

An Exploration of Realized Volatility and Returns in the Chinese Stock Market

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Abstract. This paper uses high-frequency stock index data to construct realized volatilities for the Chinese stock market and applies in-sample and out-of-sample R^2 to test the predictive power of realized volatility on Chinese stock market returns. The empirical results show that realized volatility can significantly predict the excess return of the Chinese stock market in the next month, and the in-sample and out-of-sample regression models R^2 are positive, and the out-of-sample R^2 . The p-value of the regression model is significant. And after controlling for a range of other stock predictor variables, we find that the regression coefficient of realized volatility is still significant, and we find that after adding realized volatility, the in-sample adj- R^2 increases with the inclusion of realized volatility, suggesting that realized volatility does have components that are not explained by other economic variables. Also based on a different construction method, the realized variance still has significant predictive power after averaging the realized variance. After combining two different realized variance indicators, the predictive power is still better. In terms of economic interpretation, this paper finds that the predictive power of realized variance on stock returns is through influencing the turnover rate (market trading activity), which in turn influences stock market returns. We find that realized volatility has a significant effect on the turnover rate, and when we use realized volatility to predict the turnover rate, which in turn predicts the excess return, we find that the coefficient is highly significant, indicating that realized volatility can indeed cause changes in excess return by affecting the turnover rate.

Keywords: Realized volatility; Chinese stock market; out-of-sample forecasts.

1. Introduction

According to Merton's (1980) ICAPM theory, stock market investors need to receive higher expected excess returns as compensation for taking higher market risk, i.e., there is a positive correlation between market risk and expected excess returns of stocks. And we generally define realized volatility as risk. Harvey and Siddique (2000a, 2000b) introduced skewness risk on top of Merton's, which considered skewness risk on top of the original market risk.

In order to better study realized volatility, Engle and Gallo (2006) proposed the MEM model by adding two realized volatilities to the original GARCH model, in addition to the original return squared, which are the intra-day extreme deviation (daily maximum price of one day minimum) and the realized variance. The realized volatility used in this paper is the realized variance. In contrast, the HEAVY model proposed by Shephard and Sheppard (2010) incorporates the Realized kernel. These two models are distinguished from the traditional GARCH models by the inclusion of realized variance. Based on these new models, Hansen et al. (2011) propose a model called Realized GARCH, which adds a metric equation as a bridge to link the realized variance and the return equation.

Zhengguo Xu and Shiyong Zhang (2004) compare the fit of various volatility models with the actual capital market through empirical analysis based on Shanghai market data. It is found that the models of the self-implemented variance class perform better than both stochastic volatility and ARCH class models. An empirical study by Yi-Wen Yu (2006) also has similar findings. It shows that realized volatility does have a relationship with future returns.

Chen, Guojin and Wang, Zhanhai (2010) take the above decomposition of realized volatility a step further through a rigorous numerical analysis. And empirical analysis of the leverage effect and the

scale effect over the sample time finds that the scale effect is more significant relative to the leverage effect.

This paper examines the predictive power of realized volatility of the Chinese stock market on market returns. Its predictive power is found to be indeed better than that of general economic variables. Jiang Fuwei et al. (2011) suggest that economic variables can predict stock returns. This paper argues on this basis.

In the empirical analysis, this paper first constructs the realized variance of the Chinese stock market as realized volatility, and referring to Amaya et al. (2015), this paper uses the 5-minute high frequency data of the SSE index from April 2005 to May 2017 to calculate the realized variance of the market as a proxy variable for risk.

After calculating the realized variance of the Chinese stock market, this paper tests the predictive power of realized volatility on the excess return of the stock market in the coming month through a predictive regression model. The results show that the parameter estimate of the beta coefficient in the regression model is -0.14 and has a t-value of -1.92, which is significant at the 10% confidence level. This indicates that lower realized market volatility can predict higher market returns, which is consistent with the results of Amaya et al. (2015). The predictive power of realized volatility remains statistically significant when we add realized skewness, realized kurtosis, and a range of economic variables to the forecasting model as in Jian Chen (2018). This suggests that realized variance contains unexplained forecasting information that is not available in these forecasting variables. Therefore, volatility risk should be fully considered in actual portfolio management to help improve investment returns. This paper finds that realized variance has a strong out-of-sample predictive power, with its out-of-sample R^2 reached 9.12% and was statistically significant. This indicates that the out-of-sample predictive power of realized variance is better than the benchmark indicator.

When assuming a risk aversion factor of 3 for investors, the model based on realized variance yields an annualized utility gain (CER gain) of 4.89% with a Sharpe ratio (SR) of 0.10 (here, the SR of realized volatility minus the SR of the benchmark). The highest CER gain for other variables with significant predictions is 4.36% less than the value of realized volatility. The results of the in-sample and out-of-sample empirical tests show that realized volatility has a better predictive power.

Next, this paper explains this predictive power in economic terms. By examining the relationship between realized volatility and stock market turnover, we find that a change in realized volatility does lead to a change in turnover, with greater market turnover accompanied by higher market liquidity. However, due to the increased market risk, we find that while market liquidity increases, the demand for excess returns still becomes higher. Further, this paper finds a significant positive correlation between expected market trading activity and excess return in the stock market, indicating that investors need a higher risk premium. In summary, realized volatility is negatively correlated with future equity excess returns.

Finally, to illustrate the robustness of the realized variance forecasting ability, a series of robustness experiments are done in this paper. It is found that realized volatility remains significant under different construction methods, and the regression coefficients are also significant using the means of different construction methods. It indicates that realized variance does enable a better predictive power for future excess returns.

The article is structured as follows: Part II explains the calculation of realized volatility with the explanatory econometric test methodology, Part III presents the empirical evidence, and Part IV concludes the entire article.

2. Model and measurement test methods

2.1 Construction method of realized variance

Referring to Amaya et al. (2015), the realized volatility in this paper is the realized variance, and the realized variance is calculated in the following steps:

In the first step, daily stock returns are constructed using 5-minute intra-day high-frequency index prices:

$$r_{t,i} = p_{t,i} - p_{t,(i-1)} \quad (1)$$

Where $r_{t,i}$ denotes the logarithmic rate of return at the moment i of day t , and $p_{t,i}$ denotes the logarithmic price at the moment of day t day i . The time periods are the market prices at 9:30-11:30 and 13:00-15:00 of each trading day. There are 48 log returns in a trading day.

In the second step, the daily realized variance is calculated. First, the daily realized variance (RDvar) is the sum of the squares of the intra-day returns, according to Anderson and Bollerslev (1998) and a subsequent series of literature on the construction of realized variances or volatilities:

$$RDVar_t = \sum_{i=1}^N r_{t,i}^2 \quad (2)$$

In the third step, the monthly realized variance (Rvar) is the sum of the daily realized variances of all trading days in the month:

$$Rvar_t = \frac{1}{22} \sum_{i=0}^{21} RDvar_{t-i} \quad (3)$$

Where 22 indicates 22 trading days in a month.

2.2 Test methods for in-sample prediction

Referring to Jiang Fuwei et al. (2011) and other related literature on stock forecasting, this paper examines the predictive power of realized skewness on stock market returns through a univariate predictive regression model:

$$R_{t+1} = \alpha + \beta Rvar_t + \varepsilon_{t+1} \quad (4)$$

Where R_{t+1} is the excess stock market return at moment $t+1$, and $Rvar_t$ is the realized variance at moment t , and ε_{t+1} is the residual term. To determine the predictive power of realized variance on stock excess return, the main objective is to estimate β in model (4) by least squares (OLS) to obtain the predicted value of the estimate β and the corresponding t -statistic. The original hypothesis of the test is $\beta = 0$, which means that realized variance has no predictive power; the alternative hypothesis is $\beta \neq 0$, which means that realized volatility can predict future stock excess returns.

To compare the realized variance with the predictive power of the economic variables, first, the predictive power of these economic variables is examined.

$$R_{t+1} = \alpha + \beta Rvar_t + \sum \phi_i X_{i,t} + \varepsilon_{t+1} \quad (5)$$

If β remains statistically significant in model (5), it indicates that the realized variance contains additional forecasting information that cannot be explained by other economic variables. Then, when forecasting Chinese stock market returns, realized variance should be added to the forecasting model to improve the forecasting power of the model.

2.3 Test methods for out-of-sample prediction

According to Campbell and Thompson (2008) and Welch and Goyal (2008), the out-of-sample test method first requires dividing the total sample observations into two parts: an in-sample initial estimation period consisting of n_1 observations and an out-of-sample detection period consisting of n_2 observations. In the in-sample initial estimation period, the initial window length of this paper is 24, and the first out-of-sample predicted stock return is obtained by bringing in data from model (4):

$$\hat{R}_{n_1+1} = \hat{\alpha}_{n_1} + \hat{\beta}_{n_1} Rvar_{n_1} \tag{6}$$

$\hat{\alpha}_{n_1}$ And $\hat{\beta}_{n_1}$ is the number of terms that can be added according to model (4) to $\{R_{t+1}\}_{t=1}^{n_1-1}$ to the constant term and $\{Rvar_t\}_{t=1}^{n_1-1}$ the parameter estimates obtained by doing linear regression. The next period is extended by one period and the out-of-sample prediction model for the next period is:

$$\hat{R}_{n_1+2} = \hat{\alpha}_{n_1+1} + \hat{\beta}_{n_1+1} Rvar_{n_1+1} \tag{7}$$

$\hat{\alpha}_{n_1+1}$ And $\hat{\beta}_{n_1+1}$ is the number of terms that can be added according to model (5) to $\{R_{t+1}\}_{t=1}^{n_1}$ to the constant term and $\{Rvar_t\}_{t=1}^{n_1}$ the parameter estimates obtained by doing a linear regression. And so on, continuously expanding the estimation window, a total of n_2 out-of-sample stock return predictions can be obtained \hat{R}_{t+1} .

Contrast this with the forecast model based on realized volatility (4), where the benchmark forecast model (BENCH) is the historical average return of.

$$\bar{R}_{t+1} = \frac{1}{t} \sum_{j=1}^t R_j \tag{8}$$

If the out-of-sample R_{OS}^2 is greater than zero, it indicates that realized volatility has stronger forecasting power than the historical mean, which ignores useful forecasting information. According to Campbell and Thompson (2008), out-of-sample R^2 (R_{OS}^2) is defined as.

$$R_{OS}^2 = 1 - \frac{\sum_{k=1}^{n_2} (R_{n_1+k} - \hat{R}_{n_1+k})^2}{\sum_{k=1}^{n_2} (R_{n_1+k} - \bar{R}_{n_1+k})^2} \tag{9}$$

When $R_{OS}^2 > 0$, it indicates that \hat{R}_{t+1} the out-of-sample ability of is stronger than the \bar{R}_{t+1} the out-of-sample forecasting ability. Conversely, it indicates that the out-of-sample forecasting ability of realized volatility is weaker than the historical average forecast. Clark and West (2007) propose an MSFE-adjusted statistic for $R_{OS}^2 > 0$ for hypothesis testing.

2.4 Asset allocation

According to Campbell and Thompson (2008), this paper examines the out-of-sample predictive power of realized volatility in addition to the economic significance of its predictive power. We use the traditional CER measure and SR (Sharpe Ratio), assuming that stock investors can use the out-of-sample forecasts of realized volatility to make asset allocations to purchase a risky asset (stocks) and a risk-free asset (bonds). According to Markowitz's mean-variance utility function, at time t for satisfying utility maximization, the optimal weight of the stock held by the investor is:

$$\omega_t = \frac{1}{\gamma} \frac{\hat{R}_{t+1}}{\hat{\sigma}_{t+1}^2} \tag{10}$$

Where γ is the risk aversion coefficient, and \hat{R}_{t+1} is the out-of-sample predicted value of the excess stock return, and $\hat{\sigma}_{t+1}$ is the predicted value of the variance of returns. Correspondingly, the weight assigned by the investor to the risk-free asset is $1 - \omega_t$. Thus, the portfolio return at moment t+1 is:

$$R_{t+1}^p = \omega_t R_{t+1} + R_{t+1}^f \tag{11}$$

Where R_{t+1}^p the total portfolio is return, and R_{t+1} is the excess return on equity, and R_{t+1}^f is the return on risk-free assets.

In this paper, we refer to the parameter setting of Chen Jian (2018) to estimate the future variance using stock returns over a two-year rolling window, with stocks allowing up to 50% leverage for short selling and a risk aversion factor given as 3^6 . Towards the same as in Chen Jian (2018), we use CER and SR to measure returns.

$$CER = \hat{\mu}_p - 0.5\gamma\hat{\sigma}_p^2 \tag{12}$$

$\hat{\mu}_p$ And $\hat{\sigma}_p^2$ are, respectively, the out-of-sample test period portfolio returns (R_{t+1}^p) of the mean and variance. Cer can be interpreted as the equivalent risk-free return that investors are willing to forego risky investments and thus earn. The Sharpe ratio (SR) is the mean of the portfolio returns divided by the standard deviation.

3. Empirical analysis

3.1 Data description

According to models (1)-(3), this paper constructs the monthly realized variance of the SSE market using the 5-minute high-frequency data of the SSE index, which is collated from the wind database with the sample period from April 2005 to June 2017. Figure 1 gives the monthly realized variance time series of the Shanghai stock market. From Figure 1, we can see that the realized variance is larger at the time of stock debt, such as the financial crisis in 2008 and the stock market crash in 2015, and smaller at other times. At that time, people's sentiment was more pessimistic and herding effect was more obvious due to the stock market crash, which made it easier to form the scenario of a sharp rise and fall, resulting in a greater realized volatility of the stock market. In this paper, we choose monthly data of SSE index to calculate the log return of the stock market, and the excess return is the monthly return minus the monthly risk-free rate.

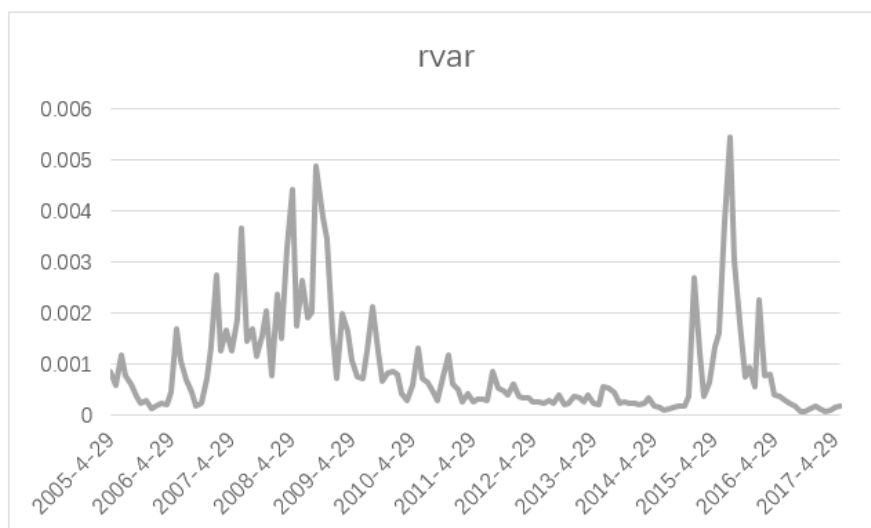


Figure 1. Time series with realized variance (Rvar).

Also in this paper, we refer to Welch and Goyal (2008) Chen Jian and Zhang Yifan (2018) and Jiang Fuwei et al. (2011) to select 10 other predictor variables for comparison of predictive power, including the realized skewness of the stock market (Rskew), and the realized kurtosis of the stock market, constructed with reference to Amaya et al. (2015); the in-flux cash growth rate (MG); dividend price ratio (d/p) is the difference between the logarithm of the sum of dividends and the logarithm of market capitalization for all listed A-shares; dividend yield (d/y) is the difference

between the logarithm of the sum of dividends and the logarithm of the sum of lagged market capitalization for all listed A-shares; face value to market value ratio (bm) is the ratio of the logarithm of the sum of equity to the logarithm of the sum of market capitalization for all listed A-shares; turnover rate (T0) total listed A-share Inflation rate (Inf) is the monthly year-on-year growth rate of consumer price index (CPI); producer price index (PPI) is the monthly year-on-year growth rate; according to the stock market illiquidity indicator (Illi) constructed by Amihud (2002), we choose the absolute value of daily return of SSE index divided by the daily trading volume, and average it by month to obtain Monthly illiquidity index.

Table 1. Descriptive statistics of the data.

	mean	std	skew	Kurt	min	max	p
return	-1.47	8.74	1.11	-0.27	-27.23	25.33	0.18
rvar	9.26	10.16	4.82	2.12	0.00	0.01	-0.99
skew	0.01	0.25	3.73	-0.81	-1.22	0.72	-0.89
kurt	4.59	1.41	5.74	2.16	2.75	11.13	-0.90
mg	0.16	0.04	1.75	1.28	0.09	0.30	-0.95
d/p	0.00	0.07	0.90	0.51	-0.17	0.21	-0.98
b/m	-0.92	0.19	0.20	0.63	-1.33	-0.47	-0.95
t0	15.83	9.92	5.76	2.19	3.98	56.04	-0.52
inf	0.03	0.02	0.70	0.70	-0.02	0.09	-0.99
PPI	0.01	0.05	-1.11	-0.09	-0.08	0.10	-0.97
ill	0.37	0.36	7.76	2.55	0.07	2.26	-0.32
d/y	0.00	0.09	0.83	-0.48	-0.27	0.22	-0.98

Note: The rate of return, inflation rate, and producer price index are given in percentage form, and the realized variance is given as a millionth ratio. The sample period is 2005:04-2017:06, with 147 observations.

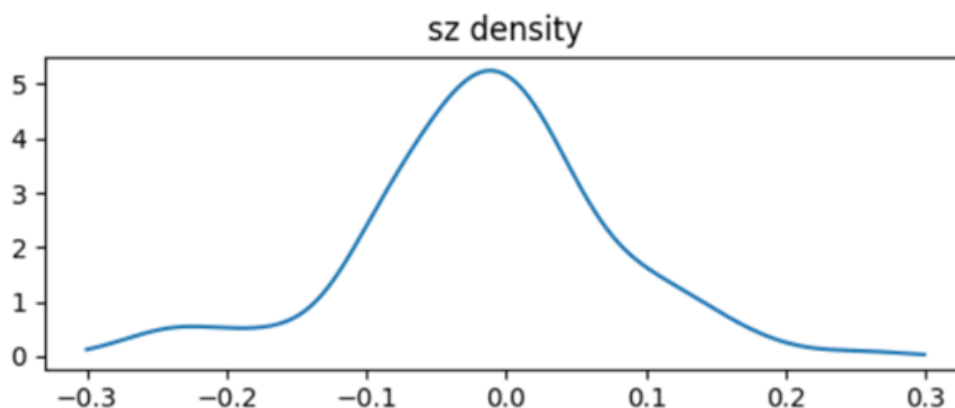


Figure 2. Probability Distribution of Shanghai Market Yield.

The descriptive statistics of all variables are given in Table 1. First, the stock market excess return (return) is the logarithmic return of the SSE index minus the risk-free rate, with a mean of -1.47%, a standard deviation of 8.74, and a sample skewness of 1.11. The Shanghai stock market return is characterized by a "right skew". The probability distribution is plotted in Figure 2. The Sharpe ratio of stock returns is 0.06. The mean of realized variance is 0.092, the standard deviation is 10.16, and the skewness is 4.82. The autocorrelation coefficient (ρ_1) of realized variance is also high, while the autocorrelation coefficients of most economic variables are relatively high.

3.2 Main empirical results

3.2.1 In-sample prediction results

Table 2. presents the parameter estimation results for the forecasting models (4) and (5), reporting the beta parameter estimates, the corresponding t-statistics (NW-t), and the adjusted regression model R^2 , we can find significant beta parameter estimates for realized variance, which indicates that lower realized variance can predict higher future excess market returns. This finding is consistent with previous human studies.

Table 2. Univariate regression results.

	β	t	Adj-R2		β	t	Adj-R2
skew	-2.7	0.93	-0.001	b/m	11.5***	3.09	0.055
kurt	-0.23	-0.449	-0.005	t0	0.08	1.2	0.003
rvar	-0.14*	-1.92	0.018	inf	-131.49***	-3.975	0.092
mg	20.97	1.27	0.004	PPI	35.99**	-2.34	0.03
d/p	-10.13	-1.00	0	ill	-3.83	-1.916	0.018
d/y	11.89	1.44	0.07				

Note: The Adj-R2 in the table is the adjusted R^2 , which is given as a percentage.***, **, and * represent statistical significance at 1%, 5%, and 10%, respectively. The sample period is 2005:05 to 2017:6, with 147 observations

Compared to the other predictor variables, it can be found that most of the β are insignificant (except for b/m, t0, PPI). In particular, it can be seen that the predictive power of realized skewness and realized kurtosis is not significant, suggesting that volatility risk is more important in the Chinese market. Moreover, the adj based on these predictor variables R^2 are -0.5% to 0.4%, which are smaller than the realized variance. In addition the predictive power of the non-liquidity indicators in Table 2. Is not significant and is not consistent with the results of Amihud (2002). However, the results of Ben-Rephael et al. (2015) using Amihud liquidity indicators on the liquidity premium of the U.S. equity market found that the liquidity premium of the U.S. equity market has been decreasing in significance over time. The reason for this is mainly because the illiquidity (Illiquidity) premium is gradually disappearing as the stock market has become much more liquid in recent years with regulatory reforms and technological advances, making trading activities increasingly frequent.

We run a regression using model (5) and find that when other economic variables are added to the model, we find that the realized variance remains significant, indicating that the realized variance does predict earnings and contains a component that is not explained by other economic variables. The results are shown in Table 3, where we find that the coefficient of realized variance is still significant when other economic variables are added and R^2 is increased, indicating that the realized variance does have a part that cannot be explained by other economic variables. Considering that some economic variables are strongly correlated, only one of the inclusion of d/y, d/p, b /m is considered when adding economic variables.

Table 3. Regression results after controlling for economic variables.

	(1)	(2)	(3)
rvar	-5.997** (-2.02)	-0.198** (-2.11)	-0.169* (-1.82)
skew	-5.997* (-1.891)	-5.56* (-1.699)	-3.35 (-1.17)
kurt	0.12 (0.199)	0.17 (0.27)	-0.13 (-0.209)
mg	8.41 (0.473)	9.06 (0.508)	12.9 (0.74)
T0	0.128 (1.51)	0.13 (1.58)	0.21** (2.44)
Inf	-136.37** (-2.49)	-134.74** (-2.45)	-68.46 (-1.14)
ppi	4.08 (0.19)	4.25 (0.196)	-7.34 (-0.34)
ill	3.72 (1.12)	3.42 (1.034)	2.07 (0.643)
d/y	12.04 (1.28)		
d/p		-9.87 (-0.838)	
b/m			12.15** (2.479)
R2-adj	0.099	0.093	0.127

Note: The adj- R^2 in the table is the adjusted R^2 , which is given as a percentage.***, **, and * represent statistical significance at 1%, 5%, and 10%, respectively. The sample period is 2005:05 to 2017:6, with 147 observations

3.2.2 Out-of-sample prediction results

Out-of-sample forecasts are more instructive for investors' investments. Therefore, this section will examine the out-of-sample forecasting ability of realized volatility. The sample test period is from April 2008 to June 2017, and the out-of-sample is calculated according to the tests given in equations (8) to (11) R_{os}^2 and their p-value statistics. The results are shown in Table 4 and it can be seen that the realized variance of out-of-sample R_{os}^2 is positive and significant, indicating a good predictive power, and we find that the out-of-sample realized variance R_{os}^2 is also extremely significant for the other economic variables R_{os}^2 , but considering that the predictions of economic variables are not significant, but the realized variance is still significant, indicating that the realized variance has a stronger explanatory power among a series of explanatory variables.

Table 4. Out-of-sample prediction tests.

	R_{os}^2	p-value		R_{os}^2	p-value
skew	0.062***	0.002	Inf	0.19***	0.005
rvar	0.0912*	0.07	ppi	0.10***	0.00
kurt	0.067***	0.00	ill	0.098***	0.00
mg	0.088***	0.00	d/y	0.059***	0.001
t0	0.073	0.5	bm	0.13***	0.00
d/p	0.057***	0.00			

3.3 Asset Allocation

The strong forecasting power of realized volatility has been shown above, and the next step is to analyze the role of this forecasting power in enhancing portfolio returns. We can calculate the utility return spread (CER gain) and the Sharpe ratio spread (SR) for portfolios constructed using out-of-sample forecasts based on Equations (12) to (14). As in the economic sense, the result can be interpreted as the annualized management fee that the investor is willing to pay in order to obtain an investment strategy based on realized variance of 489 basis points. In an economic sense, the result can be interpreted as an annualized management fee of 489 basis points that an investor is willing to pay in order to obtain an investment strategy based on realized skewness.

Table 5. Asset Allocation Table.

	Cer gain	sr		Cer gain	sr
skew	2.75	0.05	Inf	4.36	0.09
rvar	4.89	0.10	ppi	3.28	0.06
kurt	4.31	0.08	ill	4.11	0.08
mg	4.93	0.098	d/y	4.74	0.096
t0	3.40	0.07	bm	4.07	0.08
d/p	4.70	0.09			

Notes: ***, and** , and * represent statistical significance at 1%, 5%, and 10%, respectively. The sample period is 2008:04 to 2017:6, with 123 observations

3.4 Economic explanation of predictive power

This section wants to explain the economic interpretation of realized volatility on the predictive power of the Chinese stock market. A decrease in realized volatility indicates a decrease in the risk of the market. Considering that the activity of the trading market may affect stock prices and returns, the turnover rate of the stock market is chosen to test whether realized volatility affects future excess returns through the turnover rate.

For this purpose we use the method used in Chen, Jian, and Zhang, Yifan (2018), first Granger test, and secondly by stepwise regression model to test the transmission mechanism between realized variance, market trading activity, and future stock market returns. The specific steps are as follows. In the first step, the relationship between realized variance and stock trading activity.

$$Y_{t+1} = \alpha + \beta RSkew_t + \sum \phi_i X_{i,t} + \varepsilon_{t+1} \tag{13}$$

Y_{t+1} denotes the stock market turnover rate in period t+1 (T0). $X_{i,t}$ Represents the control variables in period t: rvar, rkurt, MG, T0, Inflation, PPI, Illiq Step 2, the relationship between the expected market trading activity and the stock market excess return.

$$R_{t+1} = \alpha' + \beta' \hat{Y}_{t+1} + \sum \phi'_i X_{i,t} + \varepsilon_{t+1} \tag{14}$$

\hat{Y}_{t+1} Is the expected turnover rate in period t+1 (Expt0) obtained from the regression model above, R_{t+1} denotes the stock market return in period t+1.

For the Chinese market, Zhang, Zheng and Liu, Li (2006) find that there is a negative correlation between the rate of change of hands and the rate of return in the Chinese stock market.

From Table 6 we can see that realized variance does affect the turnover rate, and we can also explain the return with the turnover rate predicted by realized variance. Table 7 shows that realized variance becomes larger, market risk becomes larger, market turnover rate increases, which affects people's expectation and market excess return rises.

Table 6. Granger's test.

Granger Inspection		
	F-value	p-value
H0:rvar does not cause t0	3.35	0.06
H0:t0 does not cause rvar	0.38	0.53

Table 7. Test of economic explanation regression results.

$Y_{t+1} = \alpha + \beta Rrvar_t + \sum \phi_i X_{i,t} + \varepsilon_{t+1}$ $R_{t+1} = \alpha' + \beta' \hat{Y}_{t+1} + \sum \phi'_i X_{i,t} + \varepsilon_{t+1}$							
	β	t-value	p-value		β	t-value	p-value
t0	0.31***	4.052	0.00	expt0	0.92***	27.7	0.00

Notes: ***, and** , and * represent statistical significance at 1%, 5%, and 10%, respectively. The sample period is 2008:04 to 2017:6, with 123 observations

3.5 Robustness tests

This section examines the robustness of the forecast results by first constructing the realized variance using different construction methods and then using different markets to see if this law is useful.

Referring to Amaya et al. (2015), this paper utilizes an alternative method to construct the realized variance adjusted by the mean of the realized variance (Rvar _Drift). The in-sample and out-of-sample prediction results of realized skewness obtained based on this different construction method are given in Table 8.

As can be seen, consistent with the results in Tables 3, 4, and 5, this different realized variance still significantly predicts future stock market returns. Specifically, the in-sample test results with negative and statistically significant estimates of the β parameter indicate that low variance (i.e., high downside risk) predicts high expected future returns.

In addition, we further enhance the predictive power of skewness by combining realized skewness indicators obtained from different construction methods based on the existing empirical evidence. Referring to Rapach et al. (2010), we use Mean Combination to forecast the Chinese stock market. The results of the combined forecasts are given in the last row of Table 8, respectively. It can be seen that the beta coefficients obtained from the combined forecasting approach remain significant and are consistent with the forecasting results of the single variance risk indicator.

Table 8. Robustness test table.

	β	T-value	P-value	R^2_{os}	P-value
Rvar_drift	-0.136*	-1.92	0.057	0.092***	0.00
Rvar_mean	-0.135*	-1.92	0.057	0.091***	0.00

Notes: ***, and** , and * represent statistical significance at 1%, 5%, and 10%, respectively. The sample period is from 2005:04 to 2017:6, with a total of 147 observations

4. Conclusion

This paper focuses on verifying the predictive power of realized variance in the Chinese market for stock market excess returns. The results show that realized variance can predict the future one-month stock market excess return significantly, and this predictive power remains significant even after considering other predictor variables of the Chinese stock market. Moreover, adding realized volatility to the model with existing predictor variables R^2 this is a significant improvement. This indicates that realized volatility contains predictive information that cannot be explained by other predictor variables. Moreover, we can explain how realized variance affects the market from the

turnover rate. When the market risk increases, people feel that there are higher returns in the market at this time, and the trading activity in the market increases, which shows that the turnover rate increases, although taking into account the decrease in liquidity premium, high market risk still requires high stock market excess return, which is consistent with the high risk and high return characteristics. Finally, in the robustness test, we find that the results are basically consistent and have strong predictive power in different markets with realized variance.

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