Chinese Exchange Rate Policy: Lessons for Global Investors

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Abstract

Chinese currency policy has had a strong impact on the value of investors portfolio's in recent years. On August 11, 2015, the People's Bank of China announced a new exchange rate policy where the RMB central parity rate against the USD would be determined each morning by the previous day's closing rate, market demand and supply, and valuations of other currencies. This new policy suggests an investment strategy for trading the CNH. In this paper we create a forecasting model based on information regarding the central parity rate, implied volatilities and other control variables which outperforms the standard random walk benchmark. The exchange rate forecast is then used to manage the global investor's problem of mitigating the currency risk inherent in Chinese equity positions. All currency hedging strategies add value to the equity portfolio. A dynamic currency overlay strategy, where the forecasting model is used as a trading signal to take long and short positions in CNH, performs particularly well.

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1. Introduction

Chinese exchange rate policy has been the subject of much discussion and debate in recent years. Policymakers have discussed managed exchange rates that might confer a competitive advantage for a country that maintains an exchange rate at an artificially low level. Investors and the financial press have discussed policy decisions and resulting asset price dynamics that have created new risks and opportunities for global investors. The events of recent years should teach investors lessons about managing risks around Chinese policy events. The surprise devaluations of the RMB on 11 August 2015 and 6 January 2016 had a large impact on global markets. The 2015 event involved a 3% devaluation against the dollar and the 2016 event only a 1% devaluation. However, in both cases, the market interpreted the surprises as a signal of the beginning of a larger depreciation, so large capital outflows were associated with each. In addition, there were repercussions that reached outside China. Global equity markets fell substantially after each event. In the case of 11 August 2015, the US S&P 500 stock market index fell 0.3% after 1 week and was down 7% after 1 month. The German DAX index was down 6% after 1 week and 14% after 1 month. The most substantial effect was in China with the SHCOMP index down 5% in 1 week and 21% in 1 month. While the 6 January 2016 devaluation was only 1%, the effect on global stock markets was approximately the same as the earlier event as each time there was a fear of capital outflows from China and further RMB depreciation. In the January 2016 episode, the 1-week and 1-month effects were: −6 and −7% for the USA; −11 and −17% for China; and −3 and −10% for Germany. It is for good reason that global investors consider policy changes in China as a major risk factor. This risk comes in addition to the external factors and political uncertainty that were largely responsible for the depreciation in summer of 2018.

In addition to the devaluations, the 2015 and 2016 period was also notable for other major policy events. The IMF added the Chinese renminbi (RMB) to its SDR currency basket in October 2016 following several policy steps aimed at liberalizing RMB use by global market participants. A major step was the move to allow a greater role for market forces in exchange rate determination. On the same day as the first devaluation, August 11, 2015, the People's Bank of

China announced that the RMB central parity against the US dollar would be determined each morning by consideration of the following factors: the previous day's closing rate, market demand and supply, and valuations of other currencies.[1] We take this policy change as a useful indicator of a break in the data that changes the predictability of the freely tradable and deliverable CNH currency traded in Hong Kong and used by offshore investors to take positions in Chinese assets.[2] Our paper will proceed as follows: in section 2 we construct forecasts of CNH and demonstrate the importance of the change in the central parity formation announced on August 11, 2015. To anticipate the results, the policy change resulted in the CNH and central parity rate moving much closer together over time so that the parity rate, along with some other conditioning variables, is a useful forecaster of CNH. Then, after establishing forecast ability in the post August 11, 2015 period, we consider the problem of the global investor holding a position in Chinese equities. The investor has a long exposure to CNH by virtue of owning a position in Chinese equities. In section 3, we will analyze the portfolio performance of alternative approaches to managing the foreign exchange risk of the equity position. An international investor can continuously hedge the exposure with a constant hedge ratio over time. Alternatively, a dynamic hedge can be employed where the size and sign of the hedge position varies with an exchange rate forecast. Section 3 will present evidence that the greater forecast power for CNH in the period after August 11, 2015 results in a successful dynamic hedging strategy. Finally, section 4 will offer a summary and conclusions.

2. Forecasting the CNH

The literature on currency forecasting is vast. A useful summary and analysis of this literature is provided by Rossi (2013). Her extensive review of exchange rate forecasting finds that most models that have appeared in the literature are of questionable use. However, there appears to be some robust forecasting ability with certain specifications: "Predictability is most apparent when one or more of the following holds: the predictors are Taylor rule or net foreign

[1] See Cheung, Hui, and Tsang (2018) for analysis of this change.

[2] The People's Bank of China (PBOC) and the Hong Kong Monetary Authority (HKMA) jointly announced on July 19, 2010 that the RMB will be traded as a deliverable currency in Hong Kong. The new offshore currency in Hong Kong is denoted by CNH. The onshore currency is denoted by CNY.

assets, the model is linear, and a small number of parameters are estimated. The toughest benchmark is the random walk without drift" (p. 1063). For the CNH, we use neither Taylor rules nor net foreign assets but specify a model guided by the announced policy of the PBOC. We do implement a linear model and estimate a small number of parameters and then compare our forecast to a random walk benchmark.

2.a. *Chinese policy as a guide to modeling*

On August 11, 2015, the PBOC released the following statement: "Effective beginning on Aug 11, daily central parity quotes reported to the China Foreign Exchange Trade System before the market opens should be based on the closing rate of the inter-bank foreign exchange rate market on the previous day, supply and demand in the market, and price movement of major currencies." The PBOC stated that the goal was to make the central parity rate more market oriented. Prior to the policy change, the central parity rate (P) and the CNH (C) were subject to significant divergence that often persisted for quite some time. Figure 1 illustrates the path of the two. The vertical bar in the figure represents the point in time when the new more market-oriented policy was implemented. One can clearly see that P and C track much more closely following the new policy. Our hypothesis is that the P that is announced prior to the market opening in China, will influence trading and will cause C to adjust towards the new P each day. So with C the dependent variable of interest, the first determinant is the daily P.[3] At this point we have a model of daily change in C as

$$d \log C_t = \alpha + \beta d \log P_t \ . \tag{1}$$

However, one additional lesson from the Chinese authorities' reaction function is that in times of high volatility, the link between C and P is weakened as policy is temporarily aimed at

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[3] Cheung, et al. model P as a function of yesterday's C and other factors, as they want to test hypotheses regarding the PBOC policy reaction function. Our model inverts the relationship as we seek to forecast C, the more market oriented exchange rate in Hong Kong that global investors can trade. As stated in Funke et al. (p. 15) "market participants maintain that the offshore CNH market provides genuine price discovery, free from the influence of onshore interventions at least partially driven by political considerations. There are plenty of precedents where offshore FX market prices more closely resemble reality than official policy views at the time."

moderating volatility. Cheung, et al. find that interacting realized CNH volatility with other explanatory variables in their P reaction function model significantly reduces their effect on P. The use of CNH volatility is "motivated by the information role of the offshore market that reflects market views on RMB valuation outside China" (Cheung et al., p. 230). Drawing upon this policy-reaction-function finding, we interact P with CNH volatility. However, we differ from the earlier analysis in that we use the implied volatility from option prices rather than realized historical volatility of CNH. Since we want to approach the problem from the global investor's view, a forward-looking measure of volatility is more in keeping with the investor's problem than historical volatility, so we include the variable IV in our model. So now we have a model where the effect of P on C is modified by IV, so the *β* coefficient of equation (1) capturing the effect of *dlogP* on *dlogC* should vary with IV as in

$$\beta_t = \beta_1 + \beta_2 \log IV_{t-1} \tag{2}$$

and the amended model is

$$d\log C_t = \alpha + \beta_1 d\log P_t + \beta_2 d\log P_t * \log IV_{t-1}. \tag{3}$$

IV and P are the key building blocks of our forecasting model. We add additional factors to explore the sensitivity and robustness of results to additional effects beyond those of P and IV. Additional factors include lags of CNH (C), the deviation of yesterday's C from today's P, and the premium between A- and H-shares for Chinese equities. It is well known that the prices of firms traded jointly in Hong Kong (H-shares) and the mainland (A-shares) are not equal and reflect investment barriers, information asymmetry, risk preferences, and other factors. Our basic model specification is:

$$\begin{aligned} d\log C_t &= \alpha + \beta_1 d\log P_t + \beta_2 (d\log P_t * \log IV_{t-1}) + \beta_3 d\log C_{t-1} \\ &+ \beta_4 (\log C_{t-1} - \log P_t) + \beta_5 \log AHP_{t-1} \end{aligned} \tag{4}$$

2.b Model Estimation

Estimates of equation 4, and various permutations are presented in Table 1 for the period since the new policy of 11 August 2015. The first 2 models estimated and reported in columns numbered 1 and 2, are for the specifications in equations (1) and (3) above. Model 1 suggests that this morning's P (observed before the market opens) is a significant determinant of today's C (as of 4pm in Hong Kong). Model 2, incorporates the varying parameter effect of equation (3) above. As expected, the greater volatility, the smaller the effect of P on C. In Model 1, a 1 percent change in P is associated with a little more than a 0.39 percent change in C in the same direction. Evaluating the model 2 derivative with respect to P, at the mean log of IV, we find that a 1 percent change in P is associated with about a 0.45 percent change in C in the same direction. Evaluating the derivative with respect to P for periods when volatility is especially large, we use the maximum value of log(IV) and find that a 1 percent change in P is associated with about a 0.18 percent change in C in the *opposite* direction. So in normal times, the market follows a change in the central parity price by moving the CNH price by a little less than half the change in P, but in highly volatile times, the market adjustment to CNH seems to be detached from P and actually moves in the other direction from the change in P.

Comparing the adjusted R-squares for different models in Table 1, we see the big jump associated with the interactive term for volatility. The remaining models in columns labeled 3 through 5 add marginal explanatory power relative to model 2. Model 3 incorporates the lag of the dependent variable and finds a positive, but statistically insignificant effect. Model 4 includes the deviation of the lagged C and P. The coefficient is a small negative value, suggesting that beyond the levels of P and lagged C, their deviation matters for today's C determination. Given yesterday's C, if today's P is set lower so that the deviation is wider, then today's C will fall and partially close the gap between them. Finally, Model 5 includes the A-H shares premium and finds a small positive effect with marginal significance, while the other coefficients are relatively unchanged. The larger the premium of A-shares over H-shares, the greater the value of C, other things equal. As stated earlier, the A-H premium may reflect trading frictions, information asymmetry, liquidity differences, and risk aversion. An increase in any of those factors could reasonably be associated with depreciation of the currency.

Table 2 reports the same model results for the entire 2011-2018 sample period for which we have data on all variables. Including the period before the August 2015 policy change on the central parity rate, results in lower explanatory power of the models. In this earlier period, the CNH and central parity exchange rate would often diverge for extended periods of time, as was shown in Figure 1. A model that links the two is really combining two different regimes. A Chow test for a structural break at 11 August 2015, yields an F-statistic of 21.06 with a p-value of 0.000. The data clearly support a break in structure, yet Table 2 does show similar qualitative findings as Table 1. The coefficients tend to be smaller than in Table 1. Lagged CNH is still insignificant, and the most important feature is the interaction of implied volatility with the central parity rate.

2.c. Forecasting CNH

Since the landmark study of Meese and Rogoff (1983), academic papers on forecasting exchange rates typically use mean-square-error (MSE) as the relevant metric for evaluation. The benchmark measure to beat is a random walk. This measure is confirmed in the Rossi review article as she states "The toughest benchmark is the random walk without drift" (p. 1063). As a result, we use the MSE of a random walk model as the target for outperformance of our forecast. [4]

Given the limited number of observations since the 11 August 2015 policy change, we will train our forecasting model over the early sample period up to the period of the policy change and then forecast out-of-sample from 11 August 2015 forward. The previous section provided evidence that there was a structural break at the date of the policy change, so we may create an unfavorable bias downward in our out-of-sample forecast performance. However, the qualitative nature of the coefficient estimates are similar in the two periods, with the early period coefficient estimates smaller than the post-policy change period.

[4] While MSE has been popular in academic studies of currency forecasting, Melvin, Prins, and Shand (2013) discuss MSE as being unimportant for constructing a currency investment strategy. A successful long-short currency strategy requires an accurate ranking of currencies in terms of most likely to appreciate or depreciate.

The forecast is created as follows. First, the full model, designated as Model 5 in Tables 1 and 2, is estimated over the in-sample period of 4 January 2011 to 10 August 2015. Then, out-of-sample forecasts are generated by recursively re-estimating the model each day and using the new estimates to forecast the CNH one-day-ahead. The MSE of our forecast model versus the random walk is presented in Table 3. Note that the forecast MSE is only slightly smaller than the random walk. To further assess the differences, we construct the direction of change statistic that reports the fraction of days for which the forecast was in the correct direction. The forecast model produces the correct direction of the CNH on about 60% of days, while the random walk gets it right on 50 percent of days. For currency hedging purposes, knowing the direction of change is the requirement for successful dynamic hedging of currency exposures. It is to this task that we turn next.

3. Hedging the currency exposure of Chinese equities

Global investors holding positions in Chinese equities are holding a long position in CNH (or CNY) by virtue of their equity investment. Consider the case of a U.S.-based investment fund that exchanges dollars (USD) for Chinese currency (CNH) in order to purchase a portfolio of Chinese equities. The fund wants exposure to Chinese equities with the expectation that the price of the equities will rise over time. However, since the equities are denominated in CNH (or CNY), as the USDCNH exchange rate changes, the value of the equity position will change even if there is no change in equity prices in China. Global investors often seek to hedge the foreign exchange risk of their global equity investments in order to remove or reduce the effect of exchange rates on their portfolio returns. A survey by Mercer Consulting (Mercer,2009) of European pension fund managers with a total of EUR400 billion under management finds that 92% of respondents hedge half or more of the currency risk in their equity portfolios, and 50% hedge more than three-quarters.[5]

[5] See Melvin and Prins (2015) for an extensive discussion of hedging the currency risk of global equity portfolios.

3.a. Building the currency overlay strategy

We consider a U.S. investor with a position in the Shanghai A-shares equity index. The international investor wants to hedge the foreign exchange risk of the equity position by a position in the CNH currency. First, we take the simple approach of a spot position in CNH where the investor chooses to be long or short CNH based upon the direction of change forecast from the forecasting model detailed in section 2.3. If the CNH forecast signals appreciation, then there is no hedge. If the CNH forecast is depreciation, then the investor takes a short position in CNH. We construct the direction of change indicator in two ways. First, we simply take the forecasted direction of change for each day as the measure DC. Then, we construct a second measure, which only signals a change for days in which the forecasted change is greater than 1 standard deviation of *dlogC* and call this measure DCL. Figure 2 displays the frequency with which each measure of change switches on (a value of 1) and signals a short position to hedge the currency risk. It is clear that DC involves much trading in and out of positions relative to DCL. DC is short CNH on 477 days out of the 755 days in the out-of-sample period. DCL is short 117 days. More importantly for trading cost and implementation considerations, the DC indicator trades 319 times while DCL trades 196 times during the forecast period. Finally, we also consider a long-short strategy that reacts to both appreciation and depreciation signals, by taking long and short positions in the CNH.

3.b. Returns to a currency overlay strategy

We now compare performance of the A-shares equity portfolio for the U.S.-based investor by comparing an unhedged portfolio that includes the exchange rate changes with a portfolio that invests \$1 in the equity index and invests another \$1 in the CNH model as a currency overlay portfolio. Figure 3 plots the value of the A-shares portfolio to a U.S. investor in USD terms with no currency overlay. This is the case of the investor choosing to take the currency risk of holding the equity position. Figure 3 illustrates the dramatic events of August 2015 and December 2016. Right at the start of the out-of-sample period, the equity index drops by 25 percent. Then from late-December 2015 to late-January 2016, there is another substantial fall in the equity index. By January 28, 2016, the initial \$1 position invested is worth less than

$0.65. Despite the increases in the index after January 2016, by the end of the sample period the value of the portfolio stands at just $0.81.

Now consider the case where the investor combines the equity portfolio with a currency overlay portfolio that starts with $1 invested in CNH and then proceeds through time as guided by the exchange rate forecasting model. We consider 5 alternatives:

- First, always short CNH at every date to hedge the long CNH position inherent in being long A-shares.
- Second, dynamically hedge CNH exposure as guided by the DC indicator.
- Third, dynamically hedge CNH exposure as guided by the DCL indicator.
- Fourth, invest in a long-short dynamic currency overlay strategy as guided by the DC indicator.
- Fifth, invest in a long-short dynamic currency overlay strategy as guided by the DCL indicator.

Figure 4 illustrates the cumulative returns of the 5 currency portfolios. The currency hedging strategy of always being short CNH adds modest value to the unhedged portfolio of Figure 3 as it starts at $1 and ends the sample with a value of $1.06. In the early part of the sample, when the stock market suffered large losses, the CNH depreciated significantly so that the short CNH position was quite helpful in this early period. Later, when the CNH appreciated, the short position detracted value. More recently, as the CNH again depreciated against the USD, the hedge strategy added value. The dynamic hedge based upon DCL added more value, ending with a value of $1.13. The long-short overlay strategy based upon DCL, the large direction of change indicator, added more value ending at a value of $1.18. The dynamic hedge based upon all signals was better still with an ending value of $1.25. The most active long-short strategy based upon DC added the most value ending at a value of $1.47. Over the sample considered, this strategy was quite successful at guiding long and short positions at the right time. The dynamic currency overlay strategy shows how combining a position in CNH with the A-shares position can add additional return to the U.S. investor's investment in Chinese equities.

So far, we have ignored transaction costs in our analysis. We assume the investor is holding a long position in the A-shares index with no trading occurring over the out-of-sample period. The active trading is in the CNH portfolio. The strategy of selling CNH and holding a short position throughout the sample incurs no trading costs over the sample and simply receives a daily mark-to-market. The other currency strategies of long-short overlay and dynamic hedging actively trade CNH. The long-short DCL strategy trades 302 times during the sample while the long-short DC strategy trades 319 times. Such active trading could incur substantial trading costs. Good data on emerging market currency trading costs are not easily found and are, consequently, frequently ignored in academic studies of exchange rates. However, recently Melvin, Pan, and Wikstrom (2018) calculate trading costs by sweep-to-fill costs of executing trades on the major electronic brokerages for foreign exchange and find for CNH that the cost of a trade, as measured by the ½ spread at the top of the order book averages 0.43 basis points (bps) over their sample period. This is a very tight spread compared to other emerging market currencies and is reflective of the very low volatility experienced by CNH relative to other currencies. If we consider the cost of trading relative to the initial $1 invested, we see that such frequent trading erodes some of the gains from the currency overlay over the sample.

Table 4 reports summary statistics for the different portfolios after costs are subtracted. The equity portfolio alone has a negative return over the sample period, as seen at the top of Table 4. The returns to the currency strategies are summarized in the middle of Table 4. Finally, equally weighting the equity and currency portfolios yields results as shown in the bottom portion of Table 4. Compared to the equity strategy by itself, the static hedge increases the annualized return from -5.9% to -2%. The dynamic hedge using all signals increases annualized return to 1.1%. Most impressively, the long-short currency strategy using all signals results in the combined equity and currency portfolio yielding an annualized return of 4.9%. The final column of Table 4 reports the information ratio measuring return/risk. The best performing portfolio generates an information ratio of 0.5. Over this sample period, that particular construction worked quite well.

4. Summary and Conclusions

At times, changes in Chinese exchange rates have had a surprisingly large impact on global financial markets. The surprise devaluations of RMB on August 11, 2015 and January 6, 2016 were associated with large sell-offs in global equity markets as there was fear of capital flight from China and further RMB depreciation. Global investors follow events in China with keen interest as they realize how important Chinese policy changes can be for financial markets both inside and outside China.

On the same day as the RMB devaluation of August 11, 2015, the People's Bank of China announced a new exchange rate policy where the RMB central parity rate against the USD would be determined each morning by the previous day's closing rate, market demand and supply, and valuations of other currencies. This new policy suggests an investment strategy for trading the CNH, the freely tradable and deliverable Chinese currency traded in Hong Kong and used by offshore investors to take positions in Chinese assets. Our hypothesis is that the central parity rate that is announced prior to the market opening in China, will influence trading and will cause the CNH exchange rate to adjust towards the new parity rate each day. Earlier literature on the central bank policy reaction function suggests that this link between CNH and the parity rate will be weakened in times of high volatility when the PBOC aims policy at moderating volatility. Our empirical findings support the hypothesized model. CNH does adjust to the change in the parity rate, and the relationship is weaker in times of heightened volatility. These empirical results are used as the foundation for forecasting CNH. Additional factors were explored to guage the sensitivity and robustness of our forecasting model. These included lags of the CNH exchange rate, the deviation of yesterdays' CNH from today's parity rate, and the premium between A-and H-shares in the equity market. Our CNH forecasts were modestly better than a random walk by the MSE metric but much better by the direction of change metric.

We next consider the problem of a U.S. investor holding the Chinese equity market index portfolio. We employ the CNH forecasting model as a tool to generate currency portfolios that can be used to hedge or actively invest in CNH as a complement to the equity buy-and-hold portfolio. The currency portfolios considered include

a) A static hedge, where one holds a short position in CNH to offset the currency risk inherent in being long Chinese equities.
b) A dynamic hedge, where the CNH forecasting model is used to forecast CNH depreciation and a hedge is on only for those periods when depreciation is expected. Two variants were considered: i) hedge only days when a large depreciation is forecast and ii) hedge all days when depreciation is forecast.
c) A long-short currency overlay strategy where the forecasting model is used as a trading signal to take long and short positions in CNH. Again two variants are considered: i) only take positions when a large change in the CNH is forecast and ii) take positions every day based on the direction of change forecast.

All currency portfolios added value to the equity portfolio by itself. The best performing currency strategy was the long-short strategy using forecasts for all days.

Our empirical findings show the importance of using changes in Chinese exchange rate policy to guide investing in Chinese financial assets. Over the sample considered, when Chinese equities did not perform well, the inclusion of an active currency overlay would have added much value for a USD-based investor.

References

Cheung, Yin-Wong, Hui, Cho-Hoi, Tsang, Andrew. 2018. The RMB central parity formation mechanism: August 2015 to December 2016. Journal of International Money and Finance. 86, 223-243.

Funke, Michael, Loermann, Julius, and Tsang, Andrew. 2017. The information content in the offshore Renminbi foreign- exchange option market: Analytics and implied USD/CNH densities. BOFIT Discussion Paper. Bank of Finland.

Meese, Richard, and Rogoff, Kenneth. 1983. Empirical exchange rate models of the seventies: Do they fit out of sample? Journal of International Economics 14, 3–24.

Melvin, Michael, Pan, Wenqiang, and Wikstrom, Petra. 2018. Retaining alpha: the effect of trade size and rebalance strategy on FX returns. Working Paper, UCSD.

Melvin, Michael and Prins, John. 2015. Equity hedging and exchange rates at the London 4 p.m. fix. Journal of Financial Markets. 22, 50-72.

Melvin, Michael, Prins, John, and Shand, Duncan. 2013. Forecasting exchange rates: an investor perspective. Handbook of Economic Forecasting (G. Elliott and A. Timmermann eds.) Elsevier.

Mercer. 2009. Asset Allocation Survey 2009. Mercer, London.

Rossi, Barbara. 2013. Exchange rate predictability. Journal of Economic Literature. 51, 1063-1119.

Table 1: Model estimation results

The table reports estimation of the following model over the sample period 11 August 2015 to 19 June 2018:

$$d\log C_t = \alpha + \beta_1 d\log P_t + \beta_2 (d\log P_t * \log IV_{t-1}) + \beta_3 d\log C_{t-1} + \beta_4 (\log C_{t-1} - \log P_t) + \beta_5 \log AHP_{t-1}$$

	1		2		3		4		5	
	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value
α	0.0001	0.4912	0.0001	0.3527	0.0001	0.3510	0.0002	0.0524	-0.0212	0.0400
β1	0.3896	0.0000	1.6287	0.0000	1.6580	0.0000	1.6102	0.0000	1.5770	0.0000
β2			-0.7957	0.0000	-0.8382	0.0000	-0.8222	0.0000	-0.8086	0.0000
β3					0.0483	0.2785	0.0839	0.0681	0.1010	0.0304
β4							-0.0734	0.0029	-0.1071	0.0003
β5									0.0044	0.0381
R-squared	0.0938		0.1648		0.1661		0.1757		0.1804	
Adj R-squared	0.0926		0.1627		0.1628		0.1714		0.1750	

Table 2: Model estimation results

The table reports estimation of the following model over the sample period 4 January 2011 to 19 June 2018:

$$d\log C_t = \alpha + \beta_1 d\log P_t + \beta_2 (d\log P_t * \log IV_{t-1}) + \beta_3 d\log C_{t-1} + \beta_4 (\log C_{t-1} - \log P_t) + \beta_5 \log AHP_{t-1}$$

	1		2		3		4		5	
	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value
α	0.0000	0.7718	0.0000	0.4034	0.0000	0.4055	0.0001	0.2178	-0.0039	0.0396
β1	0.3927	0.0000	1.2207	0.0000	1.2140	0.0000	1.2128	0.0000	1.2050	0.0000
β2			-0.5625	0.0000	-0.5498	0.0000	-0.5525	0.0000	-0.5502	0.0000
β3					-0.0170	0.5206	-0.0085	0.7500	-0.0059	0.8256
β4							-0.0150	0.0134	-0.0214	0.0016
β5									0.0008	0.0368
R-squared	0.0817		0.1201		0.1202		0.1230		0.1251	
Adj R-squared	0.0812		0.1192		0.1189		0.1212		0.1228	

Table 3: MSE forecast comparison of model versus random walk

	Forecast Model	*Random Walk*
Root Mean Square Error	0.002615	0.002665
Direction of Change Accuracy	0.5934	0.50

Table 4 Returns after adjusting for cost:

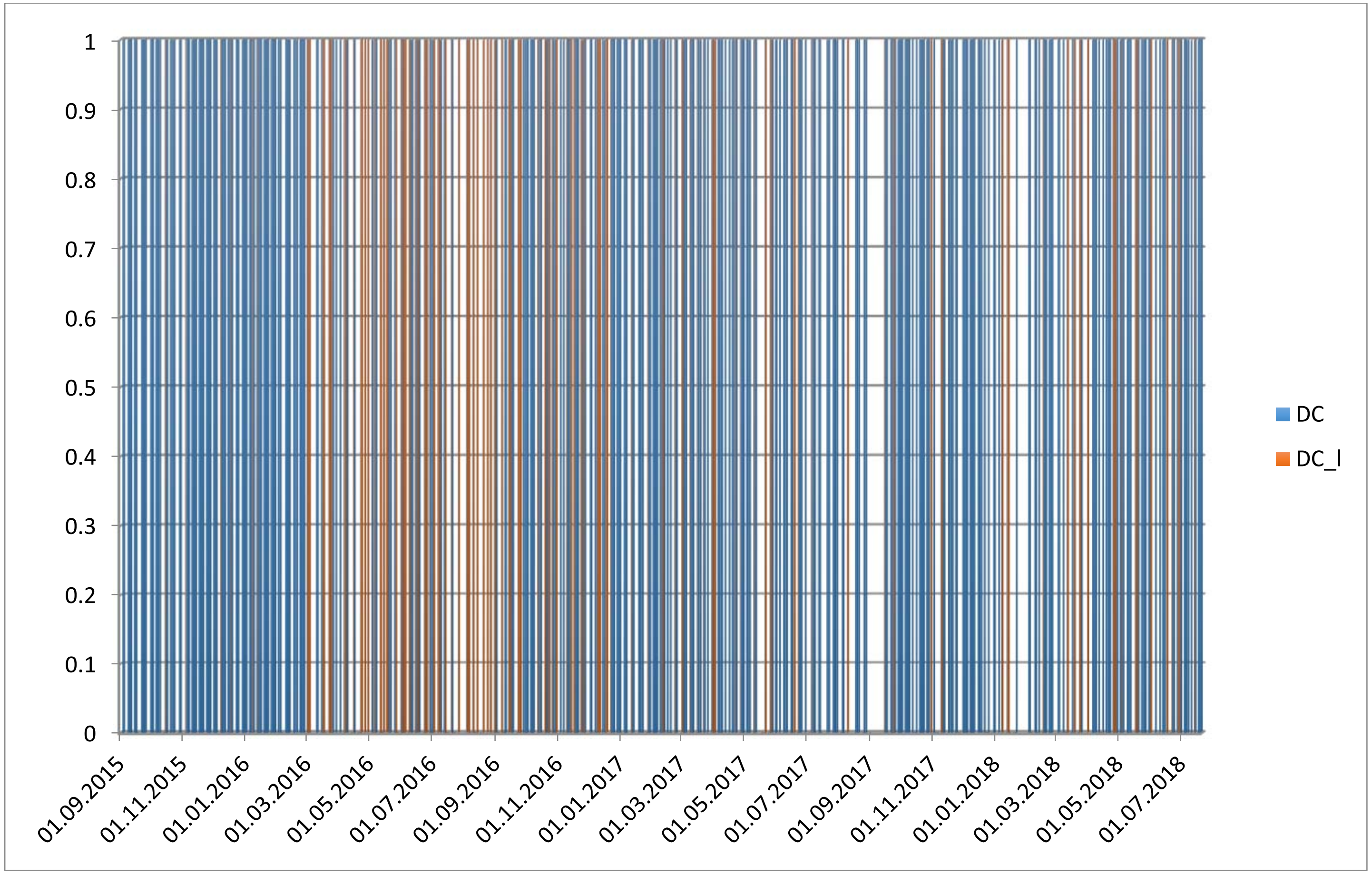
	Cumulative Return	Cost	After cost Return	Annualized Return	Std. Dev.	Information Ratio
Equity component:						
-17.2% (loss)			-17.2	-5.9	1.1941	-0.31
Currency component						
A) Always	5.7	0	5.7	1.9	0.2738	0.43
B) Dynamic (large signals)	12.6	1.4	11.2	3.9	0.098	2.47
C) Dynamic (all signals)	24.8	1.5	23.3	8.1	0.2022	2.49
D) Long-short (large signals)	17.7	1.4	16.3	5.6	0.1294	2.68
E) Long-short (all signals)	47.3	1.7	45.6	15.8	0.263	3.73
Combined, average return:						
Strategy 1) 50% Equity + 50% always hedge			-5.8	-2	0.6048	-0.21
Strategy 2) 50% Equity + 50% large signals (Dynamic)			-3	-1	0.6012	-0.1
Strategy 3) 50% Equity + 50% all signals (Dynamic)			3.1	1.1	0.5998	0.11
Strategy 4) 50% Equity + 50% large signals (Long-Short)			-0.5	-0.2	0.605	-0.02
Strategy 5) 50% Equity + 50% all signals (Long-Short)			14.2	4.9	0.6078	0.5

Figure 1: The CNH and the CNY Central Parity Rate

Source: Datastream.

Figure 2: Forecasts of direction of change for CNH

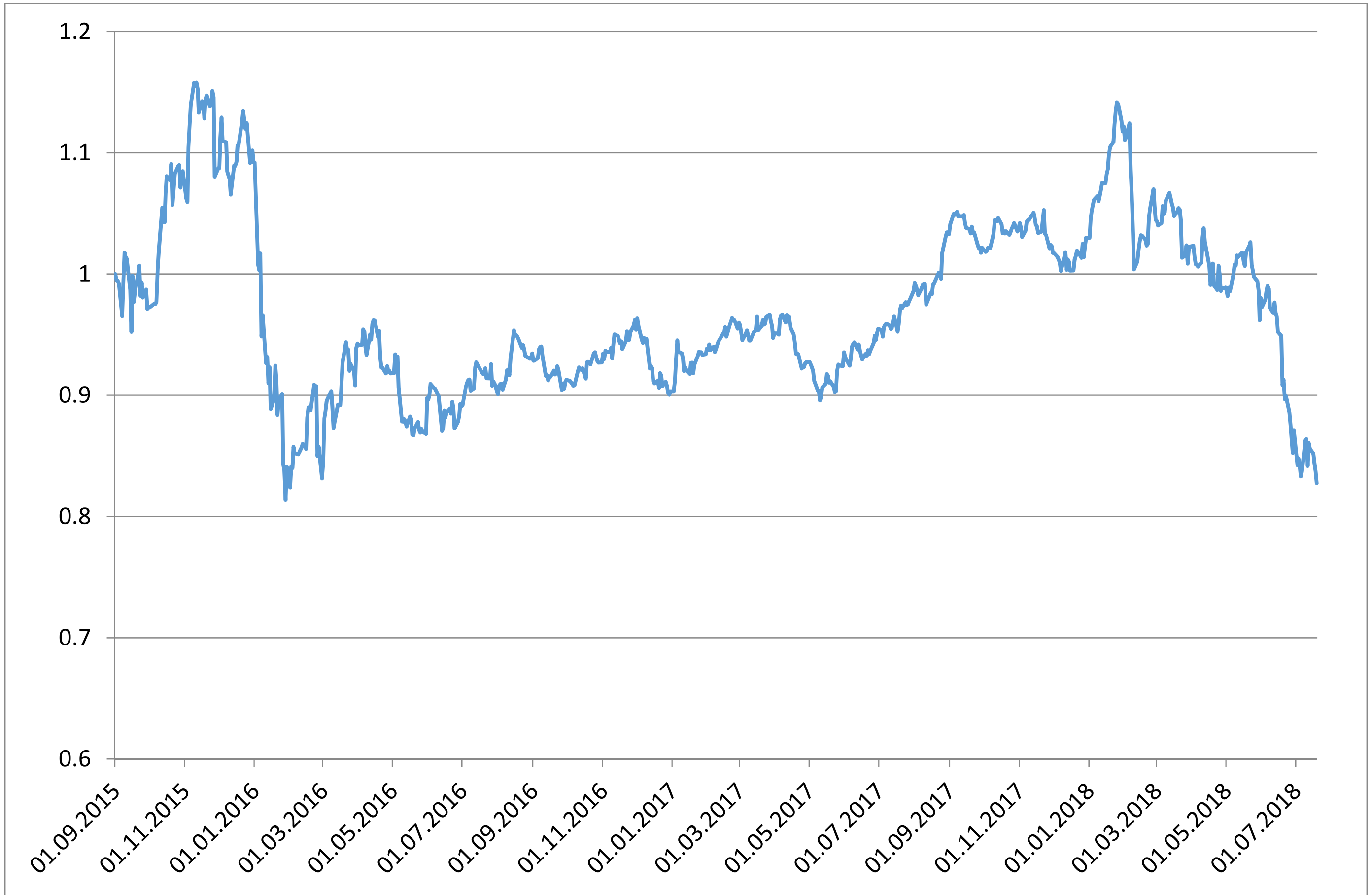
A value of 1 signals depreciation of CNH so that a hedge (short) position is held. A value of zero signals appreciation so that no hedge position is taken. DC is the simple daily direction of change forecast. DCL equals 1 only for days when the forecasted change is greater than 1 standard deviation of *dlogC*.



Source: Own calculations

Figure 3: The value of the A-shares portfolio to a U.S. investor with no currency overlay

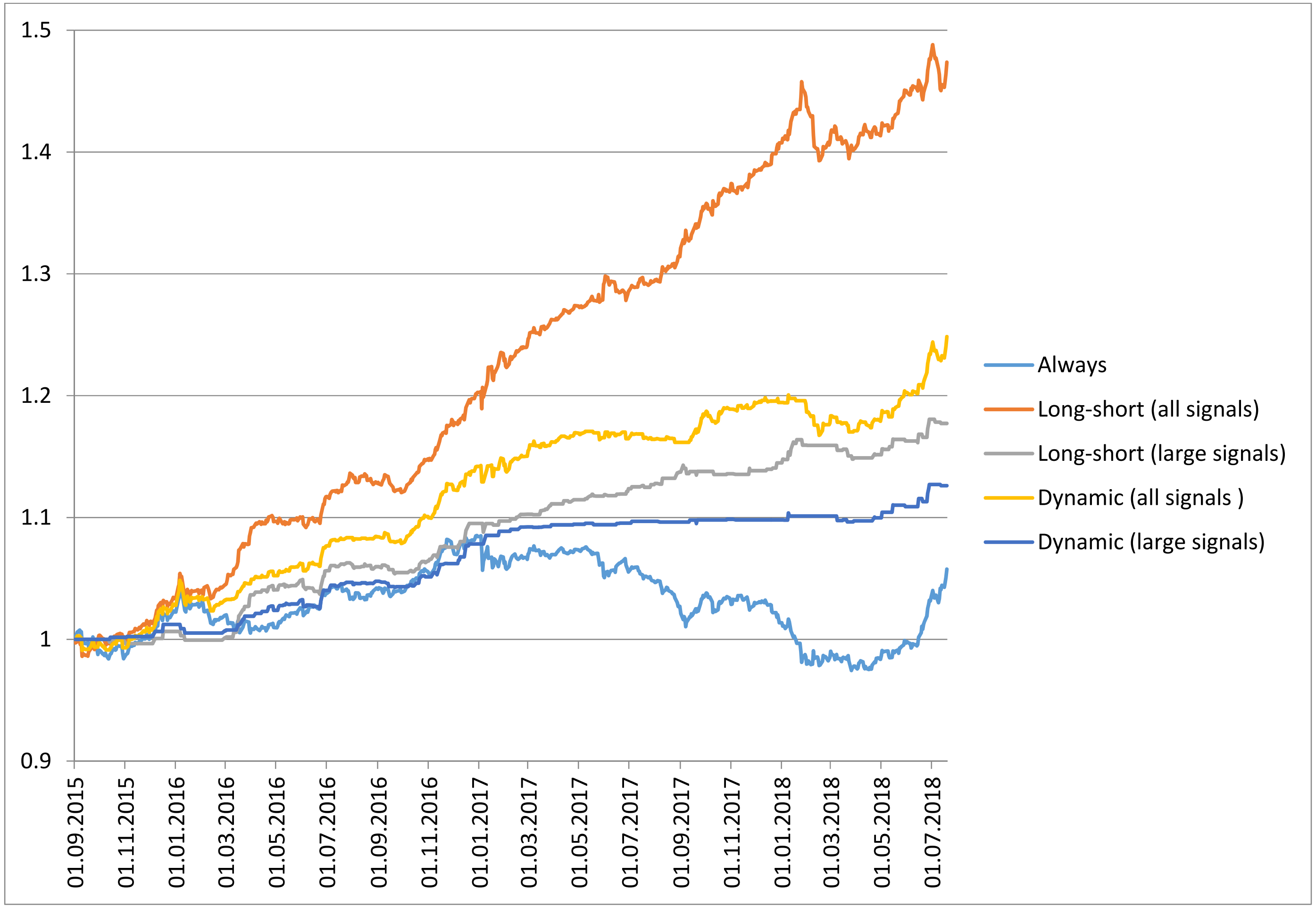
The figure shows the value of an initial $1 invested in the Chinese equity index in USD terms.



Source: Datastream.

Figure 4: The value of the currency overlay component

The figure shows the value of an initial $1 invested in CNH currency, with different trading strategies. *Always* is CNH hedge portfolio that is always short CNH.



Source: Own calculations.