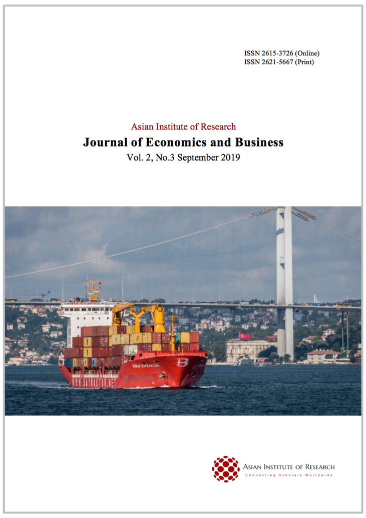

Journal of Economics and Business

Kung, James J, and Lin, Wen-Ying. (2019), How has the Chinese Yuan Evolved since the 2005 Reform? In: *Journal of Economics and* Business, Vol.2, No.3, 855-862.

ISSN 2615-3726

DOI: 10.31014/aior.1992.02.03.132

The online version of this article can be found at:
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Published by:
The Asian Institute of Research

The Asian Institute of Research
Journal of Economics and Business
Vol.2, No.3, 2019: 855-862
ISSN 2615-3726

DOI: 10.31014/aior.1992.02.03.132

How has the Chinese Yuan Evolved since the 2005 Reform?

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Abstract
This study employs the bootstrap method to explore the evolution of the Chinese yuan. We use the following three random walks to characterize the evolution of the yuan: an IID-parameterized random walk, an ARCH(3)-parameterized random walk, and a GARCH(1,1)-parameterized random walk. To proceed, we use the bootstrap method to generate 10,000 artificial yuan series from each random walk and compute the return from the trading rule (i.e., moving average or trading range break) for each of the 10,000 artificial yuan series. Then, we construct a 95% percentile interval with these 10,000 returns to determine if the interval contains the return computed from the actual yuan series. Using daily exchange rate data from 22 July 2005 to 19 July 2019, our results show that, of the three random walks, the GARCH(1,1) random walk best portrays the yuan since the 2005 exchange rate system reform.

Keywords: Yuan, Bootstrap, Random Walk, Moving Average, Trading Range Break

JEL Classification: C22, G15

1. Introduction

On 5 August 2019, the Treasury Department of the United States accused China of currency manipulation and designated it a currency manipulator, a historic move that it had not exercised since the Clinton administration. The designation came after China allowed its official currency, the yuan or the renminbi (RMB), to depreciate to an exchange rate of over 7-to-1 against the U.S. dollar. The U.S. Treasury Department claimed:

> In recent days, China has taken concrete steps to devalue its currency, while maintaining substantial foreign exchange reserves despite active use of such tools in the past. The context of these actions and the implausibility of China's market stability rationale confirm that the purpose of China's currency devaluation is to gain unfair competitive advantage in international trade.

China refuted that the U.S. accusation was groundless and not in agreement with the facts. Wang Chunying, a spokesperson for the State Administration of Foreign Exchange of China, said: "China will keep its foreign exchange management policies stable and consistent. It is the U.S.'s escalating trade friction that has affected the exchange rate of the yuan, to which the market has already fully responded."

In an annual report of China's economic policies, released on 9 August 2019, the International Monetary Fund (IMF) did not seem to be on the U.S. side. The IMF said that China actually took steps to prop up the yuan's value after it declined against the dollar between mid-June and early August 2018. Overall, the yuan was broadly stable in 2018, depreciating by just 2.5 percent against a basket of foreign currencies. IMF staff concluded the yuan's value in 2018 was broadly in line with medium-term fundamentals and desirable policies. That is, it is basically not over- or undervalued.

For many years before July 2005, China pegged the yuan to the U.S. dollar at 8.27 RMB per dollar. On 21 July 2005, the People's Bank of China (i.e., the central bank of China) initiated a major reform for the yuan, switching it from a fixed rate system to a managed floating exchange rate system, under which the yuan is allowed to float in a narrow margin around a fixed base rate with reference to a basket of foreign currencies, including the dollar, the euro, and the Japanese yen. Figure 1 shows the exchange rate between the yuan and the dollar from 22 July 2005 to 9 August 2019.

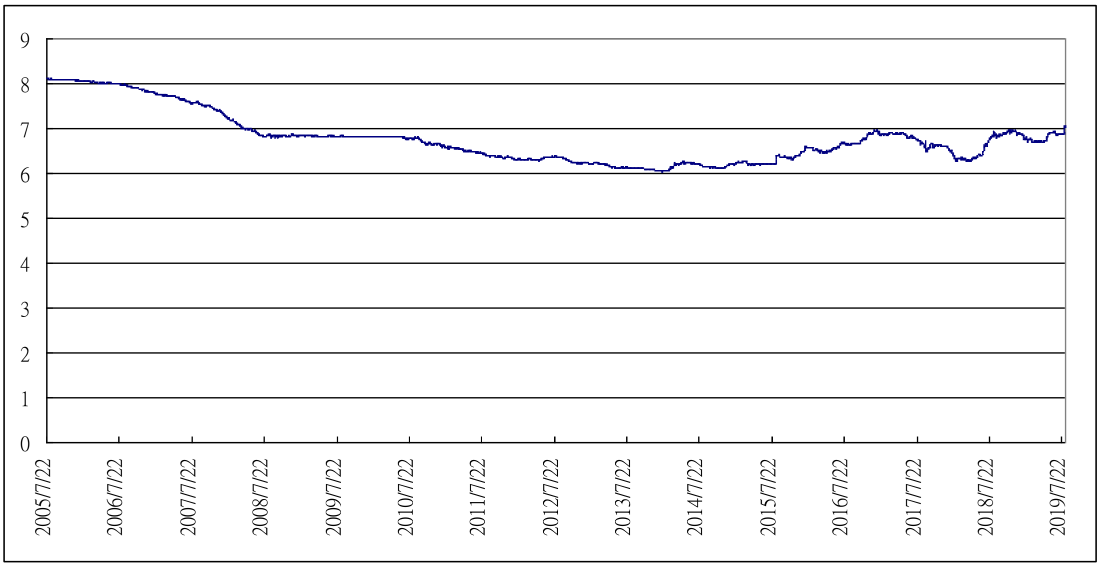

Figure 1. Yuan per US Dollar: 22 July 2005 – 9 August 2019

Given the growing importance of the yuan in the foreign exchange market over the past two decades, an interesting question among many financial economists is: How has the yuan evolved since the exchange rate system reform[1] on 21 July 2005? That said, this study attempts to explore the evolution of the yuan from 22 July 2005 up to 19 July 2019, a total of 14 years of daily exchange rate data. However, for time series data, we are constrained by the fact that we have just one series of historic data to study. It is not surprising that previous empirical findings based on different time series data are, to a certain degree, divided on how the yuan or other currencies have evolved. Given one and only one sample of time series data, is there a technique to use this only sample to assign a measure of accuracy to a statistic related to the data? The bootstrap method of Efron (1979) can be adapted for such a situation. Simply put, the bootstrap enables us to generate at random a large number of artificial data series from a given random process such that each of these artificial data series will preserve the statistical properties of the actual data series. Based on these artificial data series, we can construct a percentile interval to assign a measure of accuracy to the statistic of interest.

Accordingly, this study employs the bootstrap method to explore which of the following three popular random walks[2] best portrays the evolution of the Chinese yuan: IID-parameterized random walk, an ARCH(3)-

[1] See Funke and Rahn (2005), Goh and Kim (2006), and Ogawa and Sakane (2006).
[2] See Giddy and Duffy (1975), Mussa (1979), Meese and Rogoff (1983), Milhoj (1987), Hsieh (1988), Baillie and Bollerslev (1989), and Diebold and Nerlove (1989).

parameterized random walk, and a GARCH(1,1)-parameterized random walk[3]. In this study, the statistic of interest is the returns from two popular trading rules (moving average and trading range break), computed from either the actual yuan series or the artificial yuan series. Specifically, we use the bootstrap to generate at random from each random walk 10,000 artificial yuan series such that each of these 10,000 artificial yuan series will possess the statistical properties of the actual yuan series; then we compute the return from a given trading rule for each of these 10,000 artificial series; and finally we construct a 95% percentile interval with these 10,000 returns to determine if it contains the return computed from the actual yuan series.

The rest of the paper will proceed as follows: Section 2 gives a brief description of the bootstrap method; Section 3 describes the two trading rules (moving average and trading range break) used; Section 4 presents our empirical results; and Section 5 concludes this study.

2. The Bootstrap Method

Simply put, the bootstrap[4] for this study is to fit each random walk to the actual yuan series to obtain estimated parameters and residuals. The residuals are redrawn with replacement to form a scrambled residual series which is then used with the estimated parameters to generate artificial yuan series for a given random walk. Each of the three random walks is written as $\log(P_t) = \log(P_{t-1}) + \varepsilon_t$. For the IID random walk, ε_t's are independent and normally distributed[5]; for the ARCH(3) random walk[6], $\varepsilon_t = \sigma_t z_t$, where $\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \alpha_3 u_{t-3}^2$ and $z_t \sim N(0,1)$; and for the GARCH(1,1) random walk, $\varepsilon_t = \sigma_t z_t$, where $\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta\sigma_{t-1}^2$ and $z_t \sim N(0,1)$.

As an illustration, we use the GARCH(1,1) random walk to demonstrate how to implement the bootstrap by taking the following steps: (i) Based on the actual yuan series, we estimate the three parameters (i.e., α_0, α_1, and β) using the maximum likelihood method; (ii) Using these three estimates, we obtain a series of residuals. That is, { e_1, e_2, …, e_{5219} }; (iii) For each *j* (where *j* = 1, 2, …, 3511), we randomly pick a residual from the residual series to generate an artificial yuan series with 3511 observations[7]; (iv) We compute the returns from each of the two trading rules for buy and for sell using this artificial yuan series; (v) Repeating steps (i) – (iv), we generate 10,000 returns (denoted by $R_1^b, R_2^b, \ldots, R_{10000}^b$) for buy and 10,000 returns (denoted by $R_1^s, R_2^s, \ldots, R_{10000}^s$) for sell computed from the 10,000 artificial yuan series.

Following Efron and Tibshirani (1993), we construct a 95% percentile interval such that the 2.5th percentile and 97.5th percentile of the 10,000 returns (for buy and for sell) computed from 10,000 artificial yuan series are, respectively, the lower and upper limits for the interval. Specifically, arranging the 10,000 returns in ascending order such that $R_{(1)}^b \le R_{(2)}^b \le \ldots \le R_{(9999)}^b \le R_{(10000)}^b$ for buy and $R_{(1)}^s \le R_{(2)}^s \le \ldots \le R_{(9999)}^s \le R_{(10000)}^s$ for sell, we have that the 95% percentile interval[8] is $\left[R_{(251)}^b, R_{(9750)}^b\right]$ for buy and $\left[R_{(251)}^s, R_{(9750)}^s\right]$ for sell. That said, we determine if the returns (for buy and for sell) from each of the two trading rules computed from the actual yuan series lie within their respective 95% percentile intervals.

[3] We have tested for the ARCH(3) and GARCH(1,1) effects in the two random walks. The two random walks are found adequate for modeling the conditional heteroscedasticity of the data at the 5% significance level.
[4] For space reason, we are unable to provide a detailed description of the bootstrap. For details, see Efron (1979) and Efron and Tibshirani (1993).
[5] We have also employed the IID random walk with error terms that are independent and Student-t distributed. The results are similar to our present results with error terms that are independent and normally distributed.
[6] We have tried out ARCH(1) and ARCH(2) random walks. The results from these two random walks are not better than those from ARCH(3) random walk.
[7] There are 3511 observations for the 14 years of daily yuan exchange rates from 22 July 2005 to 19 July 2019.
[8] That is, $R_{(251)}^b$ and $R_{(9750)}^b$ are the 2.5th and 97.5th percentiles of the 10,000 returns for buy; $R_{(251)}^s$ and $R_{(9750)}^s$ are the 2.5th and 97.5th percentiles of the 10,000 returns for sell.

Our bootstrap implementation can better be understood from a different perspective. Suppose the yuan literally follows (say) the above GARCH(1,1) random walk. Then the actual yuan data series is simply a sample drawn from this GARCH(1,1) random walk. Hence, there is a high likelihood that the return computed from this actual yuan data series lies within the 95% percentile interval constructed using the 10,000 returns computed from this GARCH(1,1) random walk yuan series.

3. The Two Trading Rules

The two trading rules[9] used in this study are moving average (MA) and trading range break (TRB). The *n*-day moving average (MA) on day *t* is

$$M_{t,n} = \frac{1}{n}\sum_{k=t-n+1}^{t} P_k = \frac{1}{n}\left[P_{t-n+1} + P_{t-n+2} + \ldots + P_{t-1} + P_t\right] \tag{1}$$

where P_k is the yuan value on day *k*.

According to the MA rules, buy and sell signals are emitted by a short MA and a long MA. Buy (sell) signals are emitted when the short MA rises above (falls below) the long MA by a pre-specified percentage band. When a signal is emitted, the MA rules require that the position be maintained until the short MA penetrates the long MA again. A popular MA rule is (1, 200), where the short MA is one day and the long MA is 200 days. Since some individual investors trade on short-term basis, such MA rules as (1, 20) and (1, 50) are often in use. To implement, we use the following six MA rules: (1, 20), (1, 50), (1, 100), (1, 150), (1, 200), and (1, 250).

According to the TRB rules, a buy signal is emitted when the current exchange rate rises above the local maximum (the maximum rate over the past certain number of days) and a sell signal is emitted when the current exchange rate falls below the local minimum (the minimum rate over the past certain number of days). In notation, an *m*-day local maximum on day *t* and an *m*-day local minimum on day *t* are defined respectively as

$$L\max[m,t] = \max\left[P_{t-m}, P_{t-m+1}, \ldots P_{t-1}\right] \tag{2}$$

$$L\min[m,t] = \min\left[P_{t-m}, P_{t-m+1}, \ldots P_{t-1}\right] \tag{3}$$

where P_k ($k = t\text{-}m$, $t\text{-}m+1$, …, t-1) is the yuan value on day *k*. That is, a buy signal is emitted if $P_t > L\max[m,t]$ and a sell signal is emitted if $P_t < L\min[m,t]$. To implement, we use local maximums and minimums over the proceeding 20, 50, 100, 150, 200, and 250 days.

The data used for this study are 14 years of daily yuan exchange rates from 22 July 2005 to 19 July 2019 (a total of 3511 observations), retrieved from the DataStream database. We compute daily return R_t from day *t-1* to day *t* as the log difference of the yuan from day *t*-1 to day *t*. That is,

$$R_t = \log(P_t) - \log(P_{t-1}) \tag{4}$$

[9] See Murphy (1999) and Edwards et al. (2007) for details on these two trading rules.

Table 1. Parameter estimates for ARCH(3) and GARCH(1,1) random walks

Process	Parameter	Estimates
ARCH(3) random walk	α_0	0.000043
		(46.293422)
	α_1	0.170519
		(21.792180)
	α_2	0.062322
		(6.774321)
	α_3	0.072446
		(5.923094)
GARCH(1,1) random walk	α_0	0.000011
		(23.634343)
	α_1	0.069476
		(23.598324)
	β	0.652238
		(142.423076)

Notes: Estimations are done by maximum likelihood. Numbers in parentheses are standard *t*-ratios.

Table 2. Daily returns computed from actual yuan series

Rule	Moving average		Trading range break	
	Buy	Sell	Buy	Sell
(1, 20)	0.000143	-0.000038	0.000138	-0.000036
(1, 50)	0.000212	0.000047	0.000154	-0.000056
(1, 100)	0.000198	0.000021	0.000212	-0.000063
(1, 150)	0.000131	-0.000055	0.000091	-0.000071
(1, 200)	0.000065	-0.000102	0.000050	-0.000044
(1, 250)	0.000159	0.000027	-0.000011	-0.000036

4. Empirical Results

Table 1 shows the parameter estimates for the ARCH(3) and GARCH(1,1) random walks. Table 2 presents daily returns from the two trading rules based on actual yuan series. In Tables 3-5, “Median” is the median value of the 10,000 daily returns computed from 10,000 artificial yuan series, ” $R_{(251)}$ ” and “ $R_{(9750)}$ ” denote the 2.5th and 97.5th percentiles of the 10,000 daily returns for buy and for sell. For instance, under the (1, 20) MA rule for buy in Table 3, Median = 0.000051, $R_{(251)}$ = -0.000016, and $R_{(9750)}$ = 0.000141. That is, [-0.000016, 0.000141] is a 95% percentile interval. For visual clarity, those 95% intervals are shaded if the daily returns in Table 2 computed from the actual yuan series lie within their respective 95% intervals.

Table 3. Daily returns computed from IID random walk yuan series

Rule		Moving average Buy	Moving average Sell	Trading range break Buy	Trading range break Sell
(1, 20)	Median	0.000051	-0.000060	0.000167	0.000005
	$R_{(251)}$	-0.000016	-0.000113	0.000120	-0.000061
	$R_{(9750)}$	0.000141	-0.000011	0.000224	0.000073
(1, 50)	Median	0.000149	0.000031	0.000051	0.000102
	$R_{(251)}$	0.000083	-0.000027	-0.000009	0.000039
	$R_{(9750)}$	0.000230	0.000087	0.000117	0.000163
(1, 100)	Median	0.000125	0.000018	0.000015	-0.000012
	$R_{(251)}$	0.000071	-0.000037	-0.000048	-0.000068
	$R_{(9750)}$	0.000187	0.000071	0.000076	0.000063
(1, 150)	Median	0.000104	-0.000009	-0.000177	-0.000112
	$R_{(251)}$	0.000049	-0.000058	-0.000231	-0.000182
	$R_{(9750)}$	0.000167	0.000053	-0.000120	-0.000051
(1, 200)	Median	0.000022	-0.000109	-0.000244	0.000034
	$R_{(251)}$	-0.000039	-0.000172	-0.000301	-0.000024
	$R_{(9750)}$	0.000092	-0.000051	-0.000178	0.000097
(1, 250)	Median	0.000017	-0.000148	-0.000210	-0.000158
	$R_{(251)}$	-0.000047	-0.000216	-0.000262	-0.000219
	$R_{(9750)}$	0.000082	-0.000074	-0.000136	-0.000098

Notes: Shaded $R_{(251)}$ and $R_{(9750)}$ are the 95% percentile intervals containing the daily returns computed from the actual yuan series.

Table 3 shows the daily returns computed from the artificial IID random walk yuan series. Two MA rules for buy and four MA rules for sell result in that the daily returns from the actual yuan series lie within their respective 95% intervals. For instance, the (1, 200) MA rule for buy results in that the daily return of 0.000065 from the actual yuan series lies within [-0.000039, 0.000092]. On the other hand, only one TRB rule for buy and three TRB rules for sell result in that the daily returns from the actual yuan series lie within their respective 95% intervals.

Table 4. Daily returns computed from ARCH(3) random walk yuan series

Rule		Moving average Buy	Moving average Sell	Trading range break Buy	Trading range break Sell
(1, 20)	Median	0.000018	-0.000052	0.000092	0.000051
	$R_{(251)}$	-0.000039	-0.000116	0.000037	-0.000009
	$R_{(9750)}$	0.000081	0.000009	0.000161	0.000116
(1, 50)	Median	0.000090	0.000011	0.000287	-0.000269
	$R_{(251)}$	0.000025	-0.000050	0.000219	-0.000212

	$R_{(9750)}$	0.000164	0.000078	0.000352	-0.000338
(1, 100)	Median	0.000084	0.000019	0.000357	-0.000032
	$R_{(251)}$	0.000022	-0.000035	0.000281	-0.000097
	$R_{(9750)}$	0.000159	0.000091	0.000428	0.000040
(1, 150)	Median	0.000096	0.000020	0.000246	0.000136
	$R_{(251)}$	0.000030	-0.000049	0.000183	0.000081
	$R_{(9750)}$	0.000168	0.000091	0.000320	0.000198
(1, 200)	Median	0.000052	-0.000032	0.000317	0.000157
	$R_{(251)}$	-0.000011	-0.000094	0.000246	0.000092
	$R_{(9750)}$	0.000127	0.000039	0.000395	0.000226
(1, 250)	Median	0.000102	0.000030	0.000219	0.000048
	$R_{(251)}$	0.000039	-0.000032	0.000153	-0.000010
	$R_{(9750)}$	0.000173	0.000095	0.000291	0.000112

Notes: Shaded $R_{(251)}$ and $R_{(9750)}$ are the 95% percentile intervals containing the daily returns computed from the actual yuan series.

Table 4 shows the daily returns computed from the ARCH(3) random walk yuan series. The results in Table 4 are roughly similar to those in Table 3. Three MA rules for buy and four MA rules for sell result in that the daily returns from the actual yuan series lie within their respective 95% intervals. On the other hand, only one TRB rule for buy and one TRB rule for sell result in that the daily returns from the actual yuan series lie within their respective 95% intervals.

Table 5. Daily returns computed from GARCH(1,1) random walk yuan series

		Moving average		Trading range break	
Rule		Buy	Sell	Buy	Sell
(1, 20)	Median	0.000189	-0.000044	0.000181	-0.000202
	$R_{(251)}$	0.000108	-0.000115	0.000116	-0.000269
	$R_{(9750)}$	0.000275	0.000045	0.000260	-0.000131
(1, 50)	Median	0.000110	-0.000011	0.000071	-0.000011
	$R_{(251)}$	0.000035	-0.000079	0.000005	-0.000077
	$R_{(9750)}$	0.000188	0.000055	0.000146	0.000079
(1, 100)	Median	0.000131	-0.000063	0.000179	-0.000114
	$R_{(251)}$	0.000049	-0.000139	0.000106	-0.000181
	$R_{(9750)}$	0.000220	0.000021	0.000252	-0.000051
(1, 150)	Median	0.000127	-0.000121	0.000063	-0.000041
	$R_{(251)}$	0.000055	-0.000188	-0.000010	-0.000110
	$R_{(9750)}$	0.000206	-0.000049	0.000141	0.000037
(1, 200)	Median	0.000115	-0.000125	0.000057	-0.000134
	$R_{(251)}$	0.000043	-0.000192	-0.000005	-0.000188

	$R_{(9750)}$	0.000193	-0.000044	0.000126	-0.000071
(1, 250)	Median	0.000093	-0.000060	0.000041	-0.000165
	$R_{(251)}$	0.000021	-0.000129	-0.000016	-0.000231
	$R_{(9750)}$	0.000173	0.000014	0.000109	-0.000094

Notes: Shaded $R_{(251)}$ and $R_{(9750)}$ are the 95% percentile intervals containing the daily returns computed from the actual yuan series.

Table 5 shows the daily returns computed from the artificial GARCH(1,1) random walk yuan series. Five MA rules for buy and for sell result in that the daily returns from the actual yuan series lie within their respective 95% intervals. That is, 10 out of 12 percentile intervals contain the daily returns computed from the actual yuan series. In addition, five TRB rules for buy and three TRB rules for sell result in that the daily returns from the actual yuan series lie within their respective 95% intervals. That is, eight out of 12 percentile intervals contain the daily returns computed from the actual yuan series. In sum, the GARCH(1,1) random walk produces many more percentile intervals than the other two random walks.

5. Conclusion

For time series data, we are constrained by the fact that we have only one dataset of their history. Hence, it is not uncommon that previous empirical findings based on different time series data are, to a certain degree, divided over issues related to exchange rate. This study employs the bootstrap method to explore which of the three random walks best characterizes the evolution of the yuan. Using 14 years of daily yuan exchange rates from 22 July 2005 to 19 July 2019, our results show that, of the three random walks, the GARCH(1,1) random walk generates the most 95% percentile intervals which contain the returns computed from the actual yuan series. Given our results, we claim that the GARCH(1,1) random walk best portrays the yuan since China's exchange rate system reform on 21 July 2005.

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