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Forecasting Chinese industry return volatilities with RMB/USD exchange rate

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ABSTRACT

The purpose of this paper is to analyze whether the fluctuations of RMB/USD exchange rate can predict the Chinese industry return volatilities during post-financial crisis period. Our in-sample results show there is significant Granger causality from RMB/USD exchange rate fluctuations to China's industry return volatilities. The out-of-sample results also indicate the RMB/USD exchange rate fluctuations extracts significantly useful information from the predictors. Further analysis about the energy industry shows that simple linear regression is sufficient for capturing predictive relationships between RMB/USD exchange rate fluctuations and energy industry volatility.

1. Introduction

Over the past three decades, international equity investment has grown rapidly. The increasing trend of equity investment leads to high demand and an increase in foreign currency supply. The high demand of currencies and equity flows creates some interdependence between stock returns and exchange rate returns. Increasing interdependence also increases volatility transmission between stock and foreign exchange markets and increases the risk of international portfolio investment faced by investors. In addition, over the past three decades, emerging countries have experienced several crises: the stock market crash of 1987, the Asian currency crisis of July 1997, the Mexican currency crisis of 1994 and the subprime crisis of 2007–2008. These "turbulent" incidents have been characterized by large negative asset returns and high volatility, and their impact quickly spread to other emerging economies. Therefore, modeling and analyzing whether the fluctuations of RMB/USD exchange rate fluctuations can predict the China's industry return volatilities during post-financial crisis period is an important task in financial markets.

In recent years, many scholars have conducted empirical research on the relationship between stock prices and exchange rates. For example, Granger et al. [1] employ daily data to empirically analyze the relationship between monetary value and stock price in the context of the 1997 Asian financial crisis. Empirical results show that there is a strong co-movement between foreign exchange rates and stock prices in most Asian countries (e.g. Hong Kong, Taiwan, Malaysia,

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Singapore, Thailand, etc.). However, Nieh and Lee [2] found there is no long-run significant relationship between stock prices and exchange rates in the G-7 countries. After that, some scholars have investigated the relationships between the stock prices and foreign exchange rates from different countries or regions, (e.g., see, Dimitrova [3], Pan et al. [4], Richards et al. [5], Kutty [6], Moore and Wang [7], and Caporale et al. [8] among others). Although many studies have contributed to this literature, few studies have been conducted on China's stock prices and exchange rates.. For example, Qiao et al. [9], Zhao [10], Liu and Wan [11].

The information spillover between the two financial markets: stock market and foreign exchange market has been studied by many researchers for different countries. Most of the studies have focused on the transmission of volatility between foreign exchange market and stock market. Early studies including Jorion [12] suggest that foreign exchange rate changes offer little or no predictive power for stock returns volatility, whilst. Roll [13] claim the existence of a strong linkage between foreign exchange rate changes and stock market volatility. Contradictory conclusions attract the attention of more scholars. The developed countries have been extensively studied by most of researchers (see, for example, Antonakakis [14], Beer and Hebein [15], Grobys [16];). There are also number of studies of integration of foreign exchange market and stock market of developing countries (for example, Choi et al. [17]; Mishra et al. [18]). There are also some studies for emerging countries for instance (see, for examples, Oberholzer and Boetticher [19]; Walid et al. [20]).

It is well known that stock market volatility plays key roles in the academic literature for investigating the causes and consequences of the volatility dynamics in the stock market. The seminal paper of Welch and Goyal [21] shows the stock market volatility enjoys countercyclical movements, but the relationship between stock volatility and macroeconomic predictors is not strong from a statistical perspective. However, recent studies such as Paye [22], Christiansen et al. [23], Conrad and Loch [24], and Nonejad, [25] obtain some more encouraging results by constructing the macroeconomic and financial variables. In recent years, some scholars have paid attention to the prediction of stock volatility from different perspectives, for example, HAR-RV model (Gong and Lin [26,27], Wang et al. [28]), simple linear regression (Wang et al. [29], Feng et al. [30], Fang et al. [31]), and mixed-frequency approach (Zhang et al. [32], He et al. [33], Wen et al. [34,35]). In addition, some scholars have paid their attention to the volatility forecast of China's stock market (see, for example, Girardin and Joyeux [36], Pu et al. [37], Liu et al. [38], Yu et al. [39]).

The above studies main focus on the prediction of stock market volatility, however, little research investigates the forecasting for the industry volatilities, except for Cai et al. [40]. In this paper, we also provide empirical evidence on Chinese industry return volatilities forecasting beyond the market volatility forecasting. Our article is closely related to Cai et al. [40], which investigates the influence of thirteen Chinese economic variables representing the macroeconomic and financial fundamentals on the long-run volatility of the Chinese stock market. However, we use the fluctuations of RMB/USD exchange rate as a predictor to forecast Chinese industry return volatilities. As we know, the impact of the RMB/USD exchange rate on Chinese's import and export business is very important. Forecasting stock industry volatilities also has many practical applications in asset price, portfolio selection and risk management. Therefore, modeling and forecasting stock industry volatility is a popular research topic and an important task in financial markets in China. How does the impact of import and export trade pass to the industry portfolios volatilities? This paper aims to answer this problem and use the regression model to explore how the impact of RMB/USD exchange rate fluctuation on industry volatilities.

We use daily data spanning February 2009 to September 2018 for the daily price index of the industry data is collected, including energy, materials, industry, optional, consumption, medicine, finance, Information, telecommunications, and public ten categories which come from the WIND economic database. The RMB/USD exchange rate index is downloaded from the investing financial website. The squared daily returns in each week are summed to construct monthly realized volatility. Regarding the choice of the optimal lag order, the general study is determined using the AIC and SC information criteria. From the comparison results, it is known that the fourth step of lag is the most reasonable. Our in-sample results indicate significant Granger causality from the fluctuations of RMB/USD exchange rate to industry volatilities. We use the out-of-sample to evaluate out-of-sample performance, which is used in the literatures (Goyal and Welch [21]; Paye [22]). As we know, a positive implies that the model of interest produces more accurate forecasts. The Clark and West [41] statistic is used to test the equivalence of MSPEs between two nested models. We use both recursive and rolling estimation window to generate one-step-ahead out-of-sample forecasts of stock industry volatilities for October 2013 through July 2018. The out-of-sample results indicate the RMB/USD exchange rate fluctuation has improved the predictive ability of industry return volatility.

Our empirical analysis is further extended to nonlinear models. We consider two types of nonlinear relationships including asymmetric positive return indicator and asymmetric positive and negative return indicator. In summary, we find little evidence supporting the superiority of nonlinear models over linear specifications in forecasting industry return volatility. Our forecasting exercise is also conducted for longer horizons. We find significant predictability for horizons of 3 and 6 months. However, the predictability disappears for longer horizons.

The remainder of this paper is organized as follows. Section 2 briefly describes the empirical data and descriptive statistics. We report the predictive regressions and the forecast evaluation method in Section 3. The in-sample and out-of-sample results are presented in Sections 4 and 5. Section 6 extends our analysis. Finally, Section 7 concludes the paper.

Table 1
Descriptive statistics for all industry indexes.

Industry index	N	mean	sd	p25	p50	p75	min	max
RMB	501	−12.74	2.04	−13.79	−12.54	−11.30	−21.38	−7.73
Energy	501	−7.00	1.18	−7.71	−6.96	−6.24	−12.99	−3.56
Material	501	−6.97	1.13	−7.70	−6.95	−6.31	−11.36	−3.64
Industry	501	−7.26	1.18	−7.95	−7.21	−6.60	−11.97	−3.67
Optional	501	−7.25	1.18	−7.98	−7.18	−6.50	−11.76	−3.75
Spending	501	−7.25	1.10	−7.86	−7.21	−6.58	−13.23	−4.05
Medicine	501	−7.25	1.28	−7.91	−7.11	−6.44	−17.13	−3.91
Finance	501	−7.33	1.37	−8.06	−7.20	−6.48	−17.82	−3.85
Information	501	−6.75	1.11	−7.37	−6.71	−6.05	−12.16	−3.75
Telecom	501	−6.87	1.13	−7.55	−6.77	−6.13	−14.81	−3.51
Public	501	−7.63	1.30	−8.45	−7.65	−6.89	−12.47	−4.04

2. Data and descriptive statistics

The data of China's industry volatilities is downloaded from the WIND economic database. The daily price index of 10 industries data from Shanghai stock exchange (SHSE) and Shenzhen Stock Exchange (SZSE) is collected, including energy, materials, industry, optional, consumption, medicine, finance, Information, telecommunications, and public ten categories. From the perspective of data collection and applicability, wind's industry classification criteria are more desirable. Therefore, we select the industry closing price index of the Shanghai SSE and Shenzhen Stock Exchange from January 2009 to September 2018. The RMB exchange rate index is downloaded from the investing financial website, including the exchange rate of several currencies such as CNY/USB, CNY/GBP, CNY/JPY, and CNY/EUR.

2.1. Measuring industry index volatility

According to the guidance of the document Wang et al. [29], we use the sum of the squares of daily returns as agents of return volatility. Due to the data time limit of the industry's closing index, the sample size is too low in terms of monthly frequency. Therefore, we uses the weekly frequency to calculate the volatility of the industry index. First we calculate the daily return of the industry index as follows:

$$r_i = \ln P_i - \ln P_{i-1} \tag{1}$$

where P_i and P_{i-1} are the closing prices of the i-day industry index. Following the literatures (e.g., Paye [22]; Andersen et al. [42]), the weekly volatility is calculated based on the daily return. For a specific week, the realized volatility is defined as:

$$\mathrm{RV}_t = \sum_{j=1}^{m} r_{t,j}^2,\ j = 1, 2, \ldots m, \tag{2}$$

where $r_{t,j}$ is the jth daily return in the tth week, and m is the number of working days per week. We also use the same way as industry index volatility to calculate exchange rate fluctuation. Following the literatures (e.g., Paye [22];Wang et al. [29]), we utilize the natural logarithm as, to mitigate the impact of leptokurtic for the realized volatility in (2). As we forecast industry index volatility by using the linear regression, and the parameters of which are computed by the ordinary least squares (OLS).

2.2. Descriptive statistics

Before the model analysis of the data, in order to understand the characteristics of the data in more detail, we first give descriptive statistics of the mean, variance, median and maximum and minimum values of the industry index and the RMB exchange rate. As shown in Table 1

Table 1 reports the basis statistics of the industry index, which is shown in the first column of the table. In Table 1, P25, p50, and p75 represent 1/4, 1/2, and 3/4 quantiles, respectively, which can reflect the general distribution trend. It can be seen from Table 1 that the average of the logarithm of the closing price of the ten major industries such as energy, materials, and industry is basically around −7, and the variance is kept within the range of 1 to 1.5, and then the maximum and minimum of the industry index. The variance of exchange rate fluctuation is larger than the industry index, but the fluctuation of the RMB exchange rate is relatively small compared to the composite index. Therefore, the industry index is less volatile than the stock total index. The extreme value of the exchange rate is 13.65, which is similar to the extreme value of the industry. It can be seen that the RMB exchange rate is similar to the volatility of industry return.

3. Methodology

In this paper, we study the effects of exchange rate fluctuations on Chinese industry returns volatility. We use simple predictive regressions for Chinese industry returns volatility and take past exchange rate fluctuations as predictors in addition to lagged Chinese industry returns volatility to test the forecasting ability of RMB/USD exchange rate fluctuations from the in-sample and out-of-sample perspective.

3.1. Predictive regression

Very recently, Wang et al. [29] proposed the following lagged autoregressive model (AR) by incorporating a log realized volatility of crude oil as an additional predictor:

$$V_{t+1} = \omega + \sum_{i=0}^{p-1} \alpha_i V_{t-i} + \beta\ V_{t,oil} + \varepsilon_{i+1},$$

where $V_{t,oil}$ is the oil volatility in the tth month, and the lag order p is set equal to 6 when using monthly data. Wang et al. [29] showed that crude oil volatility is predictive of stock volatility in the short-term from both in-sample and out-of-sample perspectives.

To investigate the predictability of the RMB/USD exchange rate fluctuations, we also use the following autoregressive model (AR)

$$V_{l,t+1} = \omega + \sum_{i=0}^{p-1} \alpha_i V_{l,t-i} + \beta\ E_t + \varepsilon_{i+1}, \tag{3}$$

where $V_{l,t} = \log(RV_{l,t})$ the l industry volatility of the tth week, and E_t is the RMB/USD exchange rate fluctuations of the tth week. And the λ reflects the effects of RMB/USD exchange rate fluctuations of the tth week on the $(t+1)$th week of the l stock industry volatility, the error term $\varepsilon_{t+1} \sim N(0, 1)$, and it is assumed to be independent and identically. The use of such long lag length is to sufficiently capture the $V_t = \log(RV_t)$ strong autocorrelation in stock industry volatility. We can estimate the parameter in (4) by using the ordinary least squares (OLS). The null hypothesis of no predictability, $\alpha_i = 0$ or $\beta = 0$, are tested using the t-statistic based on the Clark and West [41] statistics method.

3.2. Out-of-sample prediction regression

To compare forecasting performance, the out-of-sample prediction is to use predict the future of value. The prediction is based on rolling and recursive estimation window techniques. Specifically, we divide the entire data into two sub-samples, the pre-M phase of the sample is used to estimate parameter evaluation, and the remaining T-M phase is used for sample prediction. Therefore, the first out-of-sample forecast of industry return volatility based on RMB/USD exchange rate fluctuation is given by:

$$\hat{V}_M = \hat{\omega}_M + \sum_{i=0}^{p-1} \hat{\alpha}_{i,M} \hat{V}_{M-i} + \hat{\beta}_M\ E_M + \varepsilon_{M+1}, \tag{4}$$

where ω_M, $\alpha_{i,M}$, and β_M are the parameter estimates of ω, α_i, and β in (4), respectively. To forecast the industry's return volatility out-of-sample, and compare it with the actual value, the model formula for the second out-of-sample prediction is

$$\hat{V}_{M+2} = \hat{\omega}_{M+1} + \sum_{i=0}^{p-1} \hat{\alpha}_{i,M+1} \hat{V}_{M-i+1} + \hat{\beta}_{M+1}\ E_{M+1} + \varepsilon_{M+1}, \tag{5}$$

We make out-of-sample predictions based on recursive and rolling window estimation techniques. The length in the rolling window sample is constant with the increase of the latter item minus the first item, the size of the window is fixed, and the window length of the recursive estimation. As the sample size increases, the size of the window increases. No matter how the window changes, the above parameters are obtained by least squares estimation of the variables, which will produce a series of T-M predicted stock return volatility.

3.3. Forecast evaluation

Following the papers about stock return and volatility forecasts (see, e.g., Campbell and Thompson [43], Wang et al. [29]; Dai and Wen [44]; Dai et al. [45,46], Gong and Lin [47,48], and Wen et al. [49]), we utilize the out-of-sample

Table 2
Selection of lag order.

Lag order	AIC	SC
0	3.048	3.065
1	2.933	2.959
2	2.870	2.903
3	2.844	2.886
4	2.825	2.876
5	2.828	2.888
6	2.834	2.902
7	2.835	2.911
8	2.830	2.915
9	2.835	2.929
10	2.835	2.938
11	2.840	2.951
12	2.846	2.966

$R^2(R^2_{OOS})$ to evaluate the predictive performance of a forecast model relative to the benchmark model of AR(6) in (3). The out-of-sample $R^2(R^2_{OOS})$ statistic is defined as following

$$R^2_{oos} = 1 - \frac{\sum_{k=1}^{q}\left(V_{m+k} - \hat{V}_{m+k}\right)^2}{\sum_{k=1}^{q}\left(V_{m+k} - \bar{V}_{m+k}\right)^2}, \tag{6}$$

where V_{m+k} $\bar{V}_{m+k}$ and $\hat{V}_{m+k}$ are the actual value, benchmark model value, and forecast of log realized volatility, respectively, at month $m+k$. We utilize Clark and West [41] statistics to further measure whether the prediction model produced significant statistical improvements in the reduction in mean squared forecast error (MSFE). Mathematically, Clark and West [41] statistics are defined as following.

$$f_t = \left(V_t - \bar{V}_t\right)^2 - \left(V_t - \hat{V}_t\right)^2 + \left(\bar{V}_t - \hat{V}_t\right)^2, \tag{7}$$

where V_t $\bar{V}_t$ and $\hat{V}_t$ are the actual volatility, the benchmark of stock volatility, and the stock volatility prediction of interest, respectively. Through regression $\{f_s\}_{s=m+1}^{T}$ on a constant, we can easily get the C-W statistics, that just is t-statistics for the constant. In addition, the p-value of one-sided test can be easily obtained from the standard normal distribution.

The comparison principle of the predicted results is whether adding the RMB exchange rate variable improves the accuracy of the model's prediction. If $R^2_{OOS} > 0$ means that the mean square error of the variable model is smaller than the benchmark model, that is, the model of RMB/USD exchange rate fluctuation is closer to the true value than the predicted value of the benchmark model.

4. Analysis of in-sample results

4.1. Selection of optimal lag order

Regarding the choice of the optimal lag order, the general study is determined using the Akaike information criterion (AIC) by Akaike [50] and Schwarz Criterion (SC) by Schwarz [51]. AIC is a measure of the superiority of statistical models, the value is smaller, the model is better. The −12-order ordinary least squares regression is used to extract the values of the AIC and SC information criteria from the regression results. Comparing the values of the different orders, we take it as the lag order with the smallest AIC and SC values. From the comparison results, it is known that the fourth step of lag is the most reasonable. Taking the energy industry as an example, the AIC and SC values of the 0–12 order lag regression are shown in Table 2:

From Table 2, we can obtain that the optimal lag order is four for the forecasting for energy industry return volatility. For the forecasting of the other industry return volatilities, the optimal lag order also is four. In addition, for the prediction of volatility in other industries, the optimal order is also four. Hence, we select four as the lagged order.

4.2. In-sample results

After descriptive analysis, it is necessary to quantitatively analyze the variables, that is, mainly describe the industry return volatilities autoregressive model and the parameter estimation value of the model after adding the exchange rate variable. According to the results from Inoue and Kilian [52], in-sample prediction is an important basis for out-of-sample evaluation. The results of out-of-sample prediction without in-sample results are unscientific and unreasonable. Hence, predictions in-sample is essential.

Table 3
In sample results for 10 industry return volatilities.

	Ene	Mat	Ind	Opt	Spe	Med	Fin	Inf	Tel	Pub
ω	−1.078	−1.001	−1.308	−1.145	−1.939	−1.319	−1.520	−1.156	−1.655	−0.809
	(2.379)	(2.574)	(2.837)	(2.913)	(4.163)	(2.771)	(3.016)	(2.635)	(3.235)	(1.915)
α_1	0.172	0.160	0.215	0.224	0.248	0.216	0.131	0.210	0.176	0.220
	(4.199)	(3.746)	(4.906)	(4.885)	(4.284)	(4.758)	(2.985)	(3.840)	(3.944)	(4.374)
α_2	0.173	0.174	0.221	0.207	0.159	0.178	0.189	0.208	0.165	0.193
	(3.906)	(3.833)	(4.508)	(4.290)	(3.638)	(3.941)	(4.596)	(4.245)	(3.924)	(4.072)
α_3	0.141	0.210	0.127	0.170	0.132	0.147	0.175	0.099	0.112	0.183
	(3.393)	(4.546)	(3.106)	(3.983)	(3.078)	(3.197)	(3.589)	(2.808)	(2.728)	(4.720)
α_4	0.151	0.103	0.092	0.148	0.083	0.149	0.124	0.169	0.184	0.171
	(3.428)	(2.374)	(2.120)	(3.456)	(1.944)	(3.747)	(2.558)	(3.791)	(4.270)	(4.299)
α_5	0.162	0.163	0.133	0.076	0.090	0.103	0.142	0.107	0.093	0.107
	(3.659)	(4.359)	(3.468)	(2.066)	(2.286)	(2.396)	(2.364)	(2.775)	(2.453)	(2.458)

Table 4
Out-of-sample results during whole out-of-sample period.

	Ene	Mat	Ind	Opt	Spe	Med	Fin	Inf	Tele	Pub
Recursive window										
R^2_{oos}	29.58***	32.20***	36.33**	47.32***	29.88*	34.95*	24.89*	35.86*	28.98*	48.99*
	0.041	0.043	0.026	0.003	0.064	0.072	0.064	0.061	0.069	0.058
Rolling window										
R^2_{oos}	27.86***	30.74***	36.93**	47.63**	27.05***	35.37**	24.73***	34.85*	27.86***	48.45***
	0.009	0.005	0.017	0.042	0.030	0.038	0.021	0.093	0.021	0.008

Table 3 displays the estimated coefficients of the predictive regression models by (4) for 10 industry return volatilities of energy, materials, industry, optional, consumption, medicine, finance, Information, telecommunications, and public, as well as the t-statistics based on the Newey–West covariance correction for serial correlation.

It can be seen from Table 3 that the coefficients α_1, α_2, α_3 and α_4 of the fourth-order lag period are positive, and the coefficient β of the E_t variable is also greater than 0, indicating that E_t is one of the explanatory factors of V_t. The most affected are energy and materials, followed by the financial industry. Their coefficient values are 0.162, 0.163 and 0.141. Take the materials industry as an example. When the RMB/USD exchange rate rose by 1% this week, the energy industry volatility index rose by 0.163%. Of course, there are some coefficient values that are too small, such as the SSE option and the SSE consumer industry volatility index. Their coefficient values are 0.075 and 0.089 respectively, which means that a 1% increase in the Euro-RMB exchange rate this week will result in an option (The industry's return volatility index rose by 0.075 (0.089)%, which is less affected than other industries. In addition, the t-statistics based on the Newey–West indicate there exists very significant Granger causality from RMB/USD exchange rate fluctuations to stock industry volatility.

5. Out-of-sample results

A strong proof is given in the intra-sample prediction. Both the parameter coefficient and the criterion for the estimation of the sample have achieved a good result. However, for more effective exchange rate fluctuation on China's industry volatility, out-of-sample forecasts are essential. Most scholars at home and abroad believe that out-of-sample prediction is more suitable for assessing true predictability and avoiding excessive sample problems and giving more accurate prediction results. We will generate the prediction of stock volatility from January 1998 to December 2017, and evaluated the prediction performance on various sample periods. In this paper, the data of about 10 years from 2009 to 2018 is divided by weekly frequency. There are $T = 502$ samples in total, which are sampled in three years, about $\mathrm{M} = 210$ samples, and $\mathrm{T} - \mathrm{M} = 292$ samples are used for prediction.

Table 4 reports the out-of-sample results of the predictive regression which are based on the recursive method and rolling window method. We also report the values of out-of-sample R^2_{oos}, and the corresponding p-values of Clark and West statistics. The initial estimation period is 2009:01.09–2013:10.13, while the out-of-sample period is 2013:10.14–2018:07.30. The asterisks *, **, *** denote rejections of null hypothesis at 10%, 5% and 1% significance levels, respectively.

The predictive performance of the regression model (3) with RMB/USD exchange rate fluctuations is satisfactory. The values of R^2_{oos} suggest that including RMB/USD exchange rate fluctuations in the predictive regression model can cause the reduction of MSPE from 24.73% to 48.99% during whole out-of-sample period.

The forecasting accuracy for finance industry volatility is the lowest among ten industry volatility regardless of the recursive method or rolling window method. The reason is that the finance industry volatility is unpredictable. The Optional and Public industry volatility enjoy the highest forecasting accuracy. And the P-values of Clark and West [41] test indicate that there is significant improvement of forecasting accuracy during the whole out-of-sample period, which shows that the forecasting ability of RMB/USD exchange rate fluctuations for industry return volatility is efficient.

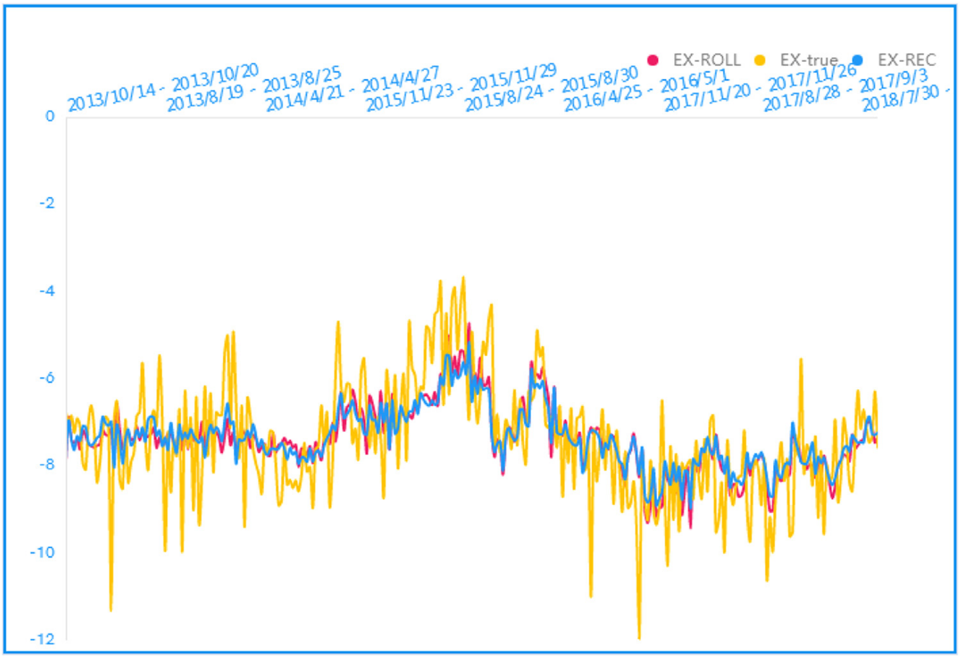

Fig. 1. Industry volatility forecast based on rolling and recursive windows.

Table 5
Out-of-sample results for energy industry during different out-of-sample period.

	2010.12–2018.9	2012.11–2018.9	2014.10–2018.9	2016.9–2018.9
Recursive	39.106***	39.148***	46.113***	60.420***
	(0.00000)	(0.00001)	(0.00000)	(4.44E−16)
Rolling	25.228***	23.011***	27.313***	43.886***
	(0.00035)	(0.00010)	(2.66E−15)	(2.16E−10)

According to the prediction results, we extract the predicted values of industry volatility made by recursion and rolling, and compares them with the real values. According to the sample taken, the number of samples is estimated by the weekly frequency. The initial predicted value starts from March 11, 2013 and ends in September 2018. We take the industrial industry as an example. The images of the three are as follows (see Fig. 1):

As can be seen from the above figure, the true value of the volatility is large. The predicted value can capture the general trend of volatility, and only the particularly large fluctuations are not well predicted. Overall, the forecasting ability of RMB/USD exchange rate fluctuations for industry return volatility is efficient.

6. Different estimation window size-energy industry as an example

Rossi and Inoue [53] have emphasized that the choice of the estimation window size has always been a concern for practitioners, since the use of different window sizes may lead to different empirical results in practice. That is, the choice of forecasting window sizes plays an important role in out-of-sample evaluation. If a predictor has significant predictability for stock volatility, it ought to be insensitive to the choice of time period. Therefore, it is necessary and reasonable to test the predictive content of the RMB/USD exchange rate fluctuations for stock volatility whether is robust to the choice of the estimation and evaluation window size.

Table 5 reports the out-of-sample prediction results based on the recursive window and the rolling window for energy industry during different out-of-sample period. We finally give the sample out-of-sample R^2_{oos} values for the four sub-intervals from December 2010 to September 2018 and the corresponding p-values of Clark and West statistics. The asterisks *, **, *** denote rejections of null hypothesis at 10%, 5% and 1% significance levels, respectively.

First, let us first look at the forecast performance of RMB/USD exchange rate fluctuation on the return fluctuation of the energy industry under the recursive window conditions. The MSPE value out-of-sample during different out-of-sample period was reduced by 25% for the recursive window method, and the P-values of Clark and West [41] statistics show a significant improvement in the prediction accuracy. There are four subsample intervals. As the prediction interval decreases, the value of R^2_{oos} is increasing, indicating that the forecasting ability of RMB/USD exchange rate fluctuation is getting stronger and stronger. In the shortest forecast interval from September 2016 to 2018, the value of R^2_{oos} was 43.886, which is more than the longest prediction interval. This gap is very large, which shows that the closer the interval exchange rate is, the stronger the prediction ability is. The value of R^2_{oos} is very high, indicating that the accuracy is much improved. On the whole, the future trend of return volatility is still greatly affected by the fluctuation of RMB exchange rate.

Let us look at the prediction based on rolling window regression, as shown in Table 5. We can find that the fluctuation of RMB exchange rate based on rolling window to predict the energy industry's return volatility is significantly higher than the benchmark regression model. In the four sub-intervals, the invariable rule is that the prediction improvement of the most recent sub-interval is the highest, reaching 43.88%, and the chance is the longest. The forecast interval is twice, indicating that as the forecast is close to the time period, the ability to predict RMB/USD exchange rate fluctuation is also constantly increasing. It can be seen from the P-values of Clark and West statistics that it is very significant, which shows that, to a certain extent, the RMB exchange rate has a strong ability to interpret the industry return volatility.

6.1. Nonlinear Relationship of Energy–Energy industry as an example

In real life, there is no simple linear relationship between any two things. They are influenced by many factors and the relationship is quite complicated. Then, can the relationship between RMB/USD exchange rate fluctuation and energy industry return volatility be better fitted by nonlinear relationships? We try to make experiments, give the results, and compare with the linear fitting relationship. If the $R^2_{oos} > 0$ value is significantly improved, the relationship between the two is more suitable to fit with the nonlinear model, if $R^2_{oos} < 0$, the value of the improvement is not better than that of the linear prediction, indicating that the nonlinear relationship between the two is not obvious, and it is more suitable for the prediction of linear relationship. In this subsection, we propose two nonlinear models that are more suitable for the exchange rate fluctuation to predict the industry's return volatility. Under different models, the lag period and the asymmetry choice will change accordingly. The basis of the model is to adjust the structure of the independent variables, one is to add the exchange rate fluctuation variable with positive return, and the other is to decompose the positive and negative of the exchange rate variable to explore the change of R^2_{oos} value.

The asymmetric effect of exchange rate fluctuation is based on the fluctuation of the impact of oil volatility on the stock market. Since the two principles are the same, that is, the relationship between them is analyzed, the nonlinear model is universal. Therefore, the impact of oil price volatility on stock market volatility is asymmetric, so oil price growth has been associated with high volatility. In this paper, there are two positive and negative volatility in the RMB exchange rate. Different return volatility will have different effects on the market. Is the positive volatility forecasting ability or the negative volatility forecasting ability strong? According to the above questions, we establish two models, one is to add a separation variable based on the previous research, that is, when $r_{t,j} > 0$ in the period t, take the volatility index of this period, if $r_{t,j} < 0$ the volatility is taken as 0, which means that only the positive direction of exchange rate fluctuation is studied, and the impact on the volatility of the energy industry and the composite index in the case of positive RMB/USD exchange rate fluctuation is observed. Our first model uses the positive return indicator variable:

$$\text{Asymmetric model I: } V_{l,t+1} = \omega + \sum_{i=0}^{p-1} \alpha_i V_{l,t-i} + \beta\ E_t I(r_t > 0) + \varepsilon_{t+1}, \tag{8}$$

where I(.) is an indicative function. When the condition $r_{t,j} > 0$ is satisfied, its value is taken as 1, otherwise it is taken as 0. The application of the explicit function separates the positive volatility well and studies the impact of the volatility under positive returns on the industry and overall quality.

The second model is based on the positive and negative direction of RMB/USD exchange rate fluctuation to study its impact on industry return volatility. This model removes the original variable of exchange rate fluctuation and separates this variable into two positive and negative variables. This model is based on the positive and negative definition of the monthly variance is determined by the positive and negative returns of the daily component, that is, the volatility in this week are based on the positive and negative direction of the daily return. The specific model is as follows:

$$\text{Asymmetric model II: } V_{l,t+1} = \omega + \sum_{i=0}^{p-1} \alpha_i V_{l,t-i} + \beta^+ E_t^+ + \beta^- E_t^- + \varepsilon_{t+1}, \tag{9}$$

where $E_t^+ = \ln(EX_t^+)$ and $E_t^- = \ln(EX_t^-)$, EX_t^+ and EX_t^- are the positive and negative summation terms of the weekly return, respectively. The definitions of them are as follows:

$$EX_t^+ = \sum_{j=1}^{M} r_{t,j}^2 I(r_{t,j} > 0), \quad t = 1, 2 \ldots, T \quad \text{and} \quad EX_t^- = \sum_{j=1}^{M} r_{t,j}^2 I(r_{t,j} < 0), \quad t = 1, 2, \ldots, T$$

where M = 7, summing in one week. $r_{t,j}$ is the exchange rate daily return on day j of the tth component.

Table 6 Out-of-sample prediction results of nonlinear models based on the recursive window and rolling window for energy industry during different out-of-sample period. The table reports the prediction results of the nonlinear prediction regression of RMB/USD exchange rate fluctuation according to two asymmetric models: asymmetric model I in (8), asymmetric model II in (9). We finally give the sample out-of-sample R^2_{oos} values for the four sub-intervals from

Table 6
Out-of-sample results for nonlinear relationship of energy.

	2010.12–2018.9	2012.11–2018.9	2014.10–2018.9	2016.9–2018.9
Asymmetry model I				
Recursive	22.486***	24.404***	26.352***	33.247***
	(0.000)	(0.00E+00)	(1.33E−15)	(1.78E−10)
Rolling	18.262***	18.176***	19.094***	32.343***
	(0.000)	(0.000)	(0.000)	(0.000)
Asymmetry model II				
Recursive	12.445***	14.435***	16.387***	20.243***
	(0.000)	(0.000)	(0.000)	(0.000)
Rolling	9.917***	11.995***	13.253***	16.445***
	(9.35E−06)	(4.09E−05)	(0.000537)	(0.000)

December 2010 to September 2018 and the corresponding p-values of Clark and West statistics. The asterisks *, **, *** denote rejections of null hypothesis at 10%, 5% and 1% significance levels, respectively.

Compared with the linear regression model (3), we find that, the prediction effect of the asymmetric model (1) is not as good as that of the linear model. The value of R^2_{oos} in the four subintervals is smaller than that of the linear model. In the subinterval, 2012.11–2018.9, the R^2_{oos} value of the linear model is 18.176%. The value of R^2_{oos} obtained from the asymmetric model I did not improve, but decreased by 20.972%. There is no better prediction of exchange rate in this interval. In addition, the most recent prediction interval from September 2016 to September 2018, the R^2_{oos} value of Model I is 32.343%, which is quite different from the linear model prediction improvement. It can be seen that in the recursive window, although the prediction ability of Model I is increasing with the accuracy of the interval, the accuracy of the prediction is not as good as that of the linear model. For the asymmetric model II, the positive and negative volatility of the exchange rate are separated to explore the impact on the industry's return volatility. Compared with the model I, the effect is not much improved. In the first three sub-intervals, although there is no linear model, the relative value of the prediction is large. But far beyond the situation of Model I, it is still advisable for Model II results. It can be seen that the nonlinear model does not perform better than the linear model. Let us compare the situation of the asymmetric model II and the linear model in the prediction. During the period from November 2012 to September 18, 2012, the linear model has a negative value of R^2_{oos}, which shows that the prediction effect is not good. The asymmetric model II has improved, and its R^2_{oos} value is 22.486%. To some extent, the predictive ability of the forecast model incorporating the RMB/USD exchange rate fluctuation has improved. Therefore, it can be said that when using the RMB/USD exchange rate fluctuation to predict the volatility in the energy industry's returns, combined with the corresponding forecasting intervals, appropriate models should be selected for prediction.

6.2. Longer horizons forecast performance-energy industry as an example

In this subsection, we will examine the energy industry's return volatility forecast performance over the longer horizons. The previous studies are all about the forecasting ability of the exchange rate in the next week. Can the forecast of the future longer horizons be predicted? Is the prediction effect good? The following is a prediction of the industry's return volatility in the future with a linear regression model. The R^2_{oos} value is used to judge whether the prediction ability changes when comparing and forecasting for longer horizons. The prediction model is given by:

$$V_{l,t+h} = \omega + \sum_{i=0}^{p-1} \alpha_i V_{l,t-i} + \beta\, E_t + \varepsilon_{i+1}, \tag{10}$$

where h is the forecast range, this paper mainly predicts the results for the next 3, 6 and 9 weeks.

Table 7 Out-of-sample prediction results of longer horizons 3, 6 and 9 weeks based on the recursive window and rolling window for energy industry during different out-of-sample period. We finally give the sample out-of-sample R^2_{oos} values for the four sub-intervals from December 2010 to September 2018 and the corresponding p-values of Clark and West statistics. The asterisks *, **, *** denote rejections of null hypothesis at 10%, 5% and 1% significance levels, respectively.

For the recursive window method, we can see that there have been some changes in the forecast range from the fluctuation of RMB exchange rate to the fluctuation of return in the energy industry. From the sample out-of-sample R^2_{oos} and the P value, the prediction ability is not so obvious in 9 weeks, but the prediction ability is strong in 3 and 6 weeks, because the period selected in this paper is 7 days per week, and the time gap is short. The longest period of 9 weeks is also two months. Usually, the forecasting ability of the exchange rate will remain for a period of time, and some can even be as long as 9 months. Therefore, this situation also has certain rationality. From the perspective of the length of the prediction interval, as the sub-interval is narrowed, the forecasting ability of the exchange rate is significantly enhanced. The highest is that the R^2_{oos} value of the last sub-interval reaches 7.336% when the forecast is 9 weeks. It has a close relationship with the return of the energy industry.

Table 7
Out-of-sample results for longer horizons of energy industry return volatility.

	2010.12–2018.9	2012.11–2018.9	2014.10–2018.9	2016.9–2018.9
Longer horizons h = 3				
Recursive	10.098**	11.157**	13.977*	14.932*
	(0.047)	(0.032)	(0.069)	(0.075)
Rolling	7.593*	8.214*	9.280*	10.071*
	(0.091)	(0.0503)	(0.0557)	(0.0554)
Longer horizons h = 6				
Recursive	13.151***	14.811**	15.079**	16.048**
	(0.003)	(0.016)	(0.041)	(0.044)
Rolling	8.792*	9.200*	10.317*	12.339*
	(0.058)	(0.067)	(0.075)	(0.075)
Longer horizons h = 9				
Recursive	5.541*	5.785*	6.044*	7.336*
	(0.088)	(0.071)	(0.065)	(0.053)
Rolling	4.334*	4.189*	5.349*	6.213*
	(0.052)	(0.0616)	(0.0712)	(0.087)

For the rolling window method, we can see that there have been some changes in the forecast range from the fluctuation of RMB exchange rate to the energy industry volatility. From the numerical point of view, the forecasting ability has not improved in 3 weeks, and the forecast value of the energy industry volatility has already had a negative value, indicating that the forecast of the RMB exchange rate on the energy industry's volatility is not desirable in the next three weeks. As with the recursive window, it is also relatively predictive in 6 and 9 weeks. From the length of the prediction interval, as the sub-interval is narrowed, the exchange rate prediction ability is significantly enhanced. The R^2_{oos} value of the subinterval reached 4.189% and 6.213%, except for the negative prediction of the second subinterval from November 2012 to September 2018. From the P worthy results, the significance is not very strong. Only when h = 6, it shows a certain significance. When there are 3 or 9 axes, there is basically not significant, which may be too short with time and hysteresis. Similarly, the R^2_{oos} value is not so large, indicating that the RMB/USD exchange rate fluctuation have a strong predictive power for the energy industry's returns in the case of rolling window forecasts.

7. Conclusions

It is well known that stock market volatility plays key roles in the academic literature for investigating the causes and consequences of the volatility dynamics in the stock market. This paper mainly uses the RMB/USD exchange rate fluctuation as a predictive indicator to analyze the impact of exchange rate on China's industry return volatility.

We establish several findings. First, in the in-sample analysis, the slope coefficient of the predicted regression of RMB/USD exchange rate fluctuation is significantly positive which shows there is very significant Granger causality from RMB/USD exchange rate fluctuations to China's industry returns volatility. Second, the out-of-sample results also indicate the RMB/USD exchange rate fluctuations has improved the predictive ability of industry return volatility. Thirdly, from the perspective of the extended model, the effect of the prediction ability of the nonlinear model under different window conditions will be different. In the case of nonlinearity, we find that the asymmetric index is not added and the prediction ability is improved, only in the individual. Fourthly, in predicting the long period, we found that the prediction ability in the short period (3 weeks) was not as good as imagined, but in the 6-week period, the prediction effect was significantly improved. Therefore, RMB/USD exchange rate fluctuations the RMB/USD exchange rate fluctuation have a strong predictive power for the industry returns volatility and the predictive ability is robust.

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References

[1] C.W.J. Granger, B.N. Huang, C.W. Yang, A bivariate causality between stock prices and exchange rates: evidence from recent asian flu, Q. Rev. Econ. Finance 40 (2000) 337–354.
[2] C.C. Nieh, C.F. Lee, Dynamic relationship between stock prices and exchange rates for G-7 countries, Q. Rev. Econ. Finance 41 (4) (2001) 477–490.
[3] D. Dimitrova, The relationship between stock prices and exchange rates: studied in multivariate model, Political Econ. 14 (2005) 1–25.
[4] M.S. Pan, R.C.W. Fok, Y.A. Liu, Dynamic linkages between exchange rates and stock prices: Evidence from East Asian markets, Int. Rev. Econ. Finance 16 (4) (2007) 503–520.

[5] N.D. Richards, J. Simpson, J. Evans, The interaction between exchange rates and stock prices: An Australian context, Int. J. Econ. Finance 1 (1) (2009) 3–23.
[6] G. Kutty, The relationship between exchange rates and stock prices: The case of Mexico, N. Am. J. Finance Bank. Res. 4 (4) (2010) 1–12.
[7] T. Moore, P. Wang, Dynamic linkage between real exchange rates and stock prices: Evidence from developed and emerging Asian markets, Int. Rev. Econ. Finance 29 (2014) 1–11.
[8] G.M. Caporale, J. Hunter, F.M. Ali, On the linkages between stock prices and exchange rates: Evidence from the banking crisis of 2007–2010, Int. Rev. Financ. Anal. 33 (2014) 87–103.
[9] Z. Qiao, Y. Li, W.-K. Wong, Policy change and lead–lag relations among China's segmented stock markets, J. Multinatl. Financ. Manage. 18 (2008) 276–289.
[10] H. Zhao, Dynamic relationship between exchange rate and stock price: evidence from China, Res. Int. Bus. Finance 24 (2010) 103–112.
[11] Li Liu, Jieqiu Wan, The relationships between shanghai stock market and CNY/USD exchange rate: New evidence based on cross-correlation analysis, structural cointegration and nonlinear causality test, Physica A 391 (23) (2012) 6051–6059.
[12] P. Jorion, The pricing of exchange rate risk in the stock market, J. Financ. Quant. Anal. 26 (1991) 363–376.
[13] R. Roll, Industrial structure and the comparative behavior on international stock market indices, J. Finance 47 (1992) 3–41.
[14] N. Antonakakis, Exchange return co-movements and volatility spillovers before and after the introduction of euro, J. Int. Financ. Market. Inst. Money 22 (5) (2012) 1091–1109.
[15] F. Beer, F. Hebein, An assessment of the stock market and exchange rate Dynamics in industrialized and emerging markets, Int. Bus. Econ. Res. J. 7 (8) (2011) 59–70.
[16] K. Grobys, Are volatility spillovers between currency and equity market driven by economic states? Evidence from the US economy, Econ. Lett. 127 (2015) 72–75.
[17] D. Choi, V. Fang, T. Fu, Volatility spillovers between New Zealand stock market returns and exchange rate changes before and after the Asian financial crisis, Asian J. Financ. Acc. 1 (2) (2010) 106–117.
[18] A. Mishra, N. Swain, D.K. Malhotra, Volatility spillover between stock and foreign exchange markets: Indian evidence, Int. J. Bus. 12 (3) (2007) 343–359.
[19] C. Walid, A. Chaker, O. Masood, J. Fry, Stock market volatility and exchange rates in emerging countries: a Markov switching approach, Emerg. Mark. Rev 12 (2011) 272–292.
[20] N. Oberholzer, S.T. Boetticher, Volatility spill-over between the JSE/FTSE indices and the south african rand, Proc. Econ. Financ. 24 (2015) 501–510.
[21] G. Schwert, Why does stock volatility change over time?, J. Finance 44 (1989) 1115–1153.
[22] B.S. Paye, Déja vol: predictive regressions for aggregate stock market volatility using macroeconomic variables, J. Financ. Econ. 106 (2012) 527–546.
[23] C. Christiansen, M. Schmeling, A. Schrimpf, A comprehensive look at financial volatility prediction by economic variables, J. Appl. Econometrics 27 (2012) 956–977.
[24] C. Conrad, K. Loch, Anticipating long-term stock market volatility, J. Appl. Econometrics 30 (2015) 1090–1114.
[25] N. Nonejad, Forecasting aggregate stock market volatility using financial and macroeconomic predictors: Which models forecast best, when and why, J. Empir. Financ. 42 (2017) 131–154.
[26] X. Gong, B. Lin, The incremental information content of investor fear gauge for volatility forecasting in the crude oil futures market, Energy Econ. 74 (2018) 370–386.
[27] X. Gong, B. Lin, Modeling stock market volatility using new HAR-type models, Physica A 516 (2019) 194–211.
[28] Y. Wang, F. Ma, Y. Wei, C. Wu, Forecasting realized volatility in a changing world: A dynamic model averaging approach, J. Bank. Financ. 64 (2016) 136–149.
[29] Y. Wang, Y. Wei, C. Wu, L. Yin, Oil and the short-term predictability of stock return volatility, J. Empir. Financ. 47 (2018) 90–104.
[30] J. Feng, Y. Wang, L. Yin, Oil volatility risk and stock market volatility predictability: Evidence from G7 countries, Energy Econ. 68 (2017) 240–254.
[31] L. Fang, Y. Qian, Y. Chen, H. Yu, How does stock market volatility react to nvix? evidence from developed countries, Physica A 505 (2018) 490–499.
[32] Y. Zhang, F. Ma, T. Wang, L. Liu, Out-of-sample volatility prediction: A new mixed- frequency approach, J. Forecast. (2019) 1–23.
[33] Z. He, L. He, F. Wen, Risk compensation and market returns: The role of investor sentiment in the stock market, Emerg. Mark. Finance Trade 55 (2019) 704–718.
[34] F. Wen, J. Xiao, C. Huang, et al., Interaction between oil and US dollar exchange rate: nonlinear causality, time-varying influence and structural breaks in volatility, Appl. Econ. 50 (2018) 319–334.
[35] F. Wen, J. Xiao, X. Xia, et al., Oil prices and chinese stock market: Nonlinear causality and volatility persistence, Emerg. Mark. Finance Trade 55 (2019) 1247–1263.
[36] E. Girardin, R. Joyeux, Macro fundamentals as a source of stock market volatility in China: A GARCH-MIDAS approach, Econ. Model. 34 (2013) 59–68.
[37] W. Pu, F. Ma, Forecasting the realized volatility in the Chinese stock market: further evidence, Appl. Econ. 48 (33) (2016) 3116–3130.
[38] J. Liu, C. Cheng, X. Yang, et al., Analysis of the efficiency of Hong Kong REITs market based on Hurst exponent, Physica A 534 (2019) 122035.
[39] H. Yu, L. Fang, W. Sun, Forecasting performance of global economic policy uncertainty for volatility of Chinese stock market, Physica A 505 (2018) 931–940.
[40] W. Cai, J. Chen, J. Hong, F. Jiang, Forecasting chinese stock market volatility with economic variables, Emerg. Mark. Finance Trade 53 (2017) 521–533.
[41] T.E. Clark, K.D. West, Approximately normal tests for equal predictive accuracy in nested models, J. Econometrics 138 (2007) 291–311.
[42] T.G. Andersen, T. Bollerslev, F.X. Diebold, P. Labys, Modeling and forecasting realized volatility, Econometrica 71 (2003) 529–626.
[43] J.Y. Campbell, S.B. Thompson, Predicting excess stock returns out of sample: Can anything beat the historical average?, Rev. Financ. Stud. 21 (2008) 1509–1531.
[44] Z. Dai, F. Wen, Some improved sparse and stable portfolio optimization problems, Finance Res. Lett. 27 (2018) 46–52.
[45] Z. Dai, H. Zhu, F. Wen, Two nonparametric approaches to mean absolute deviation portfolio selection model, J. Ind. Manag. Optim. (2019) http://dx.doi.org/10.3934/jimo.2019054.
[46] Z. Dai, H. Zhou, F. Wen, Improved forecasting of stock return volatility: oil realized volatility and stock implied volatility, Res. Int. Bus. Finance (2019) in press.
[47] Z. Dai, H. Zhou, A modified Fletcher-Reeves conjugate gradient projection method for nonlinear programming problems with linear equality constraints, Mathematics (2019) in press.
[48] X. Gong, B. Lin, Forecasting the good and bad uncertainties of crude oil prices using a HAR framework, Energy Econ. 67 (2017) 315–327.
[49] X. Gong, B. Lin, Structural breaks and volatility forecasting in the copper futures market, J. Futures Mark. 38 (3) (2018) 290–339.
[50] H. Akaike, Information theory and an extension of maximum likelihood principle, in: B.N. Petrov, F. Csaki (Eds.), Second International Symposium on Information Theory, Akademiai Kiado, Budapest, 1973, pp. 267–281.
[51] G. Schwarz, Estimating the dimension of a model, Ann. Statist. 6 (1978) 461–468.
[52] A. Inoue, L. Kilian, In-sample or out-of-sample tests of predictability: Which one should we use?, Econom. Rev. 23 (2004) 371–402.
[53] B. Rossi, A. Inoue, Out-of-sample forecast tests robust to the choice of window size, J. Bus. Econom. Statist. 30 (2012) 432–453.