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Chinese Exchange Rate Policy: Lessons for Global Investors

Abstract

Chinese currency policy has had a strong impact on the value of investors' portfolios 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 implementable 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 correctly predicts the direction of change on about 60 percent of days. 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 are shown to 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[1].

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

[1] Table A3 in the appendix shows that these events are remarkable, also in comparison to other countries. Although China has a very low standard deviation of its offshore exchange rate (CNH), the negative skewness, which is indicative of large and unexpected downward jumps, is one of the largest and is only exceeded by Singapore and Malaysia.

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.[2] We take this policy change as a useful indicator of a break in the data that strengthens 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.[3]

The main hypothesis of our paper is that the market considers the daily parity rate as useful information reflecting the authorities' view of where the market should be trading the RMB and our empirical results support this hypothesis, as CNH adjusts following the CNY parity setting. It is useful for international investors to have a model for CNH, since they are unable to trade onshore in the CNY market and, therefore, use CNH for currency exposure. The time-series history of CNH and CNY document that the two generally move together, so that both are affected by policy in China. In fact, the PBOC is able to affect the spread between them by intervening in the CNH market. For instance, if the CNH is depreciating faster than CNY, the Chinese authorities can sell short-term CNH-denominated debt in Hong Kong to reduce liquidity and push up interest rates, making it more expensive to short the CNH. Just as outright intervention can shift investor expectations regarding the future value of the CNH, so can the CNY parity setting serve as guide as to the authorities' preferences for the currency value. While CNH and CNY tend to move similarly over time, there are differences between the two that create trading opportunities. CNY is more heavily managed and has lower volatility than CNH. For instance, over the 2016-2019 period, the difference in CNH-CNY implied volatility from 1-month option prices averaged 28 basis points. The difference in volatility between the two

[2] See Cheung, Hui, and Tsang (2018) for analysis of this change.
[3] 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.

currencies varies over time and reflects expectations and market developments. For instance, on the day before the policy change announced on August 15, 2015, 1-month implied volatility was 1.1625 for CNY and 1.5200 for CNH. On August 15, implied volatility jumped to 6.3400 for CNY and 7.6775 for CNH.

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 Chinese currency 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. We point out that our hedged returns are driven by ability to forecast the RMB, while over our sample period A-shares did not perform well. We would like to emphasize that in our set-up, the decision to invest in China is exogenous.[4] Therefore, our research question is: Given that an investor holds Chinese equity, how can she reduce the risk?

[4] A good example of exogenously driven changes in investing is provided by the announcement on February 28, 2019 that MSCI will increase the weight of Chinese stocks in the MSCI Emerging Market Index from 0.7% to 3.3% by November 2019. News reports at the time suggested that this was likely to draw more than $80 billion of foreign inflows to Chinese equity investments.

2. Forecasting the CNH

The literature on currency forecasting is vast. Many different methods, data sets, and sample periods have appeared in the literature. Some researchers have explored the use of exchange rate survey data to analyze forecasting ability (a recent paper is Dick et al. (2015)). A relatively small literature is devoted to analyzing currencies that are heavily managed and have characteristics of both a floating and a fixed exchange rate. This literature analyzes a variable intended to capture the pressures on the foreign exchange market, even when the currency is being held fixed by the authorities, known as *exchange-market-pressure* (EMP). EMP is typically measured by a combination of changes in the exchange rate, foreign reserves, and/or interest rates (papers include Akram et al. (2015), Eichengreen et al. (1996), and Patnaik et al. (2017). The EMP literature finds that money aggregates, output, external imbalances, and inflation are all significant determinants of EMP, as is often found in studies analyzing floating rate currencies. A useful summary and analysis of this latter 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. The best results tend to occur when the model is linear, and a small number of parameters are estimated. In addition, she finds that the toughest benchmark to beat is the random walk without drift (p. 1063). For the CNH, we 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.

Following the evaluation of our model's forecasting ability using time-series approaches of mean-square-error (MSE) and directional forecast accuracy, we next evaluate the usefulness of the forecasts from an investor's perspective. Many papers in recent years have examined the investment performance of different currency investment strategies. While some have focused on individual currencies (see Gholampour and Van Wincoop (2018)), almost all build portfolios of currencies using a particular investment strategy to exploit cross-sectional predictive ability to enable ranking currencies for portfolio construction purposes. For instance, the carry trade is studied by Lustig and Verdelhan (2007), Burnside et al. (2007), Lustig et al. (2011), Daniel et al. (2017), and Melvin and Shand (2017), among others. Currency trend or momentum is studied by Pojarliev and Levich (2010), Burnside et al. (2011), Menkhoff et al (2012), and Asness et al. (2013), among others.

Our approach differs in that, after evaluating the performance of our currency forecasts as an investment strategy, we next consider a currency overlay strategy for a portfolio of Chinese A-shares. In this setting, the performance of a long-short CNH strategy is considered as a stand-alone strategy and then the performance of the combined equity strategy with the currency overlay is considered and compared to a strategy of always hedging the FX risk of the equities and an unhedged equity strategy, all from the perspective of a U.S. investor. Another distinguishing feature of paper is that we take the institutional knowledge about the central bank policies, and the timing of events during the trading hours into account.

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. Jermann et. al (2019) provide a detailed analysis of this policy change. The authors document the determinants of the RMB policy of the PBC and provide the institutional background. They argue that the PBC follows a two-pillar strategy, where stabilizing the RMB while maintaining a degree of exchange rate flexibility are the main objectives. [5]

Figure 1 illustrates the path of the two exchange rates. An increase in CNH or CNY denotes a depreciation, i.e. a loss in value for an USD-based investor with an unhedged long position in

[5] Jermann et. al (2019) also provide a RMB forecast evaluation, focusing on a longer-term forecast of three months, rather than day-to-day movements as in the present paper.

Chinese equity. The data in this graph, as well as the subsequent trading model are at a daily frequency. 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 each other 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. Therefore, with C the dependent variable of interest, the first determinant is the daily P.[6] At this point we have a model of daily change in C as

$$d \log C_t = \alpha + \beta d \log P_t \; .^{7} \tag{1}$$

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 moderating volatility. Cheung, et al. (2018a) 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. In the expanded

[6] 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. A simple way of replicating their findings is a Granger Causality test. In our sample period, we can reject the null that lagged C has no impact on P, at the 1% level. 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." The causality tests reveal two-way causality where lagged C predicts P and the lagged P predicts C.

[7] Note that despite both variables having the index t, it is not a contemporaneous correlation, as P is set in the morning before markets open, while C is the closing day value of the CNH.

specification, we have a model where the effect of P on C is modified by IV, and the β coefficient of equation (1), capturing the effect of *dlogP* on *dlogC,* should vary with IV as in

$$\beta_t = \beta_1 + \beta_2 \log IV_{t-1}. \quad (2)$$

The amended model is

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

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 (AHP). 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[8]. Our basic model specification is:

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

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[9]. 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

[8] Further variables considered, were the lagged onshore rate, the difference between onshore- and parity rate, and the lagged (broad) US dollar index (in logged 1st differences). The US dollar index has been found significant in Cheung et al. (2018), which may incorporate intervention effects. For further determinants see also Cheung and Rime (2014) and Ding et al. (2014). When including these variables, the adjusted R^2 increased slightly, however the out-of-sample forecasts did not improve. The cumulative return of the best performing long-short model was smaller than in our benchmark model.

[9] In response to the market turmoil that followed the August 2015 policy change, China instituted various intervention measures to rein in volatility. Some of these intervention actions reportedly took place in the CNH market. While we do not have the data to test the impact of intervention explicitly, we expect that since our CNH forecast is predicated on the morning fixing, the latter variable will capture at least part of the effect of any intervention effects on exchange rates.

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 0.29 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 0.53 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 0.37 percent change in C in the *opposite* direction. Therefore, 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. The difference between C and P fulfills the function of an error correction term in a VECM model[10]. 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

[10] Note that P is set in the morning, while C is the closing values of the previous day. Thus, in each case, we take the last observation before the markets open and the new C value is determined. Papers studying the differential between CNH and CNY include Funke et al. (2015), Ren et al. (2018), and Xu et al. (2017).

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.[11]

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, 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[12]. 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[13]. The full sample has the strongest statistical power, as it has 2166 observations. The pre-2015 sample has 1163 observations and the post-2015 sample has 1003 observations.

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

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[11] We have checked the possibility that the relationship has changed after the stock connect program was introduced on November 14th 2017 to facilitate purchases of stocks on/offshore. Empirically, we have explored an interaction term that covers the period after it was introduced (November 14th, 2017), however an interaction dummy variable after this day did not improve the fit.

[12] It is also interesting to look at the pre-2015 sample, which is reported in Table A1 in the appendix of the paper. Most variables have the same signs, but the significance levels are generally somewhat lower and the R^2 of the regressions are smaller. Our key variable, the parity rate, is significant at 5% in all regressions.

[13] We have explored various ways to incorporate this break in the forecasting exercise. For instance, controlling for the post-2015 period with a dummy variable in the regressions increases the in-sample fit (with an adjusted R^2 of 0.138). In our benchmark regression, we first included a post-2015 dummy for every variable and then dropped two variables that were statistically insignificant. Out of sample, the new extended regression with the remaining interaction terms did not forecast better, however, than our present one. The direction-of-change forecasts from the extended regression performed slightly worse, and the cumulative returns from a currency overlay were smaller than in the benchmark. We therefore did not explicitly model the break in our regressions. Given our recursive rolling regression method for forecasting, the coefficients will nevertheless update through time to capture a change in structure.

review article as she states “The toughest benchmark is the random walk without drift” (p. 1063). As a result, we initially use the MSE of a random walk model as the target for outperformance of our forecast. [14]

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. Furthermore, the recursive updating used in our daily model forecast will have the model learning over time as new data are added in the out-of-sample period.

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. The difference is not statistically significant – a simple t-test for the equality in means has the value of -0.275 and a p-value of 0.78, i.e. we cannot reject the hypothesis that the two mean square errors are the same. A better performance can be documented, when 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 67% of days, while the random walk gets it right on 50 percent of days. Here, the difference is indeed statistically significant. For instance, when we estimate a simple probit regression, the 0-1 dummy variable that signals a depreciation is statistically significant at the

[14] 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.

1% level (with a Z-Statistic of 4.527). Thus receiving a signal significantly increases the likelihood of the event of a depreciation actually occurring. The Pesaran and Timmermann test statistic for direction-of-change forecast accuracy is 8.8511, which is significant at the 1% level[15]. 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.

2.d. Further control variables

In the literature, several other control variables have been used and found to significantly impact the RMB exchange rate and the parity rate in particular. In Table A2, we show that they only marginally add to our forecasting equation.

The first variable is the lagged CNY, the onshore exchange rate. The motivation is again the PBOC's policy, as a tight link between CNY and CNH is one of their policy objectives. We find that it is statistically significant at the 10% level when added to our benchmark regression, but the adjusted R^2 hardly increases, with a minor change from 0.1455 to 0.1478. The second variable, the US Dollar index, also a part of the PBOC's objective function is significant at the one percent level, but the increase in the adjusted R^2 is even smaller, as it moves to 0.1489. The relatively minor contribution of these two variables, which play a more prominent role in earlier research, is explained by the time structure and the opening hours of financial markets. Both CNY and the US Dollar index are the previous day closing dates, while the parity rate is determined in the morning of the same trading day. It is available before markets are opening and it incorporates all information from other variables on the previous day. If we were to leave out the parity rate from the forecasting equation, the contributions of the other variables to the R^2 would become considerably larger.

Other variables we have added to the forecasting regression are statistically insignificant. These include the lagged change of the CNH forward rate and the lagged change of the CFETS index. The CFETS is also insignificant, when interacted with the implied volatility series. In the reverse

[15] As a further test, we have started with a 100 observation forecasting window and rolled it forward, one day at a time, to compute the direction of change predictions that were correct. In this robustness test, the forecasting model reliably performs well, dipping below 50% only in 5.8% of the analyzed 100-data-point windows. In more than 90% of the cases the prediction accuracy ranges between 50% and 70%, with a mean of 60%, as reported above for the full sample.

specification, i.e. when explaining the parity rate by other variables, this interaction term is significant at the 1% level, consistent with Cheung et. al (2018). But when added to our baseline-specification, it reduces the adjusted R^2.

Importantly in the context of the main objective of the paper: none of these variables add to the out-of-sample forecasting performance of our model, and do not add value to the trading strategies analyzed in the subsequent sections. Clearly a more elaborate model, using these and other variables such as additional lags or ARCH and GARCH effects is worth exploring. In particular, this would be worthwhile when predicting the exchange rate at longer horizons, such as the papers of Funke et. al (2017) and Jermann et. al (2019). Our forecasting model is useful for the one-day-ahead direction of change forecast horizon. Trying to forecast 2 days ahead makes the forecast accuracy drop to almost 50%. For illustrative purposes, we thus move forward with our rather parsimonious benchmark specification[16].

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

[16] In the literature there is evidence that macroeconomic fundamentals are a priced risk factor as well, for instance in Berg and Mark (2018a). In another paper, the authors show that a global news-based measure of macroeconomic uncertainty is a priced factor as well (see Berg and Mark (2018b)). In our data, these findings are difficult to integrate, as the data are released on a monthly basis, thus are available only for a small number of daily observations. Furthermore, even though the inclusion might improve the in-sample-fit of the regression, they are not available immediately on the day of the forecast.

92% of respondents hedge half or more of the currency risk in their equity portfolios, and 50% hedge more than three-quarters.[17]

3.a. Building the currency overlay strategy

We consider a U.S. investor with a position in the Shanghai A-shares equity index. While A-shares are priced in CNY, the international investor wants to hedge the foreign exchange risk of the equity position by taking positions in the offshore CNH currency. We will show the performance of CNH as a useful currency hedging strategy for international investors holding A-shares. 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[18]. It is clear that DC involves much trading in and out of positions relative to DCL. DC is short CNH on 640 days out of the 1004 days in the out-of-sample period. DCL is short 151 days. More importantly for trading cost and implementation considerations, the DC indicator trades 431 times while DCL trades 250 times during the forecast period. This means that under the DC indicator, the trading costs are incurred more than one-and-a-half times as often and total trading costs are more than 50% higher[19]. 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. This last signal, which turns out to be the best performing strategy, is displayed graphically in Figure 2.

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

[18] Note that large changes have been defined ex-post. We acknowledge that out-of-sample, an investor does not know yet, what is a “large” change when making her investment.

[19] Note however, that we are not minimizing the trading costs. We simply adjust the returns from our trading strategies to reflect trade costs. Frequent changes are particularly costly. Taking a short position in CNH and closing it on the following day, for instance, involves two transactions and thus creates two times the trading cost.

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[20]. This is the case of the investor choosing to take the currency risk of holding the equity position[21]. 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 $0.86.

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. This combines the passively held equity portfolio with an actively managed currency portfolio.

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[20] The index of A-Shares also reflects the dividend payments during our sample period.

[21] Over the whole sample, the Shanghai A-share index, in US Dollars has a cumulative return of -14.1%. The stock market return in domestic currency has a cumulative loss of only -7.9%, thus -6.2% is due to US-Dollar-CNY exchange rate changes. In some sub-periods, there were also substantial gains. From mid-2016 and end of 2017, the domestic stock market rose by 12.8% and the exchange rate change added value to a total gain of 15.5%. Despite this apparent positive longer-term co-movement, the daily (contemporaneous) correlation of stock market and currency returns is slightly negative at -0.12, as commonly reported in the literature. A full sample correlation thus masks how a dynamic strategy can benefit an investor if it is timed well.

- Fifth, invest in a long-short dynamic currency overlay strategy as guided by the DCL indicator.

Figure 4 illustrates the cumulative returns of the five currency portfolios. The currency hedging strategy of always being short CNH adds value to the unhedged portfolio of Figure 3 as it starts at $1 and ends the sample with a value of $1.07. 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 $1.11. The long-short overlay strategy based upon DCL, the large direction of change indicator, added more value ending at a value of $1.23. The dynamic hedge based upon all signals, as captured by DC, was better still with an ending value of $1.43. The most active long-short strategy based upon DC added the most value ending at a value of $1.99. 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 250 times during the sample while the long-short DC strategy trades 431 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 (2019) 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[22]. 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 -4.8 % to -1.3%. The dynamic hedge using all signals increases annualized return to 3.4%. Most impressively, the long-short currency strategy using all signals results in the combined equity and currency portfolio yielding an annualized return of 10.8%[23]. 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[24].

3.c. Different Sub-Periods

So far, we have focused on the major policy change that occurred on August 11, 2015, where the PBC announced a more market-based system of exchange rate management[25]. But of

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[22] As a counterfactual, we could also calculate the maximum trading cost at which the best performing strategy would still be profitable. This "break-even" cost of trading is 12.1 basis points. I.e. the cost estimation could tolerate a very large margin of error.

[23] To be clear, we are not using a portfolio optimization methodology with a trade cost constraint. We are using the same trading strategy as earlier and subtracting the cost of trading. The daily returns of the currency overlay (long-short model) are highly significant at the 1% level, with a t-stat of 5.41 The daily returns of the combined portfolio – despite the losses in the stock market – are significant at the 10% level with a t-stat of 1.81 and p-value of 0.07.

[24] Over our (forecasting) sample period, the MSCI global index has a cumulative return of 34.37%. Our 50% equity and 50% currency overlay strategy, using the best performing long-short strategy has a cumulative 41.21% after cost return. Thus, we not only outperform the random walk, but also a well-known benchmark in the financial industry.

[25] Under the new fixing design, commercial banks were asked to submit quotes that took account of the closing spot rate of the previous day as well as market supply and demand. One interpretation of this change is that the

course there has been an ongoing reform-process, in which several further steps have been taken where the PBC has either tightened or loosened its grip on exchange rate management. In this section we evaluate how the different trading strategies have performed under different turning points in exchange rate management over the past 4 years. The results are summarized in Table 5.

For instance in December 2015, the next step was the introduction of the so-called CFETS RMB basket. The effective CFETS RMB index measures the RMB's performance against a basket of 13 currencies, with weightings based mainly on international trade[26]. McCauley and Shu (2018) have argued that the new currency index in China caused a stir as policy makers seek to refocus the market's attention away from the RMB's move versus the USD and instead compare performance against a wider selection of peers.

On 26 May 2017, the PBC announced that it was changing the way it fixes the USD/CNY exchange rate at the start of the trading day again. The new method combined the previous arrangements with a "countercyclical adjustment factor" that was intended to deal with overreaction of markets driven by herding behavior[27].

Finally, two further changes occurred in 2018. On 9 January 2018, the PBC revamped the regulatory regime again, as banks that participate in setting the daily fixing rate no longer needed to include the countercyclical factor which according to market participants has supported the RMB's external value[28]. On August 24th, this countercyclical factor was reintroduced again.

We investigate whether these moves towards more or less market based vs. discretionary exchange rate policies are relevant for the performance of our trading strategies. We find that

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economic exchange rate regime may be "self-referential" in the sense of Marcet and Sargent (1989): beliefs affect the RMB data-generating process, which in turn affects the fixing and thus future beliefs.

[26] The USD has the largest weighting with 26.4 percent, followed by the euro and the yen with 21.4 percent and 14.7 percent, respectively. The measure also includes the currencies of Hong Kong, the UK, Australia, New Zealand, Singapore, Switzerland, Canada, Malaysia, Russia and Thailand.

[27] Apparently, this reform increased the flexibility of the Chinese authorities to affect exchange rate trends. China used the leeway as a backup policy. In June 2017, for example, the Chinese authorities tightened their grip on the RMB fixing to ensure that there is no pick-up in capital outflows.

[28] https://www.bloomberg.com/news/articles/2018-01-09/china-is-said-to-shift-way-itmanages-yuan-after-currency-s-jump.

the largest returns have been generated using trading strategy 5 in the last period after August 24, 2018. For some other trading strategies, the period from Dec 1, 2015 to May 25, 2017 was the most profitable. A feature shared by all currency strategies is that the period immediately after August 2015 up to December 2015, was the most challenging in terms of currency hedging and only 3 out of 5 strategies added a positive value to the portfolio. Thus a first cautious interpretation would be that the introduction of the CFETS market made the CNH exchange rate more easily predictable, even though the CFETS variable itself did not prove to be significant in our regression (we suspect that the information from the CFETS closing rates are included in the next day's morning value of the parity rate). The cyclical factor on the other hand does not appear to have a clear pattern. While in the earlier sub-period, it made the forecasting more difficult; in the latest period it displayed the overall best performance. As these windows have a considerably shorter sample size, the results on the sub-samples should be interpreted with caution.

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.

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. 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.

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Table 1: Model estimation results

The table reports estimation of the following model over the sample period 11 August 2015 to 19 June 2019:

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

	1		2		3		4		5	
	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value
α	0.0000	0.6601	0.0001	0.4844	0.0001	0.4881	0.0002	0.0255	-0.0244	0.0073
β1	0.2907	0.0000	1.6829	0.0000	1.6675	0.0000	1.5965	0.0000	1.5580	0.0000
β2			-0.8670	0.0000	-0.8423	0.0000	-0.8152	0.0000	-0.7996	0.0000
β3					-0.0306	0.4615	0.0161	0.7086	0.0339	0.4355
β4							-0.0998	0.0002	-0.1364	0.0000
β5									0.0051	0.0068
R-squared	0.0540		0.1292		0.1297		0.1433		0.1502	
Adj R-squared	0.0529		0.1273		0.1269		0.1395		0.1455	

Table 2: Model estimation results

The table reports estimation of the following model over the sample period 4 January 2011 to 19 June 2019:

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

	1		2		3		4		5	
	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value
α	0.0000	0.7169	0.0000	0.3278	0.0000	0.3323	0.0001	0.1682	-0.0044	0.0388
β1	0.3066	0.0000	1.3247	0.0000	1.3044	0.0000	1.3014	0.0000	1.2935	0.0000
β2			-0.6624	0.0000	-0.6186	0.0000	-0.6199	0.0000	-0.6176	0.0000
β3					-0.0628	0.0184	-0.0543	0.0432	-0.0511	0.0576
β4							-0.0156	0.0234	-0.0228	0.0030
β5									0.0009	0.0358
R-squared	0.0532		0.1035		0.1060		0.1083		0.1104	
Adj R-squared	0.0527		0.1026		0.1046		0.1065		0.1081	

Table 3: MSE forecast comparison of model versus random walk

	Forecast Model	*Random Walk*
Root Mean Square Error	0.002704	0.002733
Direction of Change Accuracy	0.6653	0.50

Table 4 Returns after adjusting for cost:

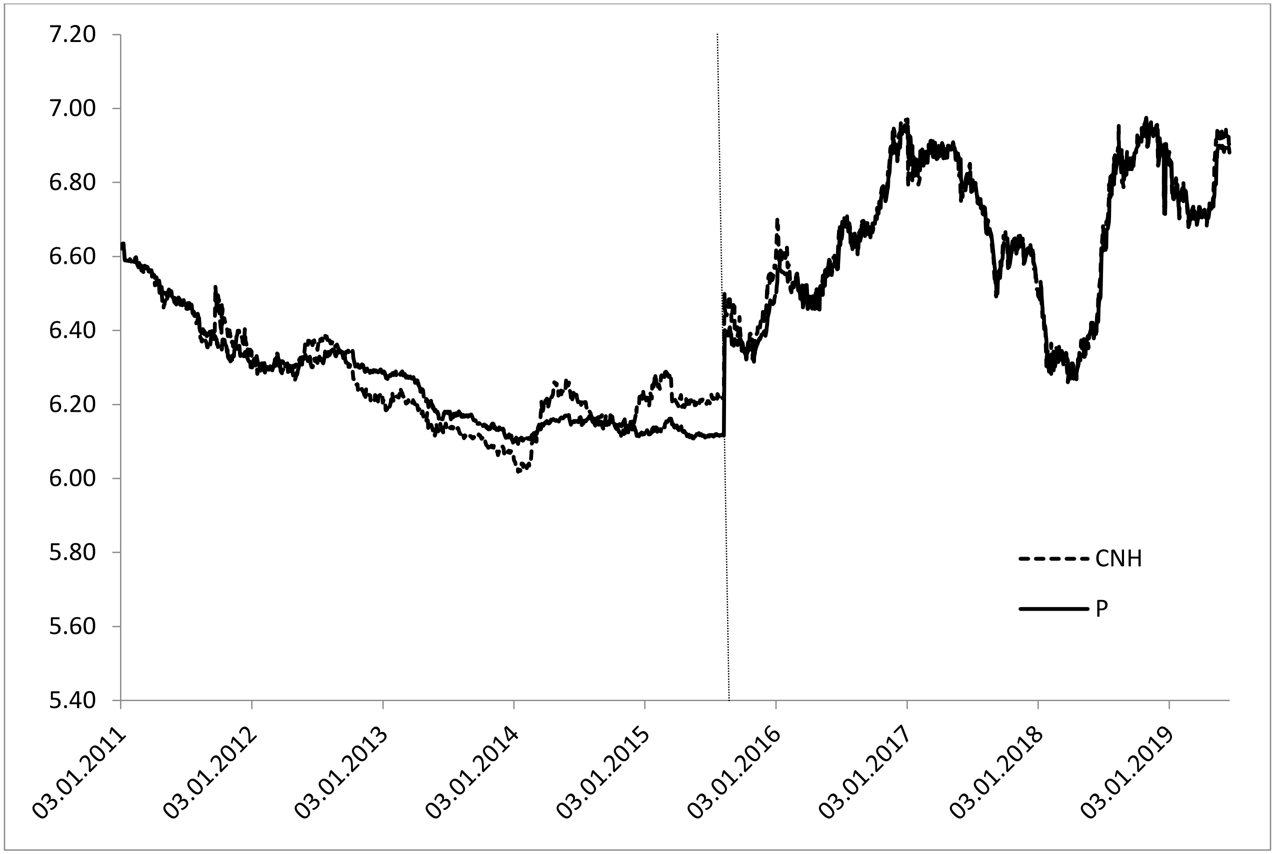
		After cost Return	Annualized Return	Ammualized Std. Dev.	Information Ratio
Equity component		-14.1	-4.8	16.6	-0.29
Currency component					
A)	Always	7.1	1.9	4.1	0.46
B)	Dynamic (large signals)	10.6	2.7	1.7	1.56
C)	Dynamic (all signals)	43.4	10.6	3.1	3.47
D)	Long-short (large signals)	23.3	6.1	2.4	2.58
E)	Long-short (all signals)	99.9	26.1	4.0	6.50
Combined, average return:					
Strategy 1)	50% Equity + 50% always hedge	-5.0	-1.3	9.3	-0.14
Strategy 2)	50% Equity + 50% large signals (Dynamic)	-3.3	-0.9	10.0	-0.09
Strategy 3)	50% Equity + 50% all signals (Dynamic)	13.1	3.4	8.9	0.38
Strategy 4)	50% Equity + 50% large signals (Long-Short)	3	0.8	10.0	0.08
Strategy 5)	50% Equity + 50% all signals (Long-Short)	41.21	10.76	9.0	1.20

Note: Cost are 0.43 basis points per trade. In Strategy 5, they amount to 5.8% cumulatively, or 1.5% annually

Table 5: Performance of Trading Strategies in different Sub-Periods (Annualized Returns)

	Always	Long-short (all signals)	Long-short (large signals)	Dynamic (all signals)	Dynamic (large signals)
Aug 11, 2015 to Nov 30, 2015	0.012	0.047	-0.049	0.024	-0.025
Dec 1, 2015 to May 25, 2017	0.039	0.164	0.080	0.092	0.058
May 26, 2017 to Jan 8, 2018	-0.071	0.211	0.067	0.046	0.004
Jan 9, 2018 to Aug 23, 2018	0.076	0.198	-0.006	0.122	-0.008
Aug 24, 2018 to Jun 19, 2019	0.015	0.571	0.108	0.222	0.036

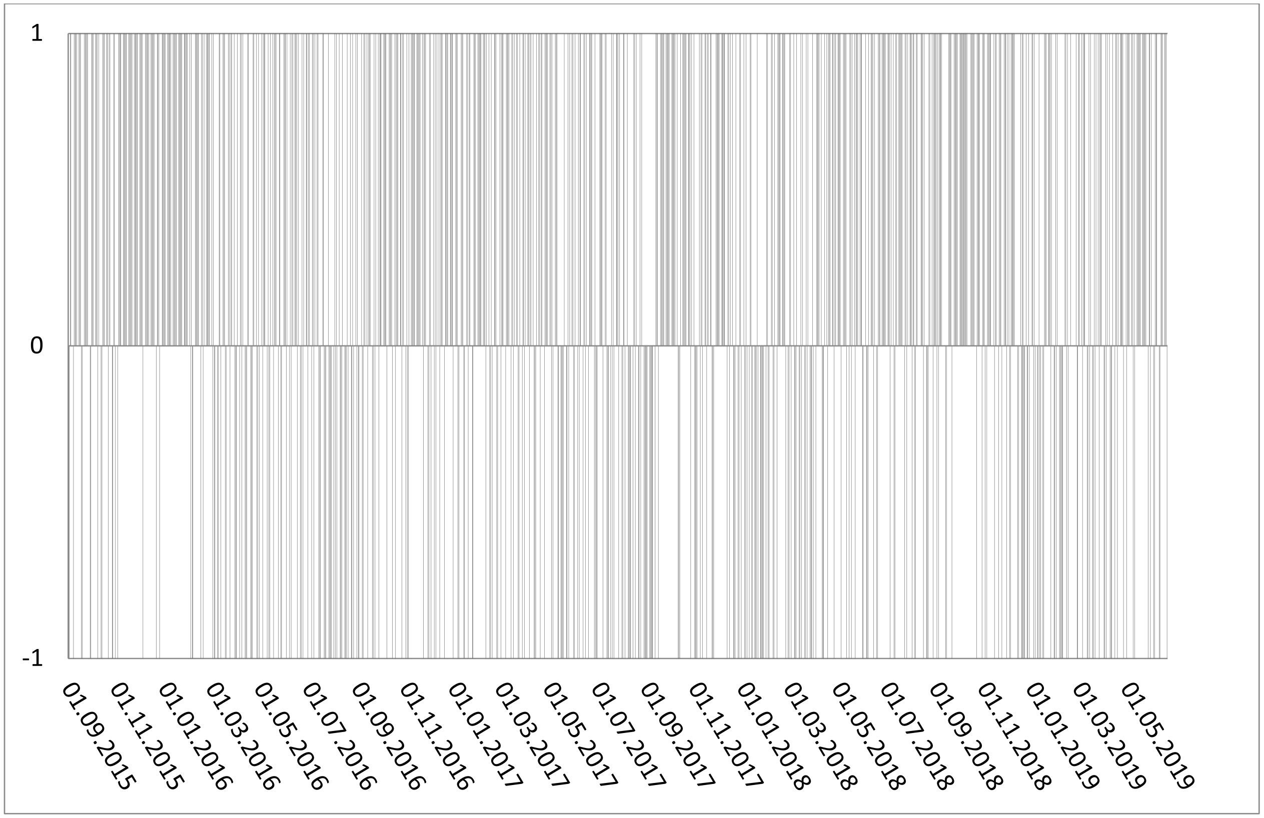
Figure 1: The CNH and the CNY Central Parity Rate (P)



Source: Datastream.

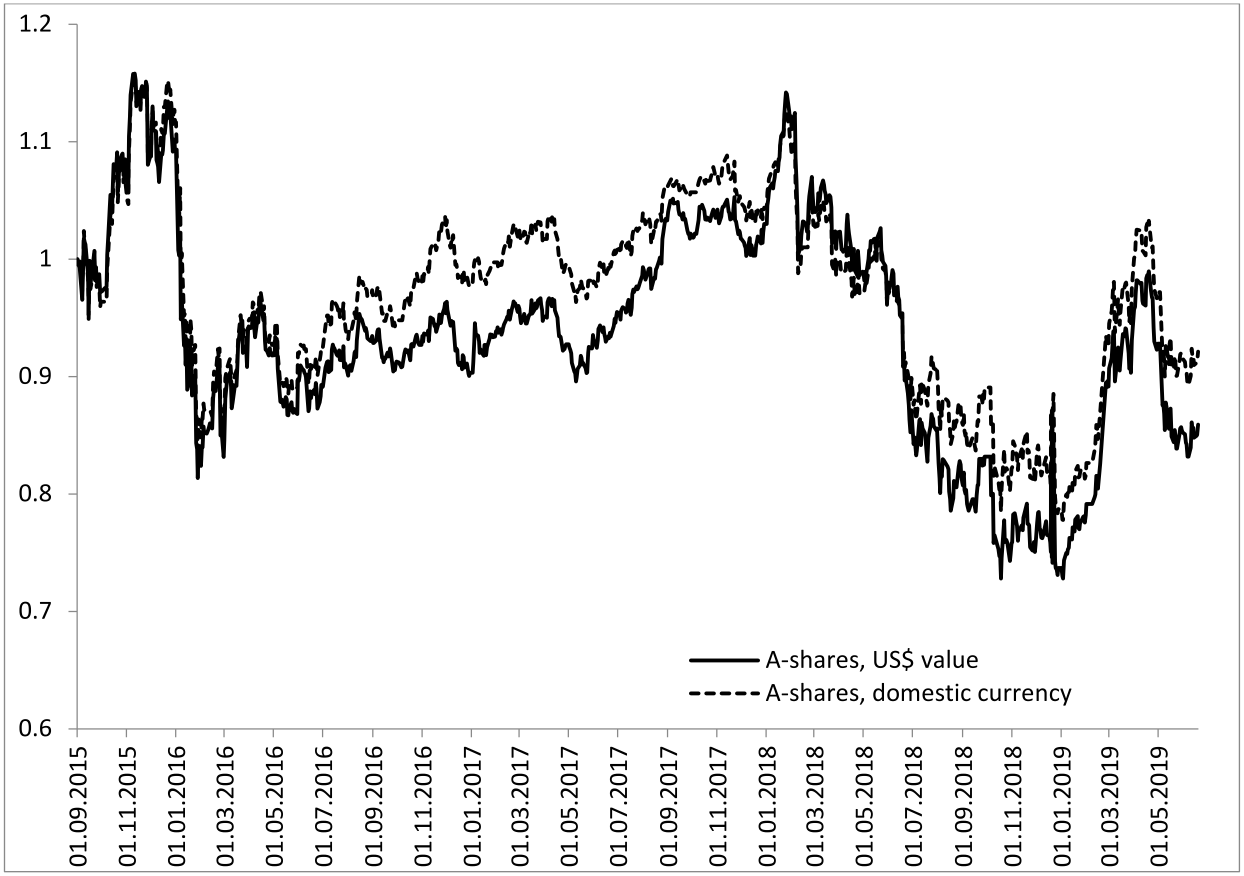
Figure 2: Forecasts of direction of change for CNH

A value of 1 signals depreciation of CNH so that a hedge (short) position is held. A value of -1 signals appreciation of CNH so that a long position is held. DC is the simple daily direction of change forecast.



Source: Own calculations

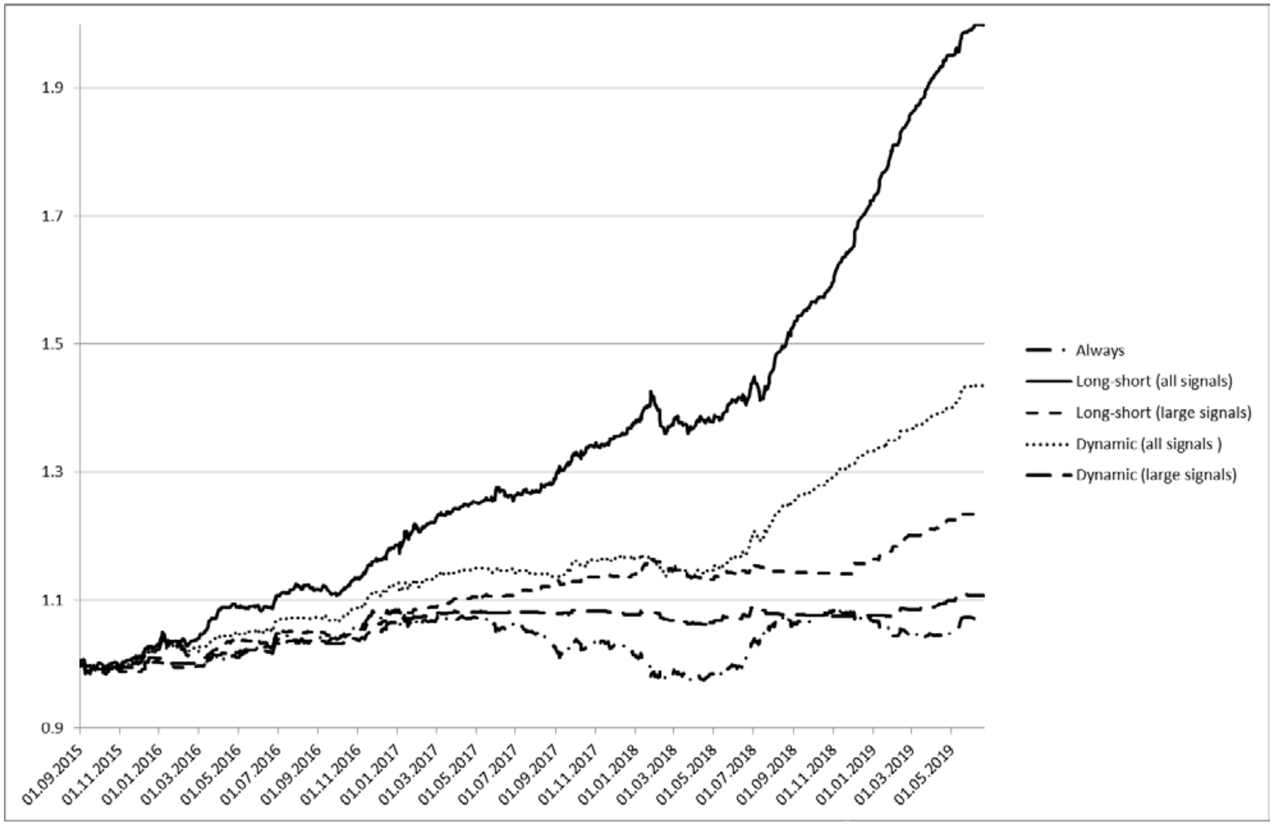
Figure 3: The value of the A-shares portfolio to a U.S. investor with no currency overlay
The figure shows the value of an initial $1 invested in the Chinese equity index



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 a CNH hedge portfolio that is always short CNH.



Source: Own calculations.

Appendix

Table A1: Model estimation results con't

The table reports estimation of the following model over the sample period from 4 Jannuary 2011 to 11 August 2015:

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

	1		2		3		4		5	
	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value
α	0.0000	0.8479	0.0000	0.7338	0.0000	0.7221	0.0000	0.6642	-0.0044	0.0568
β1	0.4463	0.0000	0.5914	0.0000	0.6194	0.0000	0.6242	0.0000	0.6237	0.0000
β2			-0.1655	0.1853	-0.1541	0.2155	-0.1604	0.1987	-0.1591	0.2019
β3					-0.1051	0.0005	-0.1031	0.0007	-0.1011	0.0009
β4							-0.0031	0.5022	-0.0100	0.0880
β5									0.0009	0.0557
R-squared	0.0546		0.0546		0.0651		0.0656		0.0688	
Adj R-squared	0.0537		0.0527		0.0624		0.0619		0.0644	

Table A2: Expanded model

The table reports estimation of the following model over the sample period from 11 August 2015 to 19 June 2019:

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

	1		2		3		4		5		6	
	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value
α	-0.0244	0.0073	-0.0234	0.0101	-0.0252	0.0056	-0.0244	0.0072	-0.0349	0.0017	-0.0348	0.0018
β1	1.5580	0.0000	1.5254	0.0000	1.5921	0.0000	1.5556	0.0000	0.5774	0.0922	0.5675	0.0994
β2	-0.7996	0.0000	-0.7539	0.0000	-0.8064	0.0000	-0.8019	0.0000	-0.2007	0.3506	-0.1938	0.3700
β3	0.0339	0.4355	0.0649	0.1624	0.0698	0.1338	-0.1011	0.5065	0.0246	0.6292	0.0252	0.6209
β4	-0.1364	0.0000	-0.1292	0.0000	-0.1408	0.0000	-0.1378	0.0000	-0.1578	0.0000	-0.1586	0.0000
β5	0.0051	0.0068	0.0049	0.0094	0.0053	0.0052	0.0051	0.0067	0.0072	0.0016	0.0072	0.0017
β6			-0.1067	0.0627								
β7					-0.0007	0.0281						
β8							0.1398	0.3548				
β9									0.0453	0.4048	0.0159	0.6396
β10											-0.0672	0.7343
R-squared	0.1502		0.1534		0.1545		0.1510					
Adj R-squared	0.1455		0.1478		0.1489		0.1453		0.0985		0.0987	

Note: β6=dlog(CNY(-1)); β7=dlog(USD(-1)); β8=dlog(CNH_Forward(-1)); β9=d(log(CFETS(-1)); β10= d(log(CFETS(-1))*log(IV_CNH(-1)).

Table A3: Descriptive statistics on exchange rate returns for advanced and emerging market economies

	Standard deviation	Skewness
Australia	0.00564	-0.00960
Canada	0.00495	-0.26372
Euro	0.00475	-0.08874
Japan	0.00568	-0.28627
New Zealand	0.00636	-0.17644
Switzerland	0.00452	-0.36651
United Kingdom	0.00641	2.13876
Brazil	0.00989	0.08185
India	0.00306	0.16565
Malaysia	0.00407	-1.06853
Mexico	0.00797	0.94433
Russia	0.00897	-0.29828
Singapore	0.00321	-0.71250
Thailand	0.00284	0.04857
Turkey	0.01131	2.43974
China (CNH)	0.00275	-0.64380