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Forecast and Application of the Yield Rate of the CSI 300

Xiaoyu Wang[a]

School of Economics and Management, Nanjing University of Science and Technology, Nanjing 210014, China

[a]2190244513@qq.com

Abstract

This paper conducts an empirical study on the yield rate of the CSI 300 index from four perspectives of international capital market volatility, domestic macro economy and investor sentiment. The research results can help policy makers accurately grasp the impact of foreign macro and investor sentiment fluctuations on the stock market. In this paper, the CSI 300 index is selected as the research sample, and four predictive variables are selected after data processing by gradual regression method to obtain the US stock market volatility index (EMV) and turnover rate (TURN). Meanwhile, the stock time window (2006-2018) is divided into two parts: training period and forecast period for out-of-sample expansion prediction, and its economic benefits are determined by calculating CER; finally, the Shanghai 50 index and change data samples are tested until June 2019. School of Economics and Management.

Keywords

SCI300; EMV; TURN.

1. Introduction

The predictability of stock yields in academic research is very interesting. Eugene and Robert are two scholars who hold opposite views on market effectiveness theory[1]. Eugene believes that all the market information is already reflected in current prices, so it is impossible to predict stock earnings if the market is effective. Schiller believes that the market is not fully effective, because there are a lot of irrational traders. But their respective theories have been tested in different historical periods. Therefore, academic researchers need to produce more adapted capital asset pricing models. The financial market is running dynamically, and the asset pricing model studied before may not adapt to the current market environment. Therefore, it is necessary to use the current domestic and foreign data to do further mining research on the current market. The rapid development of data mining technology and quantitative investment software also facilitates the in-depth study of the capital market. It can be seen from the current domestic and foreign literature review that there are many studies on mature foreign stock markets, and the views are relatively unified. However, there are few documents on prediction research adapted to the characteristics of the country's stock market, and there are many valuable and innovative factors that have not been explored. Therefore, it is of great theoretical significance to explore the useful predictors and model methods applied to China's stock market.

On November 26,1990 and December 1,1990, the Shanghai Stock Exchange and the Shenzhen Stock Exchange were formally established. Up to now, China's securities market has developed for nearly 30 years. During the nearly 30 years, China's securities market has been reforming and developing, gradually becoming a key link in the development of market economy in the new period of socialism. Although the stock market shows a growing trend in terms of companies and shareholders, the investment returns of investors, especially small and medium

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investors, in the stock market are not ideal. In the financial crisis and volatile market, most investors are in a loss state. Especially in 2018, when the global economy fell and the stock market plunged, A shares fell first in the world, among which the Shanghai Composite Index fell 24.59%, the GEM index fell 28.65%, the Shenzhen Component Index fell 34.42%, the Shanghai 50 index fell 19.83%, the small and medium-sized board index fell 37.75%, and the Shenzhen index fell 35.90%. According to the survey, the per capita loss of shareholders was 10,60,600 yuan in 2018. At the same time, the launch of the science and technology innovation board and the registration system responds to the country's confidence in the reform and improvement of the stock market, and promotes the healthy development of the capital market at various levels. Shanghai and Shenzhen 300 index, on April 8,2005 by the Shanghai and Shenzhen stock exchange jointly compiled and issued reflects the csi 300 index running financial index, due to the index sample from the Shanghai and Shenzhen two city circulation of stock market value, high market representative, strong liquidity, flexible trading, so as to reflect the investment income of market institutions, thus reflects the overall trend of the Shanghai and Shenzhen two cities. From the historical trend, the CSI 300 and the Shanghai Composite Index fit very well. Meanwhile, the CSI 300 component stocks are all leading stocks in various industries with a smooth and upward trend, which can be better used as an investment industry.

2. Literature Review

2.1. Foreign Literature Review

First, many scholars have studied the predictability of return on assets. Fama and French (1998), Lewellen et al. (2004) studied and proved that the financial data such as dividend price ratio can predict the yield of the US stock market[2-3]. Chen[4]on the basis of previous research on emerging markets, in particular, research on China's a-share market shows that China stock market participants is given priority to with retail, and retail widespread government-led concept, and with European and American market investors behavior financial deviation, including gamblers psychology, psychological account, overconfidence, loss avoidance, herd effect, such as behavior, lead to stock prices easy to deviate from the intrinsic value. At the same time, the A-share market only has the index short selling mechanism, no stock short selling mechanism, so that it is easy to arbitrage almost. These conclusions can show that China's A-share market is not effective and can predict the yield to A certain extent. It can be seen that a large number of foreign scholars believe that the return rate in the stock market of various countries has certain predictability. In China's stock market, because there is no short selling mechanism and retail-led market, there is behavior deviation and predictability.

Second, there are a lot of factors in the market affecting stock yields. With the opening of the global capital market, the international market has a great impact. Rapach et al. considered the linkage of the international market, not only studying domestic stock returns from domestic economic variables, but also collected economic data from the United States to study whether these data can track the earnings of China's A shares[5]. Research shows that China's accession to the WTO is a watershed. After China's accession to the WTO and the opening of international capital market flows, the US economic data has significant forecasts of China's A-shares. At the same time, combining US and Chinese data into multiple factorial prediction is better. Budd and Bruce[6] studied the spillover effect of the US stock market and the US stock market volatility index, and showed that the volatility of the US market will cause the volatility of the stock market in Asian countries. It can be seen that the economic variables of the United States and other international markets can be used to predict the stock return rate in China, and the prediction effect is better based combining the domestic economic variables.

In addition, some scholars have found that macroeconomic variables can predict stock returns. Chen [4] takes the S & P 500 stock as the research object. The empirical analysis shows that the

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macro data such as industrial added value, inflation rate and money supply in the United States can predict the stock yield under certain conditions, mainly through the transmission mechanism of the dividend discount model. Dhaka et al.[7] was somewhat different, using time-series vector autoregression analysis to suggest that money supply rather than industrial production and inflation affecting US stock yields. Nelson[8], Fama and Schwert[9], Campbell and Vuolteenaho[10] believe that the inflation rate is a good forecast yield. Rapach[11] concluded that interest rate was the most reliable predictor of all the macroeconomic variables studied. Moreover, the nominal interest rate was also recognized by the empirical results in the Ang and Bekaert[12] studies. Meanwhile, Fama and French[13] studied the importance of term spreads and default spreads. It can be seen that short-term interest rate, term spread, default spread, money supply, inflation rate, industrial added value and other macroeconomic indicators will significantly affect the stock price.

Along with the rise of behavioral finance, some scholars have developed a strong interest in psychology and behavioral science, and focus on the prediction effect of market sentiment. Malcolm Baker et al.[14] selected the four indicators that showed the most possible investor sentiment index according to the correlation analysis, and conducted the principal component analysis of these four indicators. Finally, the same method is used to construct the comprehensive index of investor sentiment in six capital markets of different countries, so as to study the transmission mechanism of investor sentiment to the stock market. Lemmon[15] selected the consumer sentiment index from the perspective of economic outlook expectations to measure investor sentiment, and found that the index has a certain predictive ability for the stock market. Guo[16] believes that stock market volatility and turnover rates are a good forecast of stock returns.

2.2. Internal Literature Review

Many domestic scholars have studied the forecast of stock yield rate, mainly focusing on the macro economy, corporate finance and investor sentiment.

Chen Guojin et al.[17] found that there was a long-term equilibrium relationship between economic policy uncertainty and stock yield rate, and the correlation was on the rise. Qu Jing[18] reviewed the literature on the relationship between monetary policy and the stock market, and showed that the increase of money supply will make the stock price rise, and the rise of interest rate will make the stock price fall. The empirical results of Jiangzhou and Zeng Zhijian[19] show that short-term fluctuations in stock prices are mainly affected by interest rate and money supply, but by exchange rate and inflation rate. Zhou Liang [20] selected the yield to maturity of Treasury bonds from July 2011 to July 2017, and analyzed the relationship between macro economy, capital market and interest rate maturity structure by establishing a cointegration model, and found that the factors with a significant impact on the stock market include level factor, CPI, IP, M2 and M1-M2. Niu Xinyan[21] studied the influence of monetary policy, credit spread and stock yield based on the gating vector autoregression model. In the period of tight monetary policy, there is a competitive relationship between the short-term financing interest rate and the stock yield rate, that is, the rise of the short-term financing credit spread suppresses the rise of the stock market to a certain extent, while in the stage of monetary policy easing, the fall of the short-term interest rate will promote the rise of the stock yield rate. Yuhua zhang[22] according to the CSRC listed company industry secondary classification standard of the csi 300 index underlying samples is divided into 43 categories, concluded that the PMI, GDP growth rate, exchange rate, inflation rate, money supply and industrial added value are positive impact on stock yields, and interest rates have a negative impact on the stock market. At the same time, the scale of social financing and the stock return rate have passed the Granger causality test, and this research conclusion is helpful for the Chinese government to observe the change of the scale of social finance in the macro-control and investors before making decisions.

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It can be seen that domestic scholars believe that the correlation between economic policy uncertainty and stock return is on the rise, but it is not clear whether the economic policy uncertainty has a forecast effect on stock return. Interest rate, credit spread, money supply, CPI, PMI, industrial added value, commodity export amount, exchange rate and social financing scale can significantly affect the stock return rate.

Another scholar conducts research from the perspective of corporate finance. Chen Xinyuan[23] research that the price / earnings ratio and financial leverage did not show a significant forecast ability. Gao Broad and Huang Yangyang[24] used the stock data of 134 weeks from May 2014 to December 2016 to conduct empirical tests based on the Fama-French improvement model. The results show that the book market value ratio effect exists, but the scale effect is not significant; the book market value ratio factor is negatively related to the expected return rate of GEM stocks, and the scale factor is positively correlated with the expected return rate of GEM stocks. Gan Lin min and Yang Xin[25] with artificial neural network method of China's stock market stock yield and related factors in the empirical analysis, research show that for China's stock market, company size, net asset price per share, sales income per share, cash flow per share price has a strong ability to explain, volume has certain interpretation ability, annual earnings price interpretation ability is weak. It can be seen that the scale and book market value ratio factor, net asset price per share, sales revenue price per share, cash flow price per share have significant predictive, and the prediction ability of financial leverage, price / earnings ratio per share is weak.

Behavioral finance began to develop rapidly in China at the beginning of the 21st century, and some scholars began to study the influence of investor sentiment on the stock yield rate and its prediction ability. Wang Zhen and Liu Liwen [26] analyzed the changes of the returns of different types of stocks in the optimistic and pessimistic periods, and the research showed that the fluctuation of investor sentiment was very obvious in the impact of stock returns. Through statistical analysis, Chen Ke and Chen Wei[27] found that the number of newly opened accounts was linearly correlated with the Shanghai Composite Index and Shenzhen Composite Index. The number of newly opened accounts peaked in 2-3 months, and the number of new accounts significantly promoted the stock yield within 4 months. Hu Changsheng and Tao Zhu [28] studied from the perspective of text information of individual investors, and reflected investor sentiment by the daily amount of posts and comments. The study found that the emotions spread through new media have a significant impact on the stock return rate, so rational investors can assist investment decisions according to the amount of online posts. It can be seen that the number of newly opened accounts, trading volume, turnover rate and other indicators to measure investor sentiment all have a significant prediction effect on the stock yield to a certain extent.

3. Empirical Analysis

3.1. Sample Selection and Data Processing

This paper takes the yield rate of CSI 300 index as the research object and is calculated by formula (1).

$$R = \log\frac{P_{\mathrm{t}}}{P_{t-1}} \tag{1}$$

Among them, Pt is the t-month closing price of the CSI 300 index, and the data comes from the Reith database.Since the CSI 300 Index was established in China in 2005, the time range was set from January 2006 to December 2018 considering the availability of data, with 156 data for

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each variable. The data are from Guotai Taian database.The following predictive independent variables are also selected.

US Stock Market Volatility Index (EMV). Drawing on Steven J. Davisc and Kyle Kostd, a newspaper-based stock market volatility (EMV) tracking system, which moves with the CBOE volatility index (VIX) and with the return volatility achieved by the S & P 500 index. It is good in predicting volatility and yields in global stock markets. Data: http://www. policyuncertainty.com/categorical_epu.html.

The Consumer price Index (CPI). The consumer price index (CPI) reflects the degree of inflation and directly affects the adjustment expectation of interest rate as a means of monetary policy. The expected interest rate is an economic variable that has an important impact on the stock market, so the monthly year-on-year growth rate of CPI is selected as one of the predictors. Because the CPI index has distinct seasonal characteristics, a seasonal adjustment for the raw data is required. In addition, since CPI is lag data, CPI data of lag 2 will be used for regression below. Raw data were obtained from the NBS.

Index of investor sentiment. This paper selects two investor sentiment indexes, namely, the Consumer Confidence Index (CCI) and the turnover rate (TURN). Consumer confidence index (CCI) a more intuitive reflect most consumers of the current state of economic wealth satisfaction and the future economic situation and the expected income of psychological activities of comprehensive index, the index updated once a month, some scholars found that the index can better reflect investor sentiment, so this paper will the index as a direct index of investor sentiment index. Turnover rate (TURN) refers to the frequency of trading stocks in a certain time, which can well reflect the liquidity of the stock market. At the same time, the turnover rate index is one of the most important technical indicators reflecting the market index and the activity degree of individual stocks. Generally speaking, the higher the turnover rate, the higher the enthusiasm of investors, and on the contrary, the enthusiasm is very low. Both data are obtained from the Reith database.

3.2. Within-sample Regression Analysis

This paper uses the following predictive regression model to test the in-sample predictability of the four predictors for the CSI 300.

$$R_t = \alpha_i + \beta_i X_{i,t\text{-}1} + \varepsilon_t \tag{2}$$

Among them, R_t refers to the yield rate of CSI 300 in the first month t, $X_{i,t}$ refers to the data of the i predictor in month t, and ε_t is the error term with zero mean value.

Table 1. Prediction results within the single-factor sample

predicator	cofficient	t-statictis	p-value
EMV*	-0.0409	-1.8250	0.0699
CPI_2(SA)	1.4654	0.7762	0.4388
CCI*	-0.0016	-1.7661	0.0794
TURN***	0.0019	6.0701	0.0000

Note: * * * ** * is significant at 1%, 5%, and 10%, respectively.

According to the above table, the US Stock Market Volatility Index (EMV) and the consumer confidence index are significant at the 10% level. The turnover rate (TURN) was significant at the 1% level. The consumer price index (CPI), which was seasonally adjusted and lagged behind

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the two steps, was not significant. However, we generally believe that the consumer confidence index, as a typical investor sentiment indicator, the index rises, investor sentiment is high, and the correlation with stock earnings should be positive, so excluding the consumer confidence index. Therefore, the US Stock Market Volatility Index (EMV) and turnover rate (TURN) were finally selected as the predictors. And a full-sample multifactorial within-sample regression was performed, modelled as follows.

$$R_t = \alpha + \beta_1 X_{1,t\text{-}1} + \beta_2 X_{2,t\text{-}1} + \varepsilon_t \tag{3}$$

Table 2. Prediction results within the multifactorial samples

predicator	cofficient	t-statictis	p-value
C***	-0.0548	-4.3942	0.0000
EMV*	-0.0381	-1.8855	0.0612
TURN***	0.0019	6.0750	0.0000

From table 2 sample fitting results, the model is significant in the sample, predictor variable EMV and TURN is significant, can be seen from the regression coefficient, the current the larger the EMV index, the stock market volatility, global investors panic will rise, rational investors, especially institutional investors will reduce positions in advance, the amount of funds will make the stock market downward pressure, so makes the stock market of excess returns. And high turnover rates, suggesting high investor sentiment, will push stock yields higher.

3.3. Out-of-sample Prediction

In this paper, the sample data was divided into estimation period samples and prediction period samples. The estimation period sample was used to estimate the model, with 120 observations from January 2006 to December 2015, and the prediction period samples were used to obtain the predicted value, with a total of 36 observations from January 2016 to December 2018. In this paper, we use the extended time window strategy for prediction and make 36 extended predictions, thus obtaining 36 prediction data. The out-of-sample prediction of the CSI 300 index is realized through the following model:

$$\hat{R}_{m+1} = \hat{\alpha}_{i,m} + \hat{\beta}_{i,m} X_{i,m} \quad , \quad i = 1,2; \tag{4}$$

$$\hat{R}_{m+2} = \hat{\alpha}_{i,m+1} + \hat{\beta}_{i,m+1} X_{i,m+1} \quad , \quad i = 1,2; \tag{5}$$

In this way until the end of the out-of-sample cycle, we can get the 36 out-of-sample prediction data of the CSI 300.

Following the convention of out-of-sample prediction, we used the out-of-sample R2 statistic to assess the out-of-sample prediction accuracy of the prediction models relative to the epidemic historical average benchmark. The out-of-sample R2 statistics are calculated as follows:

$$R^2{}_{OS} = 1 - \frac{\sum_{t=m+1}^{T} (R_t - \hat{R}_t)^2}{\sum_{t=m+1}^{T} (R_t - \overline{R}_t)^2} \tag{6}$$

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Among them, R_t, $\hat{R}_t$, $\overline{R}_t$ are the actual excess return of CSI 300, forecast excess return and historical average excess return. T is the degree of the full sample period, and m is the estimated period length.

R^2_{OS} The statistics measures the decrease in the mean square prediction error (MSFE) of the earnings prediction relative to the current historical average. To further determine if the prediction model produced statistically significant improvements in the MSFE, the statistics of Clark and West (2007) were used. Specifically, Clark and West (2007) statistics tested the null hypothesis of the MSFE less than or equal to the prediction model MSFE of the benchmark model and the alternative hypothesis of the MSFE of the MSFE prediction model of the benchmark model.

Mathematically, Clark and West (2007) statistics are defined first:

$$f_t = (R_t - \overline{R}_t)^2 - (R_t - \hat{R}_t)^2 + (\overline{R}_t - \hat{R}_t)^2 \tag{7}$$

And then by performing a regression on the constant $\{f_t\}_{t=m+1}^{T}$,We can obtain the Clark and West (2007) statistic, which is equivalent to the T statistic corresponding to the constant. Furthermore, the p-values for the one-sided (upper tail) test are easily obtained with a standard normal distribution.

Table 3. Out-of-sample regression prediction results

predicator	R^2_{OS}
EMW	5.29*
TURN	9.46***
EMV TURN	14.39***

Table 3 reports the billing factor and the overall out-of-sample prediction performance. Consistent with within-sample estimates, the US Stock Market Volatility Index (EMV) produced 5.29%, while the turnover rate (TURN) alone was even higher, at 9.46%. When we used the two predictors together, the highest value was 14.39%, which is roughly equal to the sum of the individuals. This evidence shows that both the US Stock Market Volatility Index (EMV) and turnover rate (TURN) have good out-of-sample prediction capabilities and have complementary out-of-sample prediction capabilities.

4. Economic Significance

In this section, we will further measure the possible economic value of the out-of-sample forecast of the Shanghai and Shenzhen 300 in terms of asset allocation.

In this section, we calculate the deterministic equivalent return (CER) of an average variance investor with a relative risk aversion coefficient of 3 and a distribution between stocks and risk-free notes using the excess yield forecast of the CSI 300 index. At the end of the last trading day of the previous month, investors optimally weighted the stock as follows:

$$w = \frac{1}{\gamma} \frac{\hat{R}_t - R_{f,t}}{\hat{\sigma}^2{}_t} \tag{8}$$

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Among them, γ is the relative risk avoidance coefficient of investors, $\hat{R}_t$, $R_{f,t}$ respectively represents the excess return forecast of CSI 300 in the t month, and indicates the variance forecast of the last half hour return. We first calculate the volatility data using the square of the daily simple yield of the monthly trading day, and then estimate the volatility forecast through a 10-year moving window. Furthermore, we limit the weights between 0 and 1.5 to prevent short selling and allow leverage up exceeding 50%.

Use Equation (8) Investors who allocate wealth can achieve portfolio returns in month t:

$$r_t = w_t R_t + (1 - w_t) R_f \tag{9}$$

The deterministic equivalent benefit (CER) can be achieved with the following formula:

$$CER = \overline{R}_p - 0.5\gamma\sigma_p^2 \tag{10}$$

$\overline{R}_P$ and $\overline{\sigma}_P^2$ are the mean and variance of portfolio returns during the out-of-sample evaluation period, respectively. The CER return is calculated as the difference between the CER using the CSI 300 forecast and the CER that relies only on the current historical average forecast, so it can be interpreted as a portfolio management fee that investors are willing to pay to obtain a return forecast rather than a simple average forecast.

Table 4. Asset allocation income

predicator	Avg Ret(%)	Ste Dev(%)	Sharp ratio	CER(%)	CER gain(%)
$\overline{R}$	-1.30	11.41	-0.12	-3.26	-
EMW	3.50	12.98	0.26	0.97	4.23
TURN	5.84	3.03	1.90	5.71	8.97
EMV TURN	10.05	7.24	1.36	9.27	12.53

Table 4 presents the asset allocation results when the equity weight is limited within the range of 0-1.5. The historical average forecast yielded the lowest annual average portfolio return of-3.26%. In contrast, EMV and TURN have somewhat higher average returns, reaching 3.5% and 5.84% annually, respectively. Consistent with the above statistical assessment, the average turnover rate is slightly higher than the US stock market volatility index. Moreover, combining the two predictors yielded the highest average annual return rate of 10.05%.

Of course, it is necessary to consider the risks. Surprisingly, only the standard deviation of the forecast results of the volatility index of the US stock market is slightly higher than the standard deviation of the historical average, and the standard deviation of the turnover rate alone and the combination forecast is smaller than the historical mean. Overall, switching from using the random walk model to the average variance investor using the US stock market volatility index and turnover rate forecast can achieve considerable economic gains.

5. Robustness Test

5.1. Other Market Index Test

A good predictive model is not reliable conclusion if it only applies to a particular sample. The better prediction effect of a specific sample data may be just a chance. In order to exclude this

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contingency and the rigor of the model, the robustness test is the next step. In this paper, the predictor variable CSI 300 index is replaced with the Shanghai Composite Index for the robustness test.

Table 5. Results of single-factor regression in the Shanghai Composite Index sample

predicator	cofficient	t-statictis	p-value
emv*	-0.0380	-1.8178	0.0710
cpi-2(SA)	1.4847	0.8485	0.3975
cci*	-0.0015	-1.7706	0.0786
turn***	0.0016	5.6942	0.0000

Table 6. In-sample combined regression results of the Shanghai Composite Index

predicator	cofficient	t-statictis	p-value
C***	-0.0403	-3.9194	0.0000
EMW*	-0.0373	-1.9552	0.0524
TURN***	0.0016	5.7317	0.0000

Table 7. Extra-of-sample forecast results of the Shanghai Composite Index

predicator	R^2_{OS}
EMW	3.12*
TURN	10.75***
EMV TURN	13.52**

From Table 5 and Table 6, the Shanghai Composite Index, like the CSI 300, the model is significant in the sample, and the prediction variables EMV, CCI and TURN are all significant. From the regression coefficient, the larger the EMV index in the United States in the current period, the lower the stock market returns; the higher the turnover rate, the higher the investor sentiment in the current period, and the higher the yield in the next period. Table 7 shows the out-of-sample prediction results of the forecast model in the yield rate of the Shanghai Composite Index. The following conclusions can be drawn: the US stock market volatility index is 3.12%, slightly lower than the US stock market volatility index versus the CSI 300; and the turnover rate in the two forecasts is the opposite. However, both the portfolios are more than 1%. Therefore, the construction of the American stock market volatility index (EMV) and turnover rate (TURN) also has a prediction effect on the yield of Shanghai 50, indicating that the model is robust.

5.2. Other Sample Period Tests

In this paper, by changing the division of inside and outside the sample, the forecast period forward 3 months, robustness test, the training period sample time span from January 2006 to September 2014, the forecast period sample update to October 2015 to December 2018, continue to use the extended time window strategy, window length of 42.

Table 8. New out-of-sample prediction results

predicator	R^2_{OS}
EMW	6.93**
TURN	9.64***
EMV TURN	15.22***

As can be seen from Table 8, after the change of out-of-sample division, the results of US stock market volatility index (EMV), turnover rate (TURN) single-factor sample prediction results of the two combinations are significant, and both are better than the historical average benchmark model, indicating that the model constructed in this paper is robust.

6. Conclusion

A correct grasp of the predictors and prediction methods that affect the rate of return is not only the research hotspot of the capital market, but also conducive to investors' rational investment, reducing the risks brought by immature investment and assisting investment decisions. At the same time, it is conducive to academic workers to establish a more timely asset pricing model and promote the rich development of financial theory. This article first through the domestic and foreign literature review, study the influence factor of stock yield and prediction method, because considering the complexity of the financial market itself, so considering international factors, domestic macro and market sentiment, selected individual factors to the stock yield sample fitting and outside the sample forecast research, this paper from the perspective of forecasting effect, make the conclusion more robust. Considering the characteristics and status of the CSI 300 index, this paper therefore takes the CSI 300 logarithmic return rate as the empirical research object, and uses the extended time window strategy to make the out-of-sample forecast and analysis of the yield rate. Finally, the robustness test was conducted, including the predicted variables and the updated sample data.

Therefore, the following conclusions are drawn in this paper.

First of all, the volatility index of the US stock market is negatively correlated with the yield of the CSI 300 index; the increase of the volatility index of the CSI 300 index will decrease; the stability of the US stock market, the yield of the CSI 300 index will increase. The turnover rate has a positive forecast impact on the yield of CSI 300 index, that is, the higher the current investor sentiment, the rising turnover rate will promote the yield of the next period; when the investor sentiment is depressed in the current period, the falling turnover rate will further reduce the yield of the next period.

In addition, the predictability of the US stock market volatility index (EMV) and the turnover rate (TURN) can be higher than the historical average prediction method; and for the mean variance investors, it can achieve higher economic benefits compared with the historical average prediction method. At the same time, the Shanghai Composite index has passed the stability test. The date of sample update to June 2019 also passed the robustness test.

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