. However, we reject the null hypothesis for the two shorter-term series at the 5% significance level, indicating that these two forward premiums are mean-reverting.

In sum, consistent with previous studies, our results show that a unit root exists in all five exchange rates. We therefore proceed to model the exchange rates using the vector error correction model (2), first assuming no structural breaks and then explicitly accounting for their impact on estimation and inference of the model.

[8]In estimating the vector error correction model (1), the literature differs in the empirical modeling of cointegration between the spot rate (s) and forward rate (f). While some consider cointegration between s_{t+i} and f_t, we here follow Clarida and Taylor (1997) and Zivot (2000) and consider cointegration between s_t and f_t.

[9]The results are similar when three structural breaks are assumed in the data, which are available on request.

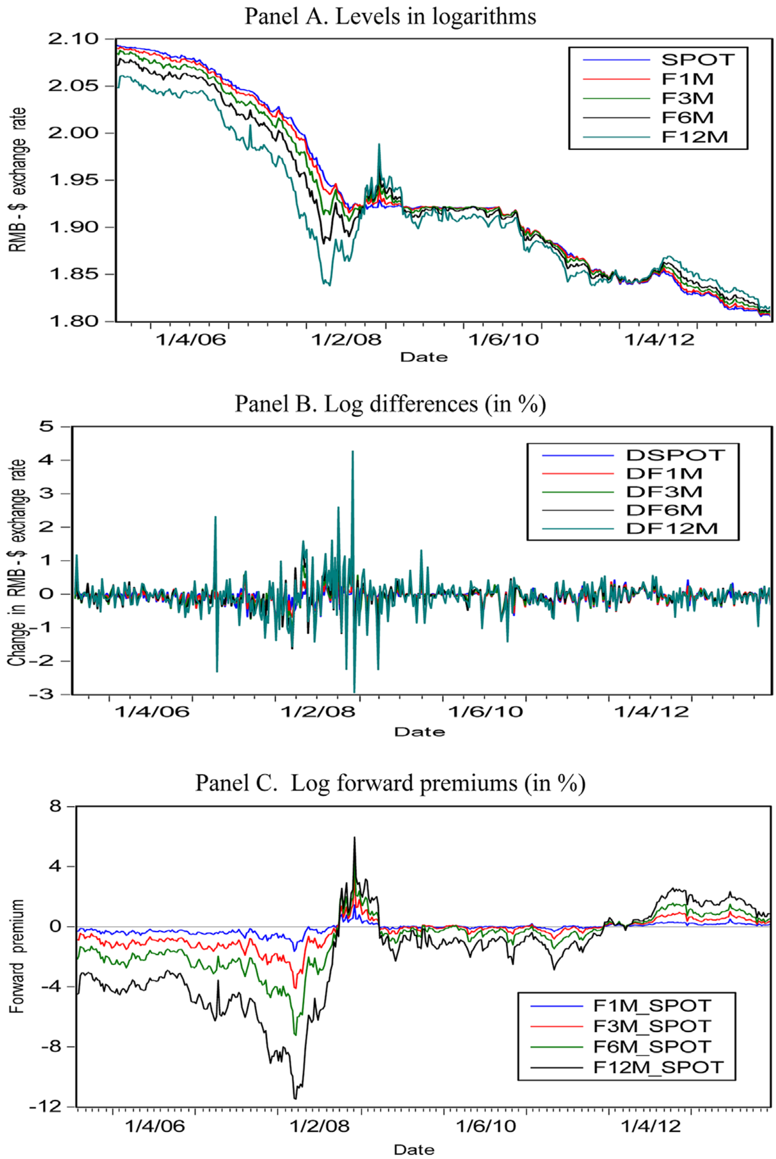

FIGURE 1

Chinese RMB/U.S. Dollar Exchange Rates. The Graph is Based on Weekly Chinese RMB/U.S. Dollar Exchange Rates from July 2005 to Dec. 2013

The data of the spot rate, 1- up to 12-month forward rates are obtained from Datastream. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

4. EMPIRICAL RESULTS

4.1. Model Estimation

The first step required for a vector autoregressions model specification is the selection of the lag order p. Based on Akaike information criterion (AIC), we include three lags ($P = 4$) in the

TABLE I
Results of Unit Root Tests

	Lag determined by AIC		*Lag determined by BIC*	
	ADF	*Lag order*	*ADF*	*Lag order*
SPOT	−1.267	2	−1.422	0
F1M	−1.339	0	−1.339	0
F3M	−1.289	0	−1.289	0
F6M	−1.306	1	−1.291	0
F12M	−1.474	0	−1.474	0
(F1M–SPOT)	−2.377	4	−2.654	2
(F3M–SPOT)	−2.124	2	−2.305	1
(F6M–SPOT)	−1.875	1	−2.102	0
(F12M–SPOT)	−1.417	1	−1.561	0

Note: This table reports the results on the augmented Dickey–Fuller test forunit root tests of Chinese RMB/U.S. dollar spot rate, forward rates, and forward premiums. They are based on a weekly sample for the period July 2005 through December 2013. The numbers of lags are selected according to the Akaike information criterion (AIC) and Schwarz's Bayesian information criterion (BIC) (the maximum number of lags considered is 4). The critical values of the augmented Dickey–Fuller unit root tests are –3.452, –2.870, and –2.571 (Nobs = 336) at the 1%, 5%, and 10% levels, respectively.

VECM.[10] Table II reports the cointegration rank test results using Johansen' s (1991) trace test and maximal eigenvalue test. At the 5% significance level, both procedures conclude with a cointegration rank of 4, consistent with those of many previous studies and theoretical predictions (e.g., Clarida and Taylor, 1997). The last two columns also indicate that the model with cointegration rank $r = 4$ achieves the minimum values for two most popular information criteria, AIC and BIC, among all six possible choices of the cointegration rank ($r = 0, 1, \ldots, 5$), meaning that the model selection approach of Phillips (1996) provides further support for the parametric tests of Johansen (1991). Therefore, throughout the paper, we model the data using the vector error correction model (VECM) with four cointegration vectors.

Table III reports the estimation results of the cointegration model. To save space the short run dynamics are not reported. Following Clarida and Taylor (1997), we attempt to identify the four cointegrating vectors possibly represented by the four forward premiums. To this end, we formally test if all four β's are actually one via the likelihood ratio test. With a χ^2 test statistic of 16.67 and 4 degrees of freedom, the null hypothesis is rejected even at the 1% significance level.[11] The evidence suggests that only the cointegrating space can be identified while we are not able to pin down cointegrating vectors exactly corresponding to the four forward premiums. Thus, the uncovered interest rate parity appears not to hold well in the case of the RMB market, which is further confirmed below. Also, as shown later, this rejection is more significant for the sample period after the first structural break around February 2008 when the global crisis started. It is also interesting to note that during the full sample all spot and forward rates have significant responses to the deviations from these long-

[10]The maximum lags we consider is 4. BIC concludes with a more parsimonious VAR with P = 1. Although we find that the number of cointegration rank r is not sensitive to the choice of the lag order, some of the residuals from the VAR(1) still contain serial correlation. To be conservative, we choose the VAR with four lags (equivalently, three lags in the VECM).

[11]If appropriate unit (and zero) restrictions on the parameters of four forward rates are not rejected, the four cointegration vectors would tend to pick up the forward premiums, and the four forward premiums should be stationary. Because the parameter restrictions are clearly rejected, the stationary cointegration relationships do not exactly correspond to the four forward premiums, which are shown to contain unit roots in Table I.

TABLE II
The Determination of Cointegration Ranks

Ho:	*T*	*C (95%)*	*λ-max*	*Critical value (95%)*	*Ho*:	*AIC*	*BIC*
$r = 0$	203.081	68.52	74.577	33.46	$r = 0$	−67.226	−66.736
$r \leq 1$	128.503	47.21	49.040	27.07	$r = 1$	−67.357	−66.971
$r \leq 2$	79.463	29.68	43.607	20.97	$r = 2$	−67.437	−67.127
$r \leq 3$	35.856	15.41	34.074	14.07	$r = 3$	−67.515	−67.194
$r \leq 4$	**1.782**	3.76	**1.782**	3.76	$r = 4$	−**67.579**	−**67.236**
					$r = 5$	−67.579	−67.226

Note: This table reports Johansen's trace test and the maximum eigenvalue test (λ-max) statistics for cointegrating ranks of the following vector processes: $\Delta Y_t = \alpha\beta' Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-i} + \mu + \epsilon_t$,(1), where Δ is the first-difference operator, $Y_t =$ (SPOT$_t$, F1M$_t$, F3M$_t$, F6M$_t$, F12M)′, a vector of Chinese RMB/U.S. dollar spot rate, forward rates, and forward premiums. The sample period is July 2005 through December 2013. *r* is the number of cointegrating vectors. T is the trace test statistics. C is the trace test critical values. The critical values are from Osterwald-Lenum (1992). Values in bold means that the test statistic is smaller than the corresponding critical value and hence we fail to reject the null hypothesis Ho in the first column.

run relationships while the spot rate and the one-month forward rate apparently have stronger responses, which are generally consistent with the results below and particularly the out-of-sample forecasting evidence.

To illustrate the economic significance and the dynamic pattern of information transmission from the forward rates to the spot rate, in Table IV we present the generalized forecast error variance decomposition—the percentage of price variations in the spot rate at time $t + k$ that are due to shocks to all five exchange rates at time t.[12] The generalized forecast error variance decomposition method developed by Pesaran and Shin (1998) has been widely applied (e.g., Yang et al., 2006; Diebold & Yilmaz, 2014).[13] The decomposition is based on the above just-identified VECM model, and the largest k considered is 52 (weeks). For simplicity, Table IV reports the decomposition at the 1-week (contemporaneous time), and the 4-, 13-, 26, and 52-week horizons (Figure 2 plots the detailed decompositions for each horizon). We also provide 90% confidence intervals for the point estimates obtained via bootstrapping.

Not surprisingly, at the contemporaneous horizon ($k = 1$), variance of the spot rate is explained most by its own shocks (34.93%). The explanatory power of the forward rates monotonically decreases with the term from 26.82% for F1M to only 8.54% for F12M. These patterns change little at the four-week horizon. The picture is quite different at the longer horizon, however. For example, at the half-year horizon, more variance is accounted for by shocks to F1M (23.95%) than by shocks to the spot rate itself (22.60%). In particular, at $k = 52$, only 17.36% of variance is due to shocks to the spot rate. At this long horizon, the four forward rates have similar effects on the spot rate.

Figure 3 plots rolling sample estimates of spot rate variance decompositions at $k = 1$. The initial sample covers the period 07/27/2005 through 08/16/2006 which includes 52 weekly observations (the first four reserved for generating lags). We observe two interesting patterns. First, the proportion of spot rate variance explained by shocks to the spot rate itself is stable except for the significant hikes based on the samples ending in October 2009 through

[12]An alternative measure to summarize the dynamics from the VAR analysis is the impulse response function (IRF). Here we use variance decomposition because, as seen from Figure 1, the sizes of shocks to the exchange rates are likely to change over the sample period and variance decompositions inherently account for the varying shock size when dynamics from different sub-samples are compared.
[13]An important feature of generalized variance decompositions is that they are invariant to the ordering of variables in a VAR.

TABLE III
Parameter Estimation Results for the Vector Error Correction Model

	Individual model of VECM					
Explanatory variable	$\Delta SPOT_t$	$\Delta F1M_t$	$\Delta F3M_t$	$\Delta F6M_t$	$\Delta F12M_t$	*Log likelihood*
	Panel A. Full sample 07/25/2005–12/11/2013					
μ	-0.009^{***}	-0.005^{**}	-0.002	0.001	0.006	14768.73
α_1	0.027	0.309^{**}	0.226	0.151	-0.462	
α_2	0.190^{***}	0.026	-0.207^{*}	-0.272^{*}	-0.206	
α_3	-0.000	-0.000	0.000	0.001^{*}	0.001^{**}	
α_4	-0.231^{***}	-0.186^{**}	-0.186^{*}	-0.159	0.063	
CI vector 1	$SPOT_{t-1} - 1.454F1M_{t-1} + 0.492F3M_{t-1} - 0.084F6M_{t-1} + 0.046F12M_{t-1}$					
CI vector 2	$SPOT_{t-1} - 2.680F1M_{t-1} + 2.232F3M_{t-1} - 0.447F6M_{t-1} - 0.099F12M_{t-1}$					
CI vector 3	$SPOT_{t-1} - 5.558F1M_{t-1} + 13.305F3M_{t-1} - 9.602F6M_{t-1} + 1.831F12M_{t-1}$					
CI vector 4	$SPOT_{t-1} - 1.789F1M_{t-1} + 0.339F3M_{t-1} + 0.894F6M_{t-1} - 0.457F12M_{t-1}$					
	Panel B. Sub-sample 07/25/2005–02/20/2008					
μ	-0.027	-0.036^{*}	-0.038	-0.039	-0.094^{**}	4568.32
α_1	0.204	0.943^{***}	0.911^{**}	0.648	-0.887	
α_2	0.080^{***}	0.055^{**}	0.029	0.038	0.067	
α_3	-0.011	0.063	0.086	0.084	0.258	
α_4	-0.274^{**}	-0.303^{**}	-0.365^{**}	-1.417	-0.134	
CI vector 1	$SPOT_{t-1} - 1.688F1M_{t-1} + 0.935F3M_{t-1} - 0.311F6M_{t-1} + 0.060F12M_{t-1}$					
CI vector 2	$SPOT_{t-1} - 5.966F1M_{t-1} + 7.376F3M_{t-1} - 2.283F6M_{t-1} - 0.006F12M_{t-1}$					
CI vector 3	$SPOT_{t-1} + 0.176F1M_{t-1} - 3.960F3M_{t-1} + 4.362F6M_{t-1} - 1.460F12M_{t-1}$					
CI vector 4	$SPOT_{t-1} - 3.351F1M_{t-1} + 3.744F3M_{t-1} - 1.441F6M_{t-1} + 0.027F12M_{t-1}$					
	Panel C. Sub-sample 12/31/2009–12/11/2013					
μ	-0.004	0.001	0.010	0.023^{***}	0.046^{***}	9336.60
α_1	-0.145	0.127	0.269	0.182	-0.020	
α_2	-0.048	0.056	-0.186	-0.146	0.608	
α_3	0.028	-0.006	-0.072^{*}	-0.160^{***}	-0.284^{***}	
α_4	0.004	0.005	0.005	-0.003	0.030	
CI vector 1	$SPOT_{t-1} - 0.918F1M_{t-1} - 0.360F3M_{t-1} + 0.224F6M_{t-1} + 0.056F12M_{t-1}$					
CI vector 2	$SPOT_{t-1} - 2.041F1M_{t-1} + 1.422F3M_{t-1} - 0.384F6M_{t-1} + 0.002F12M_{t-1}$					
CI vector 3	$SPOT_{t-1} - 0.329F1M_{t-1} - 1.541F3M_{t-1} + 0.538F6M_{t-1} + 0.414F12M_{t-1}$					
CI vector 4	$SPOT_{t-1} + 0.372F1M_{t-1} - 7.631F3M_{t-1} + 8.884F6M_{t-1} - 2.671F12M_{t-1}$					

Note: This table reports the parameter estimates of the VECM model (1) for Chinese RMB/U.S. dollar spot rate and, forward rates, for the period of July 2005 through December 2013. The cointegration rank $r = 4$. Short-run dynamics Γ_1 and Γ_2 are not shown to save space. *, **, and *** denote significant at the 10%, 5%, and 1% level, respectively.For the ease of presentation, coefficients associated the forward premiums are normalized by 100 in CI vector 3 for the full sample estimates.

mid-June 2010. Second, the impact of shocks on longer-term forward rates shows more pronounced time variation than that of shocks on shorter-term forward rates. Figure 4 plots rolling sample estimates of spot rate variance decompositions at a half-year horizon ($k = 26$). At this longer horizon, the combined impact of the forward rates on the spot rate based on samples ending after June 2010 is much more stable than the impact based on previous rolling samples. However, there is some evidence that shocks to the six- and 12-month forward rates appear to explain more variation in the spot rate near the end of the sample period, which might be a reflection of the recent development of the offshore RMB market.

4.2. Out-of-Sample Forecast Evaluation

As is clear in Figure 1 and discussed earlier in the data section, with the exception of a period of inaction immediately following the recent financial crisis, Chinese currency mostly

TABLE IV
Forecast Error Variance Decompositions of the Spot Rate

Horizon (week)	*SPOT*	*F1M*	*F3M*	*F6M*	*F12M*
1	34.93	26.82	17.29	12.42	8.54
	(32.58, 37.64)	(25.53, 28.50)	(16.39, 18.30)	(10.69, 13.77)	(6.18, 10.42)
4	33.10	26.66	18.46	13.07	8.72
	(29.40, 37.50)	(25.03, 28.74)	(17.01, 19.67)	(10.80, 14.98)	(5.47, 11.28)
13	28.42	25.54	19.26	14.95	11.84
	(23.44, 34.72)	(23.73, 27.80)	(16.98, 20.94)	(11.89, 17.41)	(8.00, 15.00)
26	22.60	23.95	20.37	17.42	15.65
	(17.86, 30.94)	(21.97, 26.51)	(17.79, 22.13)	(13.59, 19.74)	(10.59, 18.88)
52	17.36	22.42	21.36	19.67	19.18
	(13.36, 27.73)	(20.33, 26.12)	(18.48, 23.20)	(14.71, 21.94)	(12.54, 23.02)

Note: The generalized forecast error variance decomposition is conducted based on the vector error correction model (1) for Chinese RMB/U.S. dollar spot rate, forward rates, and forward premiums for the period of July 2005 through December 2013. The cointegration rank $r = 4$. The parameter estimates are reported in Table III, Panel A. Column 1 is the post-sample horizon (week 1 is the contemporaneous period). Each panel shows how much of the variance of the spot rate is explained in percentage points by shocks to the five exchange rates listed in the first row. The numbers in parentheses are 90% confidence intervals formed via the bootstrap method.

appreciated throughout the sample period. To allow for possible structural breaks in the data, and given the fact that the structural breaks are unknown *a prior*, we conduct forecasting exercises first using the rolling-window estimation method. In addition to our benchmark error correction model with cointegration rank of 4 (VECM), we also consider an error correction model imposing forward premium restrictions on cointegrating vectors, and a VAR in first differences assuming no long run equilibrium between the spot rate and the forward rates. In addition, we derive out-of-sample forecasts of the spot rate from three univariate models. One is a driftless random walk (RW), [14] and another uses the appropriate forward rate itself (FR). The third simple univariate model regresses the rate of appreciation/ depreciation on the lagged forward premium of the following form (FPR):

$$\mathrm{SPOT}_t - \mathrm{SPOT}_{t-k} = \alpha + \beta^*(f_{t-k,k} - \mathrm{SPOT}_{t-k}) + \varepsilon_t, \qquad (4)$$

where $f_{t-k,k}$ is the k-week forward rate at date $(t-k)$ (e.g., F1M for $k = 4$ and F3M for $k = 13$). FPR traditionally has been the standard model used by many authors (e.g., Fama, 1984). These three univariate forecasting models (RW, FR, and FPR) are all considered by Clarida and Taylor (1997).[15]

As before, all models except FPR are first estimated using the first 56 weekly observations (including four lags) and the first set of one- up to 26-step-ahead out-of-sample forecasts for the spot rate are generated (the first 108 observations are used in estimating the FPR).[16] Each model is then re-estimated, and new forecasts are generated after the first observation in the sample is dropped. Each of the remaining out-of-sample observations is sequentially added to the new sample; this procedure results in a series of 382 one-step-ahead

[14]A random walk with a drift performs worse than the one without a drift. The result is therefore not reported here to save space.
[15]There are various exchange rate models that can be used for forecasting exchange rates. Here we concentrate on the forward premium models. Other famous models include Taylor rule models and the PPP model. More complex nonlinear models (e.g., Clarida et al., 2003) are also not considered here.
[16]Multivariate models perform much worse in forecasting the spot rate 52 steps ahead, presumably due to multiple policy changes in the RMB market. To save space, the results are not reported here.

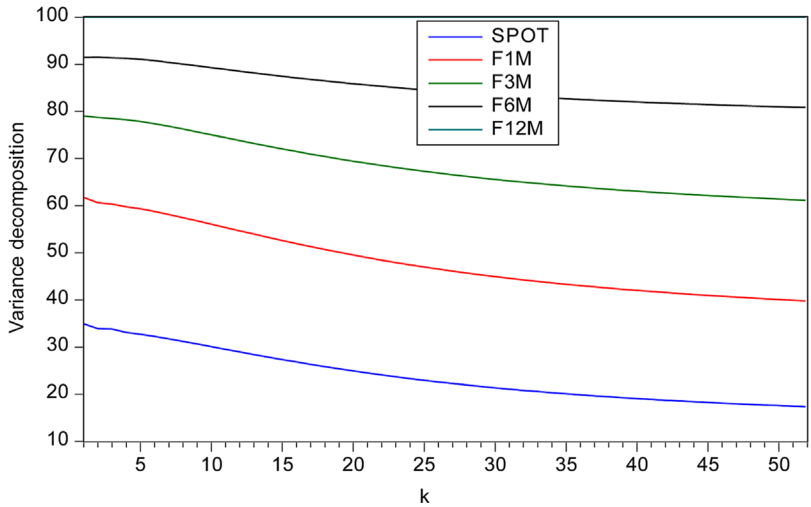

FIGURE 2

Forecast Errors Variance Decompositions of the Spot Rate (Full Sample)

The generalized forecast error variance decomposition is conducted based on the vector error correction model (2) with the cointegration rank $r = 4$. The parameter estimates are reported in Table III, Panel A. Week 1 is the contemporaneous period. The x-axis is the post-sample horizon k. The weekly Chinese RMB/U.S. dollar spot rate and four forward rates are used from July 2005 to December 2013. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

and 357 26-step-ahead out-of-sample forecasts. The forecast errors are formed by the difference between observed spot rates and the forecasts for the out-of-sample period. Table V compares the performance of the three multivariate and the three univariate models in forecasting the spot rate. Note that the term of the shortest forward rate is one month. Therefore, FPR and FR cannot be used to forecast the spot rate one-step ahead (which is one week ahead). Panel A computes the root mean squared forecast errors (RMSFE) of the competing forecasts. In forecasting one-step ahead, RW performs better than VARD, which in turn beats the two similarly performing error correction models. At $k = 4$, the two univariate models which use information on the one-month forward rate F1M perform best, followed by RW and VARD. The performance pattern remains the same at the two longer horizons: the simple forward rate (FR) performs best and the VAR in first differences perform reasonably well. In contrast, VECM and VECR perform increasingly worse as the forecasting horizon lengthens.

To test if the forecasts generated from the six models are statistically equal to those from the random walk (RW) and the simple forward rate forecasts (FR), we calculate the DM statistics and report them in Panel B of Table V. Only one- and four-step-ahead forecasts are compared because, as pointed out in Clarida et al. (2003), the original test is designed for one-step-ahead forecasts from nonnested models. Both of these two assumptions are violated in many cases in Table V and the test results are likely to be more distorted as the forecast horizon increases. Not surprisingly, RW forecasts are more accurate than the ones from the three multivariate models at $k = 1$. According to the DM statistics, the two cointegration models underperform the random walk model at $k = 4$ and no other model performs better than RW. Similarly, no model outperforms the simple FR forecasts.

The above rolling sample method allows for parameter uncertainty or other types of structural changes over time in the data generating process (DGP). However, when structural breaks are either absent, insignificant, or temporary, such a scheme precludes the

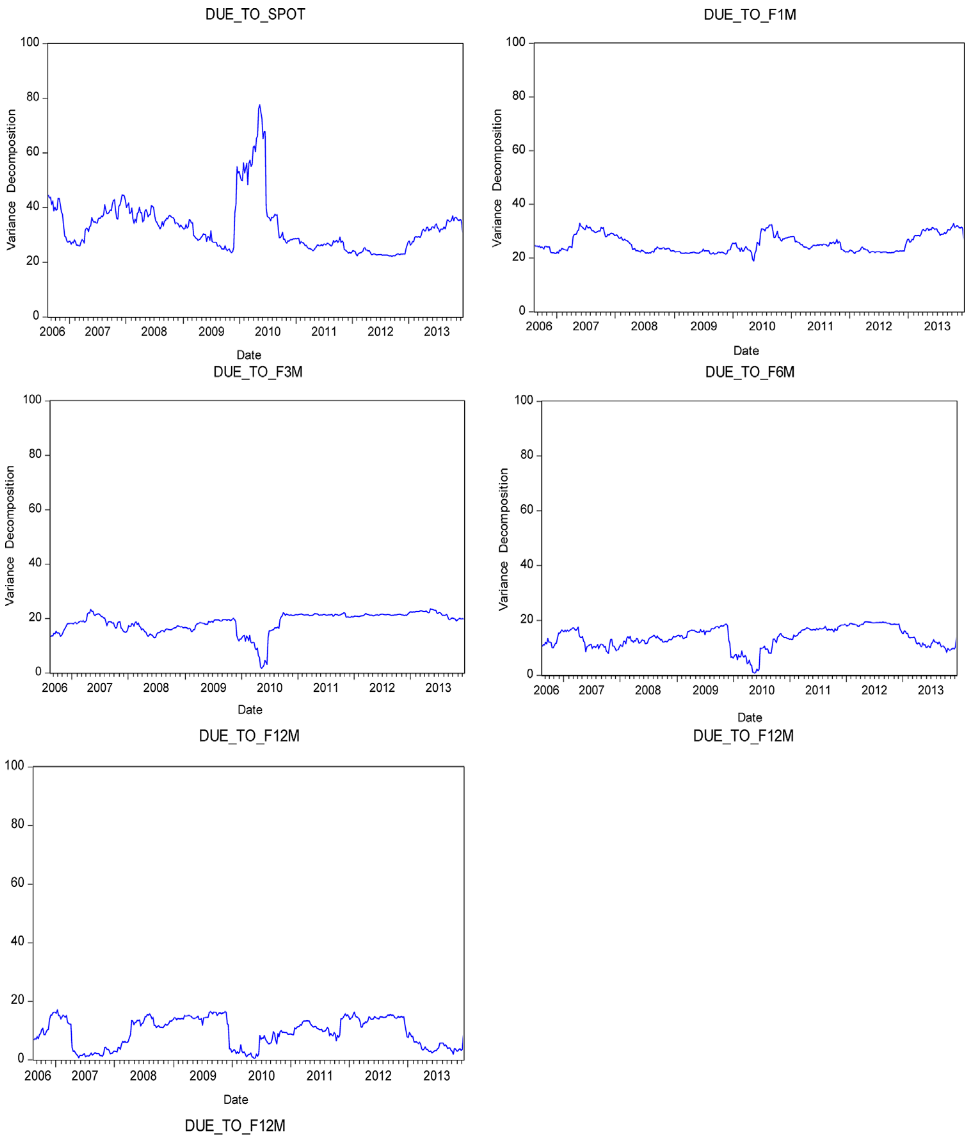

FIGURE 3

Forecast Error Variance Decompositions of the Spot Rate
(1-Year Rolling Sample, Post-Sample Horizon $k = 1$)

The generalized forecast error variance decomposition is conducted based on the vector error correction model (2) with the cointegration rank $r = 4$. The rolling window (sample) size is 52. The sample of Chinese RMB/U.S. dollar spot rand four forward rates covers the period of July 2005 through December 2013. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

possibility that the underlying DGP may evolve to a stable form. This problem becomes more serious when the overall sample size and the estimation window are small. Therefore, in Table VI we repeat the above analysis using the more popular recursive estimation and forecast method. Compared to Table V, the recursive forecasts derived from the three multivariate models are significantly smaller than the rolling forecasts in terms of both MAE and RMSFE measures, suggesting that coefficients associated with the long run equilibrium

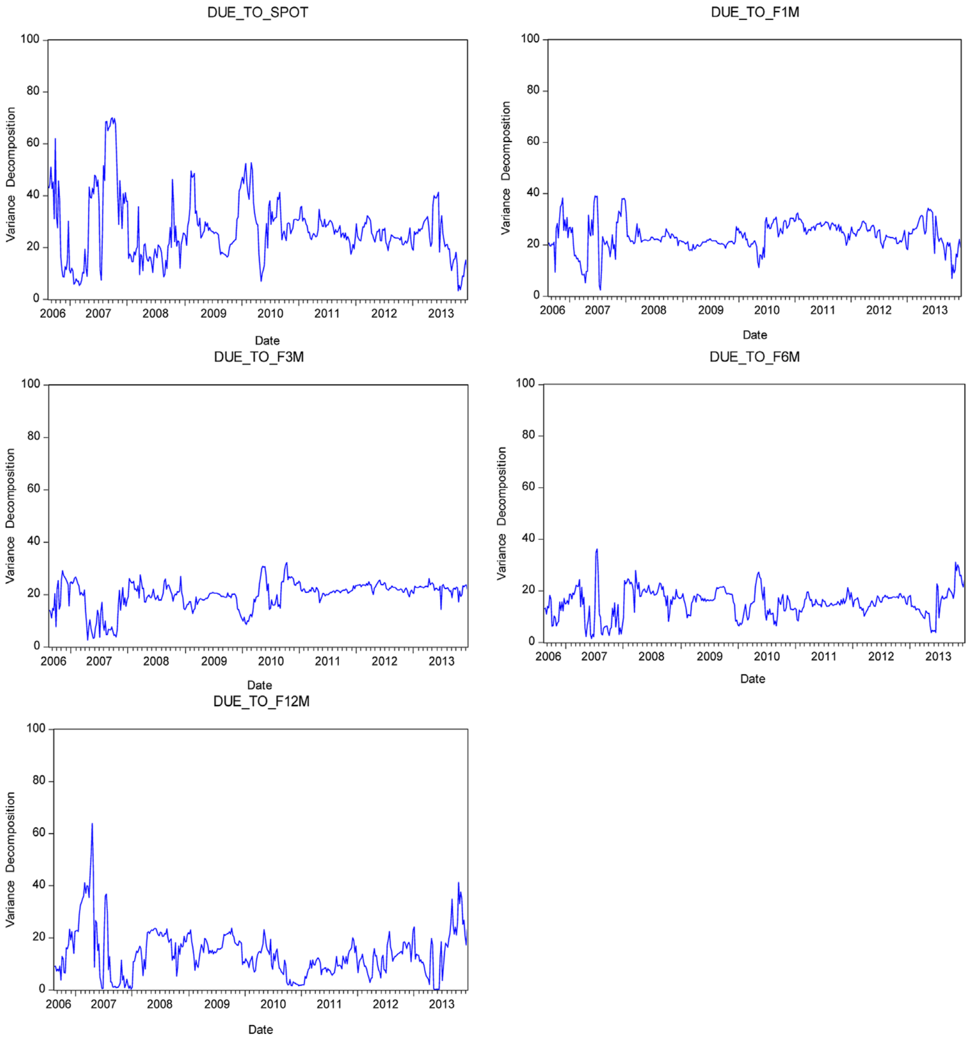

FIGURE 4

Forecast Error Variance Decompositions of the Spot Rate
(1-Year Rolling Sample, Out-of-Sample Period $k = 26$)

The generalized forecast error variance decomposition is conducted based on the vector error correction model (2) with the cointegration rank $r = 4$. The rolling window (sample) size is 52. The sample of Chinese RMB/U.S. dollar spot rand four forward rates covers the period of July 2005 through December 2013. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

relationships can be estimated more precisely in larger sample sizes. The performances of the three vector autoregressions are similar to the best performing FPR model for up to 26-step-ahead forecasts and they all beat the random walk forecasts. This is especially significant for the one-month forward rate, although the D-M null hypothesis of equality of forecast accuracy is rejected at the 10% level only for VECM and VECR.

To further confirm the forward unbiasedness hypothesis, we need the slope coefficient in the FPR model (Equation 4) to be 1. Estimates from the advanced countries' currencies are often close to negative one (-1) rather than expected positive one. Frankel and Poonawala (2010, p. 595) report a smaller bias from a sample of 14 emerging market currencies (not including China's RMB), based on the evidence that the estimates are all positive (rather than negative) numbers. Consistent with Frankel and Poonawala (2010), we find in unreported regressions (results available on request) that the slope coefficients for our RMB-dollar data are 0.44, 0.58, 0.56, and 0.47 for 4-, 13-, 26-, and 52-week forward premiums, respectively, and these estimates are all highly significant (different from 0). Nevertheless, the null hypotheses that these slope coefficients are equal to 1 are also strongly rejected. Hence, the finding here is generally consistent with Frankel and Poonawala (2010) in that the RMB forward market is still biased, but similar to most emerging currency markets, it appears to be less biased than those in most developed countries.[17]

Given the largely inconclusive evidence from the forecast equality test, we further conduct forecast encompassing tests in Panel C of Table VI. As for DM tests, we also only report the encompassing test results for 1- and 4-step (1-month) short-term forecast errors since the test is designed for 1-step forecast errors. The null hypothesis that the univariate RW and FR model forecasts encompass those of multivariate VECM, VECR, and VARD are rejected at any conventional significance levels, meaning that these multivariate models do contain information useful for forecasting future spot rates that is not fully captured by RW and FR models. Consistent with the DM test results, the null hypotheses that RW and FR encompass the forward premium regression (FPR) are also strongly rejected. The null hypothesis that RW encompasses FR is rejected at the 1% level (the test statistic is 3.10). Because the two models are not nesting each other, we also test the null hypothesis that FR encompasses RW, which is rejected at the 5% level.

4.3. Structural Breaks

One of our contributions from the empirical perspective is that we pay special attention to the influence of structural breaks on cointegration analysis. Visual inspection of the data presented in Figure 1 suggests some significant changes in the exchange rates and forward premiums. For example, the forward premiums obtain the global minimal in March 2008. It became smaller in magnitudes and the 12-month premiums hit the positive territory for the first time in October 2008. The positive 12-month premium achieves the global maximum in early December of 2008. It fell back to the negative values again in March 2009 until mid-December, 2011. We now formally test how the data are characterized by these important changes in the exchange market.

There is a large literature on testing for structural breaks in stationary variables in both univariate and multivariate contexts. The literature addressing structural breaks in the presence of cointegration for nonstationary data is relatively sparse. The few published studies may suffer from low power or size distortions. In this paper, we extend Phillips (1996) and propose using the model selection approach to estimate structural breaks in models of nonstationary variables with possible cointegration restrictions.[18] According to Maddala and Kim (1998, p. 417), the model selection approach is especially promising in this context and can be a valuable alternative to parametric tests.

[17]To facilitate a more direct comparison, we also estimate model (4) using Indian Rupee/$ exchange rates, another major emerging market. We use the same sample period and the same set of spot and forward rates as for RMB (see section 4.4 for more discussion below). The slope coefficients in the case of Indian Rupee/$ exchange rates are all positive and at 0.13, 1.33, 1.90, and 1.99 for 4-, 13-, 26-, and 52-week forward premiums, respectively. The corresponding HAC-consistent *t*-values are 0.13, 1.80, 3.00, and 3.41. Although forward markets in China and India have positive signs, based on the magnitude of the deviation from the expected positive one, Chinese forward markets apparently would be even less biased than the Indian forward market.
[18]It also extends other works on structural break tests (e.g., Bai & Perron, 2006; Wang, 2006).

TABLE V
Out-of-Sample Forecasts From the Rolling Estimation

k	*VECM*	*VECR*	*VARD*	*RW*	*FPR*	*FR*
Panel A. Root mean squared forecast errors (RMSFE)						
1	0.0027	0.0026	0.0024	0.0022		
4	0.0062	0.0061	0.0052	0.0053	0.0047	0.0049
13	0.0154	0.0161	0.0114	0.0136	0.0125	0.0104
26	0.0687	0.0686	0.0229	0.0252	0.0251	0.0181
Panel B. DM equality test statistics						
1 (vs. RW)	4.947***	4.309***	3.004***			
4 (vs. RW)	2.457**	1.938*	0.276		−1.655*	−1.123
4 (vs. FR)	3.909***	3.903**	0.916	1.123	−1.457	

Note: The table reports out-of-sample forecasts from the rolling estimation for Chinese RMB/U.S. dollar spot rate, forward rates, and forward premiums. The sample period is July 2005 through December 2013.VECM is the vector error correction model (1) with cointegration rank of 4. VECR is the VECM with imposing restrictions on cointegrating vectors. VARD is a vector autoregressions in first differences. RW is a random walk. In FR *k*-step-ahead forecast simply uses the appropriate forward rate itself. FPR is a univariate regression of the spot rate and forward rate. A negative DM statistic means that the model has a smaller MSE than that of RW (FR). The symbols ***, ** and * indicate that the null is rejected at a 1%, 5%, and 10% significance levels, respectively. The rolling sample size is 52. The sample starts with observation 57 in estimating the FPR model; it is 5 for all other five models.

Given the dimension of the model, the sample size and its weekly data frequency, we set the trimming value at 0.05. The corresponding minimal sub-sample size (duration of a regime) is 22. We choose this trimming value to allow for sufficient time spans of exchange rate data for testing the spot and future rates as a long-run relationship, and, at the same time, the time span is not so long that it contains structural breaks. We also set the maximum number of breaks (M) to be 3. Operationally, we calculate the information criteria for each model specification with m breaks ($m = 0$, 1, 2, and 3), assuming an intercept (μ) change only, an intercept and short-run dynamics (Γ_i) change, and a simultaneous change of all coefficients in the VECM model, respectively.[19] Given the number of breaks and the type of breaks, we minimize an information criterion to date the break(s) by searching over all sample observations except those trimmed from the ends. The model with the minimum information criterion among all combination of the number of breaks and the type of structural changes is selected.[20] Table VII presents the search results based on the information criterion AIC. For each of three types of structural breaks, AIC selects a VECM model with three breaks in Panel A. Among all three types of structural breaks, the third type with a break in all coefficients has the smallest information criterion (−69.226). And in this case, the first break is on February 20, 2008, when the exchange rate became significantly more volatile (panel B, Figure 1). The second and the third breaks are dated on July 23, 2008 and December 24, 2008, respectively. Two points stand out. First, following the third break, the weekly change in the exchange rate is much smaller than that between the first and the third breaks, although forward premiums do change directions in this regime. Second, the second and third breaks are both dated only 22 weeks after the previous breaks, which is at the boundary set by the trimming value. It is therefore very likely that these breaks occurred earlier. In fact, if the system were characterized by one break only, AIC puts the break during the week of November 5, 2008, when the forward premiums turned positive for the first time (see Panel C,

[19]Clarida et al. (2003) consider a cointegration model which allows for regime switching in the intercept.
[20]See Wang (2013) for simulation evidence on the performance of this model selection approach in the joint determination of cointegration and structural breaks.

TABLE VI
Out-of-Sample Forecasts From the Recursive Estimation

k	*VECM*	*VECR*	*VARD*	*RW*	*FPR*	*FR*
Panel A. Root mean squared forecast errors (RMSFE)						
1	0.0021	0.0021	0.0021	0.0022		
4	0.0046	0.0046	0.0046	0.0053	0.0044	0.0049
13	0.0104	0.0107	0.0104	0.0136	0.0102	0.0104
26	0.0235	0.0244	0.0189	0.0252	0.0180	0.0181
Panel B. DM equality test statistics						
1 (vs. RW)	−0.060	−0.057	−0.617			
4 (vs. RW)	−1.956*	−1.824*	−2.556**		−2.619***	1.123
4 (vs. FR)	−1.299	−1.395	−0.856	1.123	−2.753***	
Panel C. Encompassing test statistics						
1 (vs. RW)	60.925***	51.577***	48.102***			
4 (vs. RW)	198.586***	171.262***	138.971***		163.400***	3.100***
4 (vs. FR)	108.824***	76.046***	162.178***	2.180**	120.480***	

Note: The table reports out-of-sample forecasts from the recursive estimation for Chinese RMB/U.S. dollar spot rate, forward rates, and forward premiums. The sample period is July 2005 through December 2013.VECM is the vector error correction model (1) with cointegration rank of 4. VECR is the VECM with imposing restrictions on cointegrating vectors. VARD is a vector autoregressions in first differences. RW is a random walk. In FR *k*-step-ahead forecast simply uses the appropriate forward rate itself. FPR is a univariate regression of the spot rate and forward rate. A negative DM statistic means that the model in the first row has a smaller MSE than that of RW (FR).The null hypothesis of the encompassing test is that forecasts of the parsimonious model RW (FR) encompass those of the model in the first row. The symbols ***, ** and * indicate that the null is rejected at a 1%, 5%, and 10% significance levels, respectively. The initial sample size is 52 weeks. The sample starts with observation 57 in estimating the FPR model; it is 5 for all other five models.

TABLE VII
Structural Break Tests in Cointegration Models Using the Model Selection Approach (AIC)

	Number of breaks			
Type of breaks	*No break*	*One break*	*Two breaks*	*Three breaks*
Break in μ only				
Value of BIC	−67.579	−67.613	−67.712	−67.754
1st break date		03/19/2008	04/16/2008	04/16/2008
2nd break date			12/03/2008	12/03/2008
3rd break date				06/10/2009
Break in μ and Γ				
Value of BIC	−67.579	−67.637	−68.334	−68.495
1st break date		12/03/2008	07/23/2008	04/23/2008
2nd break date			12/24/2008	10/01/2008
3rd break date				03/25/2009
Break in all coef.				
Value of BIC	−67.579	−67.685	−68.674	−**69.266**
1st break date		10/08/2008	07/23/2008	02/20/2008
2nd break date			12/24/2008	07/23/2008
3rd break date				12/24/2008

Note: The structural break tests are based on cointegration model (1) in the text for Chinese RMB/U.S. dollar spot and forward exchange rates for the period July 2005-December 2013. The lag order p in Model (1) is 3. The cointegration rank $r = 4$. The trimming value $\in$ is 0.05 meaning that minimum (sub-) sample size is 22. Numbers in bold indicate the smallest values among all possible combinations of three number of breaks and three types of breaks for the respective criteria.

Figure 1).[21] Interestingly, a break date of late June 2008 is consistently identified in Zhao et al. (2013), which is argued to due to the impact of the global financial crisis on Chinese foreign exchange market. While they do not explicitly allow for potential breaks in cointegration space in identifying the break date, they (p.164) show in the subsequent analysis that cointegration between spot and forward rates does not exist between March 2008 and February 2009 (based on their identified break dates). Thus, their evidence is generally in line with our result of detecting breaks in 2008, verifying effectiveness of the new structural break test used here in allowing for potential breaks in the long-run relationship.

Based on the three breaks identified by AIC, we divide the sample into four subsamples, and estimate the parameters and conduct tests for the coefficient restrictions on the cointegration space for the first and the fourth sub-samples (the second and the third sub-samples each contain only 22 observations and are unlikely to produce reliable parameter estimates for vector autoregressions with four lags of variables). The results are summarized in Panel B of Table III for the first subsample (07/25/2005–02/20/2008) and in Panel C for the third subsample (12/31/2009–12/11/2013), respectively. The panels clearly show that, similar to the results from the full sample, all betas in the cointegrating vectors are closer to the unit value for the two short-term rates than for the two longer-term rates in both subsamples. Overall, the theory-implied restrictions hold better in the data before the first structural break occurred. The null hypothesis that these coefficients for the forward premium equal one for the first subsample has a smaller statistic of 9.167 than the full sample counterpart, which cannot be rejected at the 5% level. In contrast, we strongly reject the null hypothesis for the fourth subsample. Recall that the constant terms are significant for the models for SPOT and F1M, indicating a linear trend is present in these two series. In contrast, none of them are significant in the two sub-samples. These results suggest that the rejection of the null hypothesis for the fourth subsample is likely due to changes in the cointegration spaces (i.e., forward premiums) because, recalling from Panel C, the forward premiums turn from negative to positive in early December 2011 and remain so until the end of the sample.

In Table AIII, we conduct generalized forecast error variance decompositions for the above two sub-sample periods. While the overall patterns in both sub-samples are similar to those based on the full sample, there are some noticeable changes in the dynamics. For example, shocks to the spot rate are more persistent in the post-break period than in the pre-break period. By the end of a one-year horizon, about 27% of variability in the spot rate is still accounted for by its own shocks in the more recent sample, while only 18% is attributable to its own shocks in the first sub-sample. The explanatory power of the 12-month forward premium is lower in the post-break period, ranging from 6.89% to 9.83%, which is in contrast to the wider range of 6.38–19.32% in the first sub-sample.

4.4. Profitability of Carry Trade

In this sub-section we further investigate whether the findings based on econometric models above can be used to improve the profitability of currency carry trade.[22] Researchers have explored several versions of the carry trade. As an illustration, here we adopt the one most often studied in the literature.

Specifically, following Daniel et al. (2014), an dollar-based investor goes long (short) one dollar in the Chinese Renminbi (RMB) in the forward market when the forward rate $f_{k,t}$ is higher

[21]The Bayesian information criterion BIC selects a more parsimonious model with two breaks (see Table AII). The first and second breaks are dated April 16, 2008 and December 3, 2008, respectively. They are close to the first and the third breaks selected by AIC.

[22]We are thankful to the anonymous referee for suggesting additional analysis in this subsection.

(lower) than the spot rate $SPOT_t$. The carry trade is implemented as a zero investment strategy, and the dollar payoff to this simple carry trade strategy without transaction costs can be written as

$$\begin{cases} z_{t+k} = w_t\left(\dfrac{f_{t,k} - s_{t+k}}{s_{t+k}}\right) & if\, f_{t,k} > s_t \\ z_{t+k} = -w_t\left(\dfrac{f_{t,k} - s_{t+k}}{s_{t+k}}\right) & if\, f_{t,k} < s_t \\ z_{t+k} = 0 & \text{otherwise} \end{cases}$$

where w_t is the scale of forward positions and we set $w_t = \$1$ throughout the exercises.

If forward rates are an unbiased predictor and uncovered interest rate parity holds, then the carry trade profits should average to zero. However, as pointed out by Daniel et al. (2014), uncovered interest rate parity ignores the possibility that changes in the values of currencies are exposed to risk factors, in which case risk premiums can arise.[23]

To incorporate forecasting results for future spot rates from various models above, we go long one dollar in RMB if a model predicts that RMB will appreciate ($\Delta s_{t+k} < 0$) and RMB is at a discount in the forward market. We go short in RMB if the model predicts that RMB will depreciate ($\Delta s_{t+k} > 0$) and RMB is at a premium. We implement no carry trade in other cases. The dollar payoff to this carry trade can be written as

$$\begin{cases} z_{t+k} = w_t\left(\dfrac{f_{t,k} - s_{t+k}}{s_{t+k}}\right) & if \quad f_{t,k} > s_t \text{ and } \hat{s}_{t+k} < s_t \\ z_{t+k} = -w_t\left(\dfrac{f_{t,k} - s_{t+k}}{s_{t+k}}\right) & if \quad f_{t,k} < s_t \text{ and } \hat{s}_{t+k} > s_t \\ z_{t+k} = 0 & \text{otherwise} \end{cases}$$

The results are summarized in Table VIII. All of the statistics refer to annualized returns (in percentage). The first carry trade was implemented in August 2006 except for FPR-based strategy, which was done one-year later. Column 2 shows that the simple trade strategy in the 1-month forward market produces an average return of 1.37% which is statistically significant. However, returns in the 3-month and 6-month forward markets are much lower and in fact are not different from zero. The corresponding two Sharpe ratios are also close to zero.

Columns 3 through 7 report the results for the trade strategies which are based on forecasts from the four econometric models, VECM, VECR, VARD, and FPR. Note that the random walk model (RW) predicts no change in future spot rates and the forward rate model (FP) assumes that future spot rates are equal to current forward rates. Both models predict no gains from carry trade. In the 1-month forward market, the strategies based on forecasts from VECM, VARD, and FPR all generate higher average returns and Sharpe ratios than the simple trade strategy. Nevertheless, VECR model performs worse than the simple trade strategy, although it does have a slightly higher Sharpe ratio. The middle and bottom panels show that all four model-based trade strategies, including that of VECR, offer positive returns

[23]The carry trade can also be implemented in the spot market. Here we only examine the performance in the forward market for two reasons. First, as interests of this paper are in examining whether the forward rates contain useful information in capturing spot rate movements, we choose to implement it in the forward market. Second, computing payoff of the carry trade in the spot market requires both U.S. and Chinese currency interest rates. The often-used Eurocurrency interest rates exist for U.S. dollar, but not for China, India and other emerging market currencies (RMB offshore rates are only available since July 2013). Carry trades in the spot market and in the forward market are equivalent when the interest rate parity holds.

TABLE VIII
Summary Statistics of Dollar-Based RMB Carry Trade Returns

		Model based strategies			
Summary statistics	*Simple strategy*	*VECM*	*VECR*	*VARD*	*FPR*
	Panel A. 1-month forward market				
Ave. ret.	1.369***	1.758***	0.858***	1.790***	2.003***
Std. dev.	5.740	3.897	3.308	4.131	4.072
Sharpe ratio	0.238	0.451	0.259	0.433	0.492
Skewness	0.082	1.496	0.625	0.653	1.253
	Panel B. 3-month forward market				
Ave. ret.	0.213	1.194***	0.568***	1.347***	0.939***
Std. dev.	4.184	2.598	1.719	2.754	2.344
Sharpe ratio	0.051	0.460	0.330	0.489	0.401
Skewness	0.285	1.813	0.625	1.840	1.974
	Panel C. 6-month forward market				
Ave. ret.	0.082	1.002***	0.617***	1.083***	1.008***
Std. dev.	3.667	2.026	1.615	2.123	1.986
Sharpe ratio	0.022	0.494	0.382	0.510	0.508
Skewness	0.136	1.581	2.124	1.840	1.505

Note: This table presents summary statistics of a dollar-based investor's annualized returns (in percentage) on zero-investment portfolios of Indian Rupee carry trade. Five strategies are considered, a simple carry trade strategy and four model-based carry trade strategies as described in the text. The weekly data are obtained from Datastream, covering the period of July 2005-December 2013. The first fifty six weekly observations are reserved for estimating models and generating initial forecasts. The first carry trade was implemented in August 2006 (observation 56) except for FPR-based strategy, which was done one-year later. Symbol *** indicates significant at the 1% level.

in both 3-month and 6-month forward markets. VECR again performs worse than the other three models. If the strategies are compared using the shorter sample used by FPR, the average returns of the other three models and the simple trade strategy are generally higher by 0.1%∼0.2%. For example, the VECM-based strategy generates an average return of 1.910% in the 1-month forward market.

In sum, the result on the RMB carry trade shows that the annual returns ranging from 1% to 2% can be generated depending on the underlying trading strategies. They are statistically significant positive returns, and generally consistent with our findings that multivariate VEC models that incorporate various forward rates do provide useful information for forecasting future spot rate.

As a robustness check on our main results, we also take our analysis to another important emerging market, India's Rupee/$ exchange rates. While data for Rupee/Dollar exchange rates are available for a longer period, we choose to focus on the same sample period (July 2005–December 2013) as that for RMB/$ exchange rates. Therefore, the results are directly comparable to those reported earlier for the RMB market. As we focus on Chinese RMB, to save space, results for econometric model estimation, hypothesis testing, and out-of-sample forecasting for India's Rupee/$ exchange rates are not reported here (but available on request).

Table AIV compares a dollar-based investor's returns on Rupee carry trade by the simple strategy with returns from adopting four econometric-model-based trade strategies as described earlier. Three points stand out. First, the average returns from incorporating forecasts of the four models are much less volatile than those of the simple trade strategy. Second, perhaps more interestingly, the theory-imposed vector error correction model (VECR) provides forecasts of future spot rates most useful for implementing carry trade. It generates positive returns which are both statistically significant and economically meaningful at least in 1- and 3-month forward markets. The unrestricted VECM performs the second best. Third, although the four forward rates as a whole deliver higher carry trade returns, the strategy based on a single term forward rate (the FPR model) performs the worst.

5. CONCLUSIONS

We investigate Chinese RMB-U.S. dollar spot and forward exchange rates from 2005 to 2013, a managed-floating period of the RMB market. Although the RMB (onshore) spot rate is allowed to vary only within a predetermined narrow trading band, we present both in-sample and out-of-sample new evidence that the offshore RMB (NDF) forward rate is useful in predicting the future (onshore) spot rate. Extending Frankel and Poonawala (2010), we also document that although the RMB forward rates are still a biased predictor of future spot rates, such a bias also appears to be less severe than most major currencies. Nevertheless, such a bias can be exploited through carry trade strategies, generating statistically significant (albeit moderate) positive returns ranging from 1 to 2%. The empirical results from a new structural break test in the presence of cointegration also confirm that the Chinese currency market has experienced substantial institutional and important policy changes, exhibiting quite different market dynamics over time.

Obviously, there are many interesting and important issues related to the Chinese RMB market which are not explored in this study. Given accelerated internationalization process of RMB, thorough investigation using the most recent data with a greater exchange rate fluctuation band since March 2014 should be fruitful to shed more light on the crucially important currency market. The recent rapid development of offshore RMB (albeit still of very small size) market and the increasing impact of the market-based offshore RMB spot exchange rate (i.e., CNH) on the onshore spot rate (i.e., CNY) documented in Cheung and Rime (2014) tends to suggest that part of the predicative usefulness of the NDF forward rate probably relates to the participation of foreign investors outside China, which is worthy of further investigation. Finally, when the RMB non-delivery forward market (for CNY) is developed into a deliverable forward market under full currency convertibility in the future, it might be expected to function even better and could exhibit a smaller bias, due to stronger arbitrage force in place (Yang, Bessler, & Leatham, 2001).

APPENDIX

Table AI
Results of ADF Unit Root Tests With Two Structural Breaks

Variables	*ADF*	*Critical values (5%)*	*Break 1 date*	*Break 2 date*
SPOT	−1.665	−3.801	01/31/07	12/12/07
F1M	−2.294	−3.781	05/24/06	07/16/08
F3M	−2.623	−3.779	09/05/07	07/16/08
F6M	−2.669	−3.782	08/22/07	07/16/08
F12M	−2.624	−3.796	10/25/06	07/23/08
(F1M–SPOT)	−4.688**	−3.808	08/29/07	12/03/08
(F3M–SPOT)	−4.048**	−3.785	01/16/08	12/03/08
(F6M–SPOT)	−3.273	−3.777	04/11/07	03/19/08
(F12M–SPOT)	−2.604	−3.793	05/24/06	04/16/08

Note: This table reports the GLS-based unit root tests of Carrion-i-Silvestre, Kim, and Perron (2009) for Chinese RMB/U.S. dollar spot and forward exchange rates for the period July 2005-December 2013. The test allows for structural breaks under both the null and the alternative hypotheses, assuming two breaks in each series.** Indicates significant at the 5% level.Lag order is determined by modified AIC.

Table AII
Structural Break Tests in Cointegration Models Using the Model Selection Approach (BIC)

	Number of breaks			
Type of breaks	*No break*	*One break*	*Two breaks*	*Three breaks*
Break in μ only				
Value of BIC	−66.603	−66.590	**−66.642**	−66.637
1st break date		03/19/2008	04/16/2008	04/16/2008
2nd break date			12/03/2008	12/03/2008
3rd break date				06/10/2009
Break in μ and Γ				
Value of BIC	−66.603	−65.910	−65.856	−65.267
1st break date		12/03/2008	07/23/2008	04/23/2008
2nd break date			12/24/2008	10/01/2008
3rd break date				03/25/2009
Break in all coef.				
Value of BIC	−66.603	−65.733	−65.746	−65.362
1st break date		10/08/2008	07/23/2008	02/20/2008
2nd break date			12/24/2008	07/23/2008
3rd break date				12/24/2008

Note: The structural break tests are based on cointegration model (1) in the text for Chinese RMB/U.S. dollar spot and forward exchange rates for the period July 2005–December 2013. The lag order p in Model (1) is 3. The cointegration rank $r = 4$. The trimming value $\in$ is 0.05 meaning that minimum (sub-) sample size is 22. Numbers in bold indicate the smallest values among all possible combinations of three number of breaks and three types of breaks for the respective criteria.

Table AIII
Forecast Error Variance Decompositions of the Spot Rate Using Sub-Samples

Horizon (week)	*SPOT*	*F1M*	*F3M*	*F6M*	*F12M*
			Panel A. Sub-sample 07/25/2005–02/20/2008		
1	36.89	26.76	17.28	12.70	6.38
	(31.46, 44.29)	(24.35, 29.06)	(14.28, 19.13)	(9.06, 15.44)	(2.84, 10.43)
4	46.05	27.07	14.37	8.84	3.67
	(35.29, 57.28)	(22.88, 29.38)	(8.90, 18.11)	(4.93, 13.62)	(1.62, 9.23)
13	39.04	26.30	15.96	11.88	6.82
	(24.56, 60.21)	(19.95, 29.80)	(7.25, 20.06)	(4.27, 18.85)	(1.67, 16.86)
26	28.27	23.41	18.33	17.29	12.70
	(15.27, 58.80)	(16.98, 28.88)	(7.48, 22.28)	(4.76, 23.72)	(2.26, 23.12)
52	17.90	19.67	20.28	22.82	19.32
	(8.76, 54.17)	(13.08, 27.82)	(7.49, 23.94)	(5.53, 27.56)	(3.29, 29.05)
			Panel B. Sub-sample 12/31/2008–12/13/2013		
1	30.67	28.32	21.19	13.45	6.36
	(27.92, 33.43)	(26.21, 30.37)	(20.19, 22)	(11.19, 15.59)	(4.21, 8.87)
4	29.16	28.06	22.03	13.77	6.98
	(25.81, 32.78)	(25.67, 30.37)	(20.66, 23.13)	(10.99, 16.26)	(4.24, 10.19)
13	28.40	27.79	21.92	14.27	7.63
	(23.42, 33.4)	(24.61, 30.73)	(19.95, 23.65)	(10.58, 17.57)	(3.71, 12.22)
26	27.40	27.23	22.07	15.10	8.21
	(21.9, 34.21)	(23.73, 31.12)	(19.5, 23.95)	(10.37, 19.05)	(3.49, 13.55)
52	26.57	26.79	22.26	15.79	8.58
	(20.69, 34.75)	(22.73, 31.49)	(19.34, 24.1)	(9.87, 20.23)	(2.77, 14.67)

Note: The generalized forecast error variance decomposition is conducted based on the vector error correction model (1) for Chinese RMB/U.S. dollar spot rate, forward rates, and forward premiums for the period of July 2005 through December 2013. The cointegration rank $r = 4$. Column 1 is the post-sample horizon (week 1 is the contemporaneous period). Each panel shows how much of the variance of the spot rate is explained in percentage points by shocks to the five exchange rates listed in the first row. The numbers in parentheses are 90% confidence intervals formed via the bootstrap method.

Table AIV
Summary Statistics of Dollar-Based Indian Rupee Carry Trade Returns

		Model based strategies			
Summary statistics	*Simple strategy*	*VECM*	*VECR*	*VARD*	*FPR*
Panel A. 1-month forward market					
Ave. ret.	2.331	2.295**	2.723***	0.971	−1.980
Std. dev.	33.141	19.893	19.297	18.333	21.248
Sharpe ratio	0.070	0.115	0.141	0.053	−0.093
Skewness	−0.222	−0.633	−0.658	−0.733	−0.867
Panel B. 3-month forward market					
Ave. ret.	1.477	0.709	1.709**	0.195	−3.133
Std. dev.	20.361	12.394	13.382	10.536	12.047
Sharpe ratio	0.073	0.057	0.128	0.019	−0.260
Skewness	−0.623	−1.075	−0.936	−0.941	−2.154
Panel C. 6-month forward market					
Ave. ret.	0.220	−0.289	0.804	−0.827	−2.861
Std. dev.	14.217	9.156	9.637	7.713	9.928
Sharpe ratio	0.015	−0.032	0.083	−0.107	−0.288
Skewness	−0.436	−0.882	−0.635	−1.314	−1.154

Note: This table presents summary statistics of a dollar-based investor's annualized returns (in percentage) on zero-investment portfolios of Indian Rupee carry trade. Five strategies are considered, a simple carry trade strategy and four model-based carry trade strategies as described in the text. The weekly data are obtained from Datastream, covering the period of July 2005-December 2013. The first fifty six weekly observations are reserved for estimating models and generating initial forecasts. The first carry trade was implemented in August 2006 (observation 56) except for FPR-based strategy, which was done one-year later. Symbols ** and *** indicate significant at the 5% and 1% level, respectively.

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