Intelligent Prediction Model of Shanghai Composite Index Based on Technical Indicators and Big Data Analysis

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Abstract. Technical indicators provide useful information for investors to study the stock market. Based on the Shanghai Composite index from November 1994 to March 2022, we construct 20 technical indicators based on the moving-average (MA) rules, momentum (MOM) rules and volume on balance (VOL) rules, and model and analyze through ordinary least squares and extracted principal components. We found that the technical indicators provide effective information for the forecasting of the excess return rate of the Shanghai Composite index both in- and out-of sample, and the model has more superior forecasting performance in the decline period of the business cycle. In addition, this paper finds that the information provided by the technical indicators can better predict the rise of the peak front and the trough front of the business cycle. Finally, this paper studies the economic significance of the yield forecasting using technical indicators, and finds that the information in technical indicators can help investors to obtain better investment returns without transaction fees.

Keywords: technical indicators, return forecast, principal component, business cycle peaks and troughs, investment portfolio.

1. Introduction

In recent decades, the financial market has occupied an increasingly important position in China's economic development, and the stock market is the top priority of the financial market. The stock market provides a wide range of trading platforms for investors and capital seekers and is closely related to economic fluctuations.

In addition, the forecasting and modeling of returns have been important topics that cannot be ignored in financial markets. From the perspective of analysis methods, the research and analysis of market returns can be divided into two categories: fundamental analysis and technical analysis. The former starts from the intrinsic value and focuses on the analysis of various factors affecting the securities price and its trend, such as economic situation, interest rate level, inflation factors, policy influence, etc., which is applicable to the relatively mature securities market. The latter holds that the behavior of the market contains all information, the price will evolve in a trend way, and the historical price, trading volume, investors' reaction to the market can predict the future stock price.

Considering that China's securities market started late and developed not mature enough, including untimely and incomplete information disclosure of listed companies, high information cost and irrational investors, technical analysis is an easier investment analysis method to be adopted and accepted for investors in Chinese stock market. Both financial practitioners or retail investors, using technical indicators for investment operation for the practice of technical analysis has accumulated a lot of experience, thus gave birth to many technical indicators, such as relative strength index (RSI), stochastic oscillator (KD), bollingers bonds(BOLL), exponential moving average(EMV), william overbought index(WR), on balance volume(OBV) and so on. At present, there are numerous various technical indicators in the securities market, whether the use of existing technical indicators, or the construction of new technical indicators, all provide a powerful help to the forecasting of stock returns.

For investors, effective asset allocation, market risk avoidance, and obtaining a higher Sharpe ratio are all investment targets. With the help of effective information provided by technical indicators, it is necessary to predict the yield of the stock market based on technical indicators.

According to the article of Neely et al. (2014), We constructed 20 technical indicators, and extracted their first principal component to form a forecasting model to predict the excess return rate of the Shanghai Composite index of China's stock market. This paper also studies the average behavior of the sse index yield estimated by the forecasting model near the peak and trough of the business cycle. Finally, the paper considers the return performance of mean-variance investors based on the proposed forecasting model.

2. Literature Review

2.1. Research on the predictability of securities return

In 1970, Fama put forward the theory of effective market hypothesis, which believed that the securities price in the effective market always fully reflects all the information, and the price fluctuation follows the random walk hypothesis, and it is meaningless to predict the price of securities through fundamental analysis or technical analysis. Therefore, the predictability of securities yields is closely linked to the effectiveness of the securities market. However, because the effective market hypothesis is based on the three assumptions of rational investors, random trading and effective arbitrage, and the excessively stringent assumptions make it, scholars suspect that the securities market may not be effectively priced, which has triggered a long-term academic discussion on whether the return rate of securities can be predicted.

In fact, there are still many financial visions in reality that cannot be explained by traditional financial theory, such as momentum effect (Jegadeesh and Titman, 1993), scale effect (Banz, 1981; Reimganum, 1981), and overreaction (De Bondt and Thaler, 1985), etc. As more and more financial visions emerge, more and more scholars believe that the securities market is actually predictable. Breen et al. (1989) empirically studied the ability of nominal interest rate to predict the excess return of securities, and pointed out that the negative correlation between nominal interest rate and the expected excess return of securities is found. Campbell and Vuolteenaho (2004) introduced the inflation rate into the forecasting of the securities return rate and found that the inflation rate has a strong ability to explain the S & P500 index and introducing the inflation rate can improve the accuracy of judging the future trend of the S&P500 index. Henkel et al. (2011) comprehensively considered the company's financial indicators and macroeconomic indicators and found that the changes in dividend payout ratio and nominal interest rate can be provided to the market for additional information, so as to realize the forecast of short-term securities returns, and this forecasting ability is robust in different economic cycles. Some domestic scholars have also made research on the forecasting of macroeconomic variables.

In addition, in view of these financial visions, behavioral finance believes that they can be attributed to the copycat of a large number of irrational investors in the market, which leads to the distortion of asset prices, so some scholars focus on the research of technical analysis. Menkhoff (2010) studied the use of 692 fund managers from five countries and found that the vast majority of fund managers relied on technical indicators for stock selection. In addition, technical analysis is more popular among smaller asset managers. Gehrig and Menkhoff (2006) showed that technical analysis is a short-term forecasting tool, but not for a very short-term range dominated by flow analysis and is particularly popular in the foreign exchange market. Hsu et al. (2016) also verified in the foreign exchange market that temporary incomplete rational behavior and market immaturity produce technical predictability and potential excess profitability. Domestic scholars have also made some progress in studying the effectiveness of technical analysis in China's stock market.

2.2. Research on the technical index forecasting model

Scholars at home and abroad use the idea of technical indicators construction strategy to construct new technical indicators and conduct a lot of research and analysis in stocks, futures, oil, bulk, foreign exchange market, and prove the use of technical indicators for yield forecasting from the theoretical and practical sense.

In the stock market, many early scholars predicted the return of the stock market based on a single technical indicator. Brock et al. (1992) and Lo et al. (2000) proved that the technical analysis based on the moving average strategy has a certain ability to predict the stock return. Wong et al. (2005) used the moving average rules to establish multiple technical indicators to predict the stock markets of Shanghai, Hong Kong and Taiwan, China, and found that forecasting and establishing portfolios using the moving average method could generate excess returns. However, as technical analysis is more and more accepted and applied by the majority of investors, more research on technical indicators is gradually becoming popular in academia. Neely et al. (2014) utilized 14 macroeconomic variables and 14 technical indicators established according to the MA, MOM, VOL rule, through single indicator predictive analysis and principal component analysis, it is found that technical indicators have good predictive ability in the US stock market. The three technical index construction methods established by Neely et al. (2014) were later widely studied by scholars and found their superior forecasting performance in different markets. Chang, et al (2014) found that the investment strategy based on VAM technical indicators has higher returns than the investment and holding strategy, which has a certain guiding value for stock investors. Yao et al. (2021) established LASSO-EGARCH model based on technical indicators and applied it to the Chinese stock market, finding that the integration of technical indicators information can make a better calibration of the return distribution and have a better risk management when China's stock price plummeted. Dai et al. (2021) combined wavelet changes and technical indicators to generate new MA indicators and MOM indicators and found that the newly built technical indicators have a good predictive ability for the U. S. stock market. Lin (2018) through the partial least squares (PLS) integration of macroeconomic variables and technical indicators of information, eliminate the special noise component in technical indicators, and found that the new built variables to the United States, the overall stock market predictability is very strong. In addition, it can also predict according to the scale, value, power and industry ranking cross-sectional stock portfolio returns.

In the futures market, Irwin (2007) shows that early studies have empirically found that technical analysis is profitable in both the futures market and the foreign exchange market. Moskowitz et al. (2012) recorded important "time-series momentum" for stock index, currency, commodity and bond futures and found that returns for 1-12 months persisted and partially reversed over a longer time frame. A diversified portfolio of time-series momentum strategies across all asset classes provides substantial exceptional returns and are rarely influenced by standard asset pricing factors and performs best in extreme markets.

In the oil market, Yin and Yang (2016) using macroeconomic variables and technical indicators to predict WTI oil earnings, found that based on 18 macroeconomic variables and MA, MOM, VOL rules established multiple technical indicators have good forecasting ability, and proved the ability of the technical indicators to predict oil prices partly from its ability to predict mood changes, which shows that the oil market is financialization. Zhang et al. (2018) selected 18 macroeconomic variables and technical indicators and adopted the iterative combination method and found that the iterative combination method has a strong advantage in oil price forecasting. Zhang et al. (2019) conducted a further study on oil price forecast. They considered LASSO and elastic net methods based on macroeconomic variables and technical indicators and found that they have a strong ability to explain oil price forecast.

In the bulk market, Yin et al. (2016) put forward 22 macroeconomic variables and 22 technical indicators. Through the single index forecasting and analysis of principal components and equal weights, they found that technical indicators can directly predict the synergistic movement of commodity returns and provide new evidence for the financialization of the commodity market. Wang et al. (2020) momentum rules (MOM), filtering rules (FR), moving average rules (MA), ochooscillating trading rules (OSLT) and support resistance rules (SR) to establish technical indicators, and combined with macroeconomic variables, principal components, weight forecasting analysis, found that the international market of energy, energy, agriculture, beverage, food, raw materials, metals and precious metals targets have very good forecasting ability.

In the foreign exchange market, Lento and Gradojevic (2007) found the moving average cross rule, the trading range breaking rule, filtering rules can produce a certain amount of predictive power. Vajda (2014) developed trading strategies and backtests for foreign exchange markets with different time frames, and finally found that the MACD index has a good ability to explain the predicted exchange rate fluctuations. Panopoulou and Souropanis (2019) predicted the trend of six widely traded currency pairs, combining the principal component information of macroeconomic variables and technical indicators, and found that the principal component information could significantly improve and stabilize the exchange rate forecast.

In addition, more and more domestic and foreign scholars use machine learning methods to predict the benefits of applying technical indicators. They believe that machine learning can better select technical indicators and obtain more accurate forecasting results. Aldin et al. (2012) used the method of artificial neural network to find that the technical indicators have certain forecasting ability for the Tehran exchange price index through MA, RSI, CCI and MACD rules.

Looking at the existing relevant literature at home and abroad, we can know that many scholars have done a lot of valuable research on the use of technical indicators to predict securities returns, but most of the existing research focuses on the traditional technical indicators. In addition, under certain conditions, stock market returns can be effectively predicted in most countries and economies. Based on this, this paper will use a series of technical indicators to predict and study the return of China's stock market.

3. Data

3.1. Data sources

The data required for this paper includes monthly Shanghai Composite Index (SSEC) closing price, trading volume and risk-free return on the Chinese stock market.

Among them, the closing price and trading volume data of Shanghai Composite Index (SSEC) are both from a financial website [1], and the monthly data of risk-free return rate of China stock market is from Reith Database [2] The data span from November 1994 to March 2022.

3.2. Data processing

In this paper, EXCEL and MATLAB are used to initially process the data to facilitate subsequent empirical studies.

Treatment of return rate: this paper adopts the log rate of return, and the calculation formula is as follows:

$$r_{t+1} = \log(P_{t+1}) - \log(P_t) \tag{1}$$

Where r_{t+1} represents the log yield of the $t+1$ period, P_t represents the closing price of the Shanghai Composite index at time t.

(1) Treatment of excess return: this paper adopts the ordinary excess return; the calculation formula is as follows:

$$r'_{t+1} = r_{t+1} - r_{ft} \tag{2}$$

Where r_{t+1} represents the log return in the $t+1$ period, and r_{ft} indicates the risk-free return on the Chinese stock market at time t.

3.3. Construction of the technical indicators

Technical indicators are the indicators of trading and selling signals constructed by using the historical trading prices and trading volume data in the stock market, which can help stock investors to better analyze the buying and selling. This paper uses three popular technical index construction

rules to generate technical indicators to predict the yield of Shanghai Composite index. They are moving-average (MA) rule, momentum (MOM) rule, and volume on balance (VOL) rule.

(2) Moving-Average (MA) Rule

The moving-average (MA) rule generates a buy ($S_{i,t}$=1) or sell ($S_{i,t}$=0) signal by comparing short-term and long-term moving averages at time *t*. The specific construction rules are set out as follows:

$$S_{i,t} = \begin{cases} 1, \mathrm{MA}_{s,t} \geq \mathrm{MA}_{l,t} \\ 0, \mathrm{MA}_{s,t} < \mathrm{MA}_{l,t} \end{cases} \tag{3}$$

where

$$MA_{j,t} = (1/\ j)\sum_{i=0}^{j-1} P_{t-i},\ j = s, l \tag{4}$$

P_t is the closing price of the Shanghai Composite Index at time *t*, and *s*(*l*) is the length of the short-term (long-term) MA(*s*<*l*). MA(*s*,*l*) represents the moving-average (MA) indicator with lengths *s* and *l*. Intuitively, the moving-average rule can detect changes in stock price trends, because short-term MA is more sensitive to near-term price movements than long-term MA. For example, when there is a recent drop in the price, short-term MA tends to be lower than long-term MA; when prices start to rise, short-term MA tends to grow faster than long-term MA, eventually surpassing long-term MA and generating buy signals. This article sets *s*=1,2 as well as *l*=3,4,5,6. A total of 8 moving-average (MA) technical indicators were generated: MA (1,3), MA (1,4), MA (1,5), MA (1,6), MA (2,3), MA (2,4), MA (2,5), and MA (2,6).

(1) Momentum (MOM) Rule

The momentum (MOM) rule generates a signal to buy ($S_{i,t}$=1) or sell ($S_{i,t}$=0) by comparing the closing price of the Shanghai Composite Index at time *t* and *t*-*m*. The specific construction rules are described as follows:

$$S_{i,t} = \begin{cases} 1,\ P_t \geq P_{t-m} \\ 0, P_t < P_{t-m} \end{cases} \tag{5}$$

P_t is the closing price of the Shanghai Composite Index at time *t*. MOM(*m*) represents the momentum indicator with length *m*. If the stock price at time *t* is higher than the stock price at time *t*-*m*, it shows a positive momentum and may get a higher return, thus generating a buy signal. Set *m*=3,4,5,6. Four momentum technical indicators were produced: MOM (3), MOM (4), MOM (5), and MOM (6).

(2) Volume on Balance (VOL) Rule

Technical analysts often combine stock volume data with historical price information to determine market trends. According to the Granville (1963), the balance volume (OBV) is defined by the following formula:

$$OBV_t = \sum_{k=1}^{t} VOL_k D_k \tag{6}$$

where VOL_k represents the trading volume during period *k*. D_k is a binary variable, taking D_k as 1 if P_k-P_k≥0 and-1 otherwise. Buy and sell signals are formed according to VOL_k. Specifically, compare the short-term and long-term moving-average balance trading volume at time *t*, generating a buy ($S_{i,t}$=1) or sell ($S_{i,t}$=0) signal. The specific construction rules are set out as follows:

$$S_{i,t} = \begin{cases} 1,\ \mathrm{MA}_{s,t}^{OBV} \geq \mathrm{MA}_{l,t}^{OBV} \\ 0, \mathrm{MA}_{s,t}^{OBV} < \mathrm{MA}_{l,t}^{OBV} \end{cases} \tag{7}$$

Where

$$MA_{j,t}^{OBV} = (1/\ j)\sum_{i=0}^{j-1} OBV_{t-i}\ ,\ \ j = s, l \tag{8}$$

The $s(l)$ is the length of the short-term (long-term) moving-average trading volume ($s<l$). Moving-average volume is expressed in VOL(s,l), and the relatively high recent volume combined with recent stock price gains indicates a strong positive market trend and generate a buy signal. This article sets s=1,2 as well as l=3,4,5,6. A total of 8 mobile average volume technical indicators: VOL (1,3), VOL (1,4), VOL (1,5), VOL (1,6), VOL (2,3), VOL (2,4), VOL (2,5), and VOL (2,6).

4. Methodology

4.1. Porecasting regression

In this paper, the least squares method (OLS) can predict the excess yield of the Shanghai Composite Index based on three types of technical indicators. The specific estimation model is as follows:

$$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1} \tag{9}$$

where r_{t+1} represents the excess return rate of the Shanghai Composite Index at time t+1, $S_{i,t}$ is a binary explanatory variable about buying and selling, and $\varepsilon_{i,t+1}$ are error terms that follow zero mean and independent and identical distribution. We set up the following hypothesis tests:

$$H_0: \beta_i=0, H_A: \beta_i>0 \tag{10}$$

When the null hypothesis is established, $S_{i,t}$ have no predictive power for r_{t+1}; when the alternative hypothesis is true, it means that $S_{i,t}$ have certain predictive power for r_{t+1}.

In order to synthesize the forecasting ability of multiple technical indicators on the excess yield of sse index, this paper considers the forecasting regression based on principal components. Let $x_t = \left(x_{1,t},\ldots,x_{N,t}\right)'$ represent the matrix of all technical index variables (N=20), $\hat{F}_t^{\mathrm{ECON}} = \left(\hat{F}_{1,t}^{\mathrm{ECON}},\ldots,\hat{F}_{K,t}^{\mathrm{ECON}}\right)'$ represent the first K principal component matrix extracted from x_t, where K≪N. The principal component estimation model (PC) of the technical indicators is specified as follows:

$$r_{t+1} = \alpha + \sum_{k=1}^{K} \beta_k \hat{F}_{k,t} + \varepsilon_{t+1} \tag{11}$$

Indeed, the principal components simply contain information from a large number of potential predictors in the forecasting regression. The first few principal components identify key combinations between the whole set of predictors, thus filtering out most of the noise in a single predictor, effectively preventing the problem of sample overfitting.

Furthermore, according to adjusted R^2, K=1, the first principal component of all technical indicators, was selected for regression analysis.

Beyond this, this paper uses an extended window to generate forecastings outside of samples. Out-of-sample forecasting is done by the following equation:

$$\hat{r}_{t+1} = \hat{\alpha}_{t,i} + \hat{\beta}_{t,i} x_{i,t} \tag{12}$$

where $\hat{\alpha}_{t,i}$ and $\hat{\beta}_{t,i}$ are estimates of α and β derived from least squares estimation (OLS). The full sample length is T, and the first M observations serve as in-sample values, and the last T-M observations are used for out-of-sample forecasting in the extended window.

Similarly, the out-of-sample forecasting based on the principal components is done by the following equation:

$$\hat{r}_{t+1} = \hat{\alpha}_t + \sum_{k=1}^{K} \hat{\beta}_{t,k} \hat{F}_{1:t,k,t} \tag{13}$$

where $\hat{F}_{1:t,k,t}$ are the first K (the value of K is determined by adjusted R^2) principal components extracted from 20 technical indicators based on the data from period 1 to *t*. $\hat{\alpha}_t$ and $\hat{\beta}_{t,k}$ (*k*=1,2,..., K) are the least squares estimates with intercepted terms with $\{r_s\}_{s=2}^{t}$ as the explained variable and $\left\{\hat{F}_{1:t,k,s}\right\}_{s=1}^{t-1}(k=1,2,\ldots,K)$ as the explanatory variable.

We considered a popular benchmark model, namely the historical average forecasting model:

$$\hat{r}_{t+1}^{\mathrm{HA}} = (1/t)\sum_{s=1}^{t} r_s \tag{14}$$

Welch and Goyal (2008) consider this as a rigorous benchmark model for out-of-sample forecasting. This paper compares the performance of the excess return rate of the Shanghai Composite index predicted by (12) and (13) with the performance of the historical average forecasting model to evaluate the quality of the proposed model.

This paper selected December 1995 to December 2003 as the initial in-sample estimation period and the out-of-sample forecasting period from January 2004 to March 2022.

4.2. Porecasting evaluation

According to Campbell and Thompson (2008), the R^2_{OoS} was used to evaluate the forecasting performance of the model:

$$R^2_{OoS} = 1 - \frac{MSPE_{\mathrm{model}}}{MSPE_{\mathrm{bench}}} \tag{15}$$

Where $MSPE_{model}$ and $MSPE_{bench}$ are the mean squared forecast error of the given model and the benchmark model, respectively, which are calculated as follows:

$$MSPE_i = \frac{1}{T-M}\sum_{t=M+1}^{T}\left(\hat{r}_i - r_t\right)^2, i = \text{ benchmark, model} \tag{16}$$

The R^2_{OoS} measures the proportional reduction of the mean squared forecasting error (MSFE) of the proposed forecasting model relative to the historical average forecasting model. If the R^2_{OoS} is positive, it indicates that the forecasting model presented here outperforms the historical average forecasting model. Campbell and Thompson (2008) proposed that monthly R^2_{OoS} statistics appear to be small because of the inherently unpredictable portion of stock returns, so close to 0.5% monthly R^2_{OoS} is economically significant.

To determine whether R^2_{OoS} is significant, the adjusted mean squared forecasting error (adjusted MSFE) statistics were calculated using the method of Clark and West (2007). The null hypothesis of this method is that the mean squared forecasting error (MSFE) of the historical average forecasting model is less than or equal to the corresponding forecasting model ($R^2_{OoS}\leq 0$), and the alternative hypothesis is that the mean squared forecasting error (MSFE) of the historical average forecasting model is greater than the corresponding forecasting model ($R^2_{OoS}>0$). In order to calculate the adjusted mean squared forecasting error (adjusted MSFE) statistics, Clark and West (2007) first defined:

$$f_t = \left(r_t - \bar{r}_t\right)^2 - \left(r_t - \hat{r}_t\right)^2 + \left(\bar{r}_t - \hat{r}_t\right)^2 \tag{17}$$

where r_t, $\bar{r}_t$ and $\hat{r}$ respectively represent the real excess return rate, the excess return rate predicted by the historical average forecasting model and the excess return rate predicted by the corresponding forecasting model (the technical index and principal component forecasting model in this paper). By performing a constant regression on $\{f_s\}_{s=m+1}^{T}$, adjusting the mean squared forecasting error (adjusted-MSFE) statistic in the results is equal to the corresponding t statistic.

To study the potential bias-efficiency trade-off in the forecasting, MSFE is also decomposed into squared bias and variance parts:

$$\mathrm{MSFE} = (\bar{\hat{e}})^2 + \mathrm{Var}(\hat{e}) \tag{18}$$

where $\hat{e}$ represents the forecast error, $(\bar{\hat{e}})^2$ represents the squared forecast bias, and $\mathrm{Var}(\hat{e})$ represents the forecast error variance.

Also, this paper focuses on the relative strength of equity earnings predictability during the expansion and recession of the NBER business cycle. Because the whole sample R^2 cannot be cleanly decomposed into subsample R^2 based on the whole sample parameter estimate, the traditional R^2 is calculated, and the calculation formula is as follows:

$$R_c^2 = 1 - \frac{\sum_{t=1}^{T} I_t^c \hat{\varepsilon}_{i,t}^2}{\sum_{t=1}^{T} I_t^c \left(r_t - \bar{r}\right)^2}, \quad c = \mathrm{EXP}, \mathrm{REC} \tag{19}$$

where I_t^{EXP} (I_t^{REC}) is a binary variable, the value is 1 when the t month is the expansion period (decline period), otherwise the value is 0.$\hat{\varepsilon}_{i,t}^2$ is the fitted residual based on the full sample estimate, $\bar{r}$ is the mean of r_t in the full sample and T is the full number of observations in the full sample. The R_{EXP}^2 and R_{REC}^2 may be negative.

5. Empirical Results

5.1. Descriptive statistics

Through the processing of the raw yield data and the construction of technical indicators, this paper obtains a series of their descriptive data. Table 1 lists the descriptive statistics of the log yield rate of the Shanghai Composite Index. Table 2 presents the descriptive statistics for the 20 technical indicators.

Table. 1 Descriptive statistics of the yield rate

	Mean	Standard Deviation	Median	Minimum	Maximum	Skewness	Kurtosis	Autocorrelation Coeficient	Sharp ratio
r_{t+1}	-0.11	3.33	-0.09	-13.46	11.17	-0.39	2.18	0.09	1.88

Notes: This table reports the descriptive statistical results of the logarithmic return rate (%) of the Shanghai Composite Index from November 1995 to March 2022. The Sharp ratio is the mean of the log return rate divided by the margin.

The results are reported in Table 1: (1) The logarithmic return of the Shanghai Composite Index is -0.11% and the standard deviation is 3.33. This means that between November 1995 and March 2022, the average return of the Shanghai Composite Index was negative and there was some volatility in the stock market; (2) The median logarithmic return of the Shanghai Composite Index is -0.09%, the minimum yield is -13.46%, and the maximum yield is 11.17%. This shows that the distribution of logarithmic return data of the Shanghai Composite Index is relatively scattered; (3) The skewness of the logarithmic return data of the Shanghai Composite Index is -0.39 and the kurtosis is 2.18. This shows that it does not follow a normal distribution but takes on the form of a left-sided dwarf peak; (4) The logarithmic yield autocorrelation coefficient of the Shanghai Composite Index is 0.09. This indicates that its autocorrelation is weak; (5) The Sharpe ratio is 1.88, indicating that the return-risk ratio of investing in the Shanghai Composite Index is not high.

Table. 2 Descriptive statistics of the technical indicators

	Mean	Standard Deviation	Skewness	Kurtosis	Autocorrelation Coeficient
MA(1,3)	0.54	0.50	-0.15	1.99	0.34
MA(1,4)	0.54	0.50	-0.16	1.99	0.45
MA(1,5)	0.52	0.50	-0.07	2.01	0.52
MA(1,6)	0.54	0.50	-0.16	1.99	0.58
MA(2,3)	0.53	0.50	-0.12	2.00	0.36
MA(2,4)	0.52	0.50	-0.07	2.01	0.51
MA(2,5)	0.52	0.50	-0.10	2.00	0.62
MA(2,6)	0.53	0.50	-0.12	2.00	0.66
MOM(3)	0.49	0.50	0.03	2.01	0.54
MOM(4)	0.52	0.50	-0.10	2.00	0.58
MOM(5)	0.55	0.50	-0.18	1.98	0.67
MOM(6)	0.52	0.50	-0.10	2.00	0.70
VOL(1,3)	0.54	0.50	-0.15	1.99	0.06
VOL(1,4)	0.58	0.49	-0.34	1.90	0.35
VOL(1,5)	0.59	0.49	-0.35	1.89	0.44
VOL(1,6)	0.60	0.49	-0.39	1.86	0.49
VOL(2,3)	0.57	0.50	-0.28	1.94	0.08
VOL(2,4)	0.58	0.49	-0.33	1.90	0.45
VOL(2,5)	0.58	0.49	-0.34	1.90	0.58
VOL(2,6)	0.59	0.49	-0.37	1.88	0.65

Notes: This table reports the descriptive statistical results of 20 technical indicators constructed by MA, MOM, VOL rules from November 1995 to March 2022.

The results are reported in Table 2: (1) Except for MOM(3), the mean value of the other 19 technical indicators is greater than 0.5, which indicates that the probability of generating a buy signal is greater than that of a sell signal for these 19 technical indicators constructed; (2) The standard deviation of the 20 technical indicators is about 0.5, indicating that the volatility of each technical indicator is close; (3) The skewness of the 20 technical indicators was less than 0, and the kurtosis was less than 3, showing the morphology of the left dwarf peak; (4) The autocorrelation coefficients of the 20 technical indicators are quite different, the autocorrelation coefficient of VOL(1,3) is the smallest, 0.06, and the autocorrelation coefficient of MOM(6) is the largest, which is 0.7.

5.2. In-sample estimation results

The principal component of the technical index determined by the adjusted R^2 is the first principal component. Fig. 1 is a time series diagram of the first principal component F1 of the technical indicators.

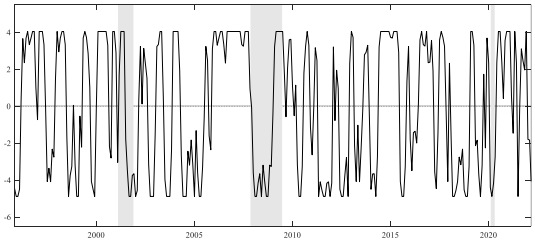

Fig. 1. Time diagram of the first principal component F1. Time span was from November 1995 to March 2022. Gray columns indicate the decline period.

As can be seen from Fig. 1, the first principal component of the technical indicators usually drops sharply from its highest level to the lowest level, with very strong volatility. Second, during the

decline of the NBER business cycle, the first principal component of technical indicators experienced an increase and decline. Near 2002, there was a sharp drop in technical indicators. During the 2008 financial crisis, the stock market volatility and the credit default gap widened sharply, with a sharp rise in the first principal component of technical indicators. Around 2021, the technical indicators have achieved a sharp decline and a sharp rise in a very short period of time. This is different from the countercyclical characteristics of the S&P500 index proposed by Neely et al. (2014), which may be caused by the immaturity of the Chinese stock market.of the NBER business cycle.

To test the differences between the first principal components of the 20 technical indicators, we also extract the load of their first principal components. Fig. 2 shows the estimated load of the first principal components of the 20 technical indicators:

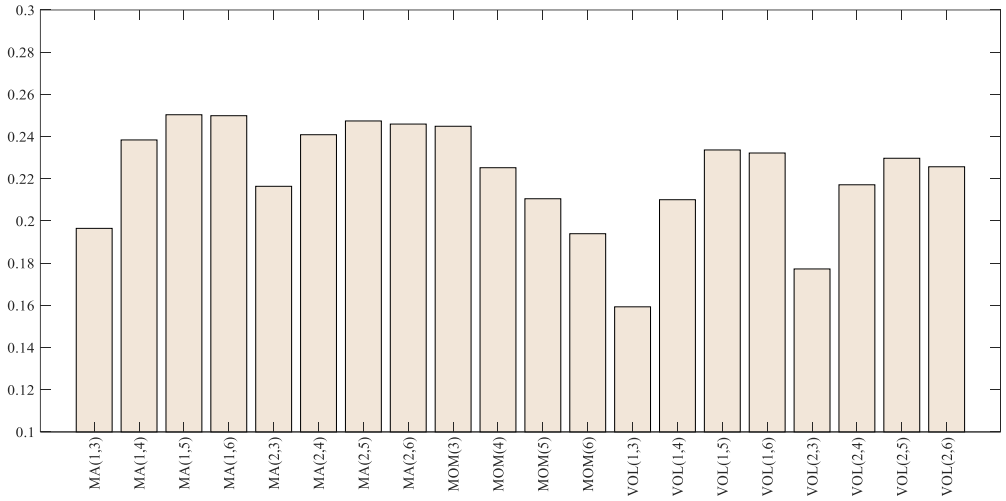

Fig. 2. Estimated load of the first principal component F1 of the technical index. This figure shows the load extracted from the first principal component F1 of the 20 technical indicators.

As can be seen from Fig. 2, the estimated load of the first principal component of the technical index is almost identical, except for the moving average trading volume indicators VOL (1,3) and VOL (2,3). This means that if the first principal component has a large (small) value, then most technical indicators give a buy (sell) signal. It's like a "consensus" indicator.

This paper is estimated based on the technical index forecasting model and the principal component forecasting model, the sample period was from November 1995 to March 2022, and the in-sample estimation results are shown in Table 3. Panel A reports the regression results based on the technical index forecasting model, and panel B reports the regression results based on the principal component forecasting model.

Table. 3 in-sample estimation results

Indicators	Coefficient	*t*	R^2	R^2_{EXC}	R^2_{REC}
Panel A: regression based on technical indicators					
MA(1,3)	0.85**	2.32	1.64%	0.14%	7.32%
MA(1,4)	0.82**	2.24	1.54%	0.28%	6.28%
MA(1,5)	0.72**	1.95	1.18%	0.05%	5.44%
MA(1,6)	0.59*	1.59	0.78%	0.21%	2.94%
MA(2,3)	0.92***	2.53	1.94%	1.10%	5.10%
MA(2,4)	1.10***	3.00	2.74%	1.15%	8.75%
MA(2,5)	0.92***	2.48	1.91%	0.55%	7.04%
MA(2,6)	0.91***	2.46	1.87%	0.29%	7.82%
MOM(3)	0.96***	2.60	2.10%	1.00%	6.25%
MOM(4)	0.86**	2.34	1.68%	0.89%	4.66%
MOM(5)	0.75**	2.02	1.26%	0.59%	3.80%
MOM(6)	0.61*	1.63	0.83%	0.38%	2.53%
VOL(1,3)	0.53*	1.44	0.64%	0.48%	1.26%
VOL(1,4)	0.75**	2.04	1.26%	1.02%	2.13%
VOL(1,5)	0.81**	2.20	1.47%	1.05%	3.05%
VOL(1,6)	0.80**	2.16	1.40%	0.86%	3.41%
VOL(2,3)	0.37	1.00	0.31%	-0.14%	2.03%
VOL(2,4)	0.77**	2.10	1.31%	1.06%	2.25%
VOL(2,5)	0.92***	2.51	1.88%	1.24%	4.30%
VOL(2,6)	0.68**	1.82	1.01%	0.23%	3.96%
Panel B: regression based on the principal component					
PC-TECH	0.14***	2.60	2.23%	0.97%	6.99%

Notes: This table reports in-sample estimates for the technical indicator forecasting model and the principal component forecasting model from November 1995 to March 2022. K=1 is the result selected by the adjusted R^2. *, * *, * * * represents results at the 10%, 5%, 1% significance level, respectively. R^2 is R^2 for the full sample R^2, R^2_{EXC} is R^2 for the expansion of the NBER business cycle and R^2_{REC} is R^2 during the NBER business cycle decline.

As can be seen from panel A in Table 3, of the 20 technical indicators, 19 (16) showed a significant forecasting ability of the excess return rate of the Shanghai Composite Index at the significance level of 10% (5%). The coefficient of technical indicators shows that the excess return of the technical index buying signal ($S_{i,t}$=1) is 37~110 basis points higher than the forecast of the selling signal ($S_{i,t}$=0). Secondly, except for the moving average trading volume index VOL (2,3), the R^2 of the other 19 technical indicators was greater than 0.5%, and the R^2 of the moving-average index MA (2,4) even reached 2.74%, which is of economic significance. The last two columns report the R^2 during the NBER expansion and recession of business. It can be seen that the R^2 in the NBER business recession is significantly greater than the R^2 in the expansion period, indicating that the technical indicators have more obvious the ability to predict the excess return rate of the Shanghai Composite Index during the decline of the business cycle.

As can be seen from panel B in Table 3, based on technical indicators of the first principal components of forecast regression, under the significance level of 1% of the Shanghai composite index excess yield, and technical indicators buy signal ($S_{i,t}$=1) forecast the Shanghai composite index next month excess yield than sell signal ($S_{i,t}$=0) forecast 68 basis points. R^2 was 2.23%, also significantly greater than 0.5%. The R^2 reached 6.99% and the expansion period was only 0.97% during the expansion period, similar to the results predicted by technical indicators.

In general, the principal component forecasting model and 19 technical index forecasting models show their significant forecasting ability of the excess return rate of the Shanghai Composite Index in the sample, and the technical indicators provide some useful information for predicting the excess return rate.

Fig. 3 is an in-sample estimation diagram of the first principal component forecasting model of the technical indicators.

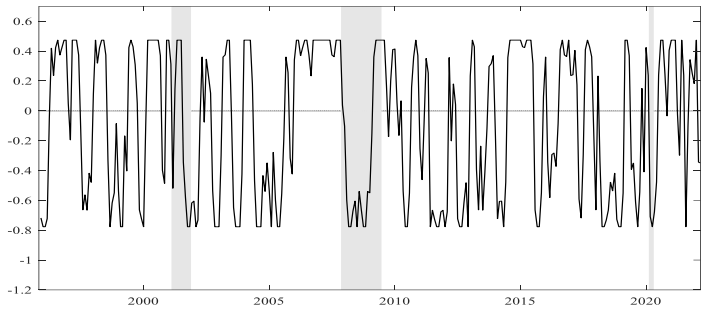

Fig. 3. In-sample estimation plots of the first principal component forecasting model for technical indicators. The sample period was from December 1995 to March 2022. Gray columns indicate the decline period of the NBER business cycle.

As can be seen from Fig. 3, the principal component forecasting model shape and the technical indicator time series plot shape are similar, both with a very sudden rise or fall trend. During the NBER business cycle decline period, the principal component forecasting model also experienced a sharp rise and a sharp decline. Neely et al. (2014) proposed that the S&P500 index has countercyclical characteristics, and the technical indicators can better capture the decline of the excess returns of stocks in the economic expansion period. Due to the differences between the Chinese and American stock markets, the conclusion obtained in this paper is still different.

5.3. Changes in excess returns near periodic peaks and troughs

This paper further reveals the average change of the excess return rate of the Shanghai Composite Index near the peak and trough of the business cycle, and conducts the regression analysis through the following equation:

$$r_t = a_{\mathrm{A}} + \sum_{m=4}^{-2} b_{\mathrm{A},m}^{\mathrm{P}} I_{t-m}^{\mathrm{P}} + \sum_{m=4}^{-2} b_{\mathrm{A},m}^{\mathrm{T}} I_{t-m}^{\mathrm{T}} + u_{\mathrm{A},t} \tag{20}$$

$$\hat{r}_t = a_{\mathrm{FC}} + \sum_{m=4}^{-2} b_{\mathrm{FC},m}^{\mathrm{P}} I_{t-m}^{\mathrm{P}} + \sum_{m=4}^{-2} b_{\mathrm{FC},m}^{\mathrm{T}} I_{t-m}^{\mathrm{T}} + u_{\mathrm{FC},t} \tag{21}$$

where $\hat{r}_t$ represents the excess yield of Sindex estimated in-sample of the principal component forecasting model. $I^P{}_t(I^T{}_t)$ is a binary variable, the value is 1 when month t is in the NBER business cycle peak (trough), otherwise the value is 0. Each $b_{\mathrm{A},m}^{\mathrm{P}}$ ($b_{\mathrm{A},m}^{\mathrm{T}}$) coefficient represents the average change in the excess return rate of the Shanghai Composite Index within m months from the peak (trough) of the NBER business cycle. Each $b_{\mathrm{FC},m}^{\mathrm{P}}$ ($b_{\mathrm{FC},m}^{\mathrm{T}}$) coefficient represents the expected value of the average change in the excess return rate of the Shanghai Composite Index for m months from the NBER business cycle peak (trough).

Since the stock market is prospective, this paper uses an asymmetric window, namely the first 4 and second 2 months of the peaks or troughs.

Fig. 4 shows the coefficient values of the estimated model, along with its 90% confidence intervals.

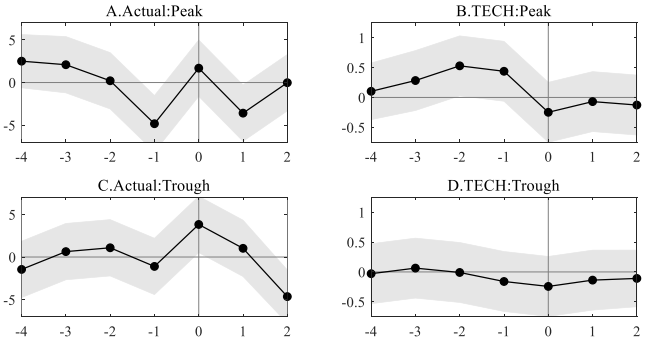

Fig. 4. Excess return behavior of the Shanghai Composite Index around the periodic peak and trough. Panel A (C) in this figure shows the changes in the actual excess returns of the four days before and two days after the periodic peak (trough). Panel B (D) shows the change in the average excess return of the principal component forecasting model within the first and two days after the periodic peaks (troughs). Gray intervals indicate the 90% confidence intervals.

As can be seen from Fig. 4: (1) the actual excess return of the Shanghai Composite index has only increased for 2 months near the peak of the business cycle. In the first 4 months of the peak of the business cycle, there was a slow rise and downward trend in the last 2 months; (2) the actual excess return of the Shanghai Composite Index showed a downward trend for 3 months near the trough of the business cycle. The estimated average excess return of the Shanghai Composite index based on the principal component forecasting model decreased for three months near the business cycle trough, and all within the first four months of the trough.

Overall, the information provided by the technical indicators can better predict the rising peak front and the falling through front of the business cycle.

5.4. Out-of-sample forecasting performance

This paper makes out-of-sample forecasting based on the technical index forecasting model and the principal component forecasting model. The initial sample period was from December 1995 to December 2003, and the out-of-sample forecasting period was from January 2004 to March 2022. We get the out-of-sample forecasting results as shown in Table 4. The table not only reports the results based on the historical average forecasting model, but panel A also reports the forecasting results based on the technical index forecast and measurement model, and panel B also reports the forecasting results based on the principal component forecasting model.

Table. 4 Out-of-sample forecasting results

Indicators	MSFE	R^2_{OoS}	*MSFE-adjusted*	$R^2_{OoS\text{-}EXP}$	$R^2_{OoS\text{-}REC}$	$(\bar{\hat{e}})^2$	Var($\hat{e}$)
HA	11.34					0.02	11.33
Panel A: regression based on technical indicators							
MA(1,3)	11.18	1.41%	1.77**	-2.06%	9.13%	0.03	11.16
MA(1,4)	11.21	1.19%	1.64*	-2.12%	8.57%	0.02	11.18
MA(1,5)	11.24	0.94%	1.48*	-1.93%	7.33%	0.02	11.22
MA(1,6)	11.30	0.34%	1.04	-1.05%	3.35%	0.03	11.28
MA(2,3)	11.31	0.33%	1.65**	-2.65%	6.90%	0.04	11.26
MA(2,4)	11.12	1.94%	2.18**	-2.48%	11.82%	0.02	11.10
MA(2,5)	11.16	1.60%	1.89**	-1.81%	9.16%	0.02	11.14
MA(2,6)	11.14	1.82%	1.95**	-1.36%	8.87%	0.02	11.12
MOM(3)	11.12	2.01%	2.08**	-0.70%	8.00%	0.01	11.10
MOM(4)	11.17	1.57%	1.88**	0.01%	4.90%	0.02	11.15
MOM(5)	11.22	1.09%	1.51*	0.29%	2.68%	0.02	11.20
MOM(6)	11.29	0.51%	1.14	-0.31%	2.21%	0.03	11.26
VOL(1,3)	11.32	0.24%	0.86	0.48%	-0.11%	0.03	11.28
VOL(1,4)	11.22	1.11%	1.60*	1.14%	1.33%	0.02	11.19
VOL(1,5)	11.20	1.30%	1.73**	0.51%	3.43%	0.02	11.17
VOL(1,6)	11.20	1.27%	1.76**	0.65%	2.98%	0.02	11.18
VOL(2,3)	11.39	-0.38%	0.39	-1.96%	3.12%	0.02	11.36
VOL(2,4)	11.28	0.54%	1.35*	0.01%	2.03%	0.02	11.26
VOL(2,5)	11.16	1.62%	1.93**	0.10%	5.48%	0.02	11.14
VOL(2,6)	11.26	0.74%	1.37*	-0.59%	4.06%	0.01	11.25
Panel B: regression based on the principal component							
PC-TECH	11.10	2.11%	1.95**	-0.58%	8.16%	0.02	11.09

Notes: This table reports the out-of-sample forecasting results based on technical indicators and principal component forecasting models with the initial sample period from December 1995 to December 2003 and the out-of-sample forecasting period from January 2004 to March 2022. K=1 is the result selected by the adjusted R^2.*, * *, * * * represents results at the 10%, 5%, 1% significance level, respectively. R^2_{Oos} represents out-of-sample R^2, $R^2_{\text{Oos-EXP}}$ represents out-of-sample R^2 during the NBER business cycle expansion period, and $R^2_{\text{Oos-REC}}$ represents out-of-sample R^2 during the NBER business cycle decline period. The last two columns represent the sum of squared forecasting error variance.

As seen from the results in row 2, (1) The MSFE of the historical average forecasting model was 11.34, By comparing the MSFE and historical average of the 20 technical indicators in panel A of Table 4, As can be seen, With 19 technical indicators, the MSFE was less than the historical average, The smallest is the momentum indicator MOM (3), Only at 11.12; (2) As can be seen from the *MSFE-adjusted* column, Among them, 16 technical indicators show the significant forecasting ability of the excess return rate of the Shanghai Composite Index under the 10% significance level; (3) Secondly, There are 19 technical indicators with a R^2_{OoS} greater than 0, This also indicates that the MSFE provided by these 19 technical indicators is lower than the historical average benchmark, The R^2_{OoS} of 12 technical indicators is greater than 1%; (4) As can be seen from the $R^2_{OoS\text{-}EXP}$ column and the $R^2_{OoS\text{-}REC}$ column, Compared to the NBER business cycle expansion period, Technical indicators have a more obvious predictive power in the recession period; (5) The last two columns report the sum of forecasting error variance, The historical average forecasting bias is squared to 0.02, The historical mean forecasting error variance was 11.33, It can be seen that the forecasting deviation square of the 20 technical indicators does not differ much, But in terms of the forecasting error, In addition to the

moving average volume indicator VOL (2, 3), The forecasting error variance of the remaining 19 technical indicators was smaller than the historical average.

As can be seen in Table 4, The principal component predicted an MSFE of 11.10, Less than the historical average forecasting model at the 5% significance level; The principal component forecasting model had an R^2_{OoS} of 2.11%, Greater than the R^2_{OoS} predicted by all 20 technical indicators; the $R^2_{OoS\text{-}REC}$ during NBER business cycle decline was 8.16%, Significantly greater than -0.58% during the expansion period, The principal component forecasting model also shows a stronger forecasting ability in the business cycle decline period; last, The principal component forecasting model square 0.02, Consistent with the historical average, However, the forecasting error variance was 11.09, Also smaller than the historical average, Is the smallest of all the forecasting models.

In general, the results of both the single technical index forecasting model are basically better than the historical average forecasting model, and the results of the principal component forecasting model are also better than any one of the 20 technical index forecasting models, indicating that the principal component method can effectively extract the useful information from the 20 technical indicators, so as to improve the forecasting ability.

Fig.5 is the out-of-sample forecast chart of the first principal component forecasting model of technical indicators. The black curve is the monthly excess return rate of the Shanghai Composite index predicted by the principal component forecasting model, and the gray curve is the monthly excess return rate of the Shanghai Composite index predicted by the historical average forecasting model.

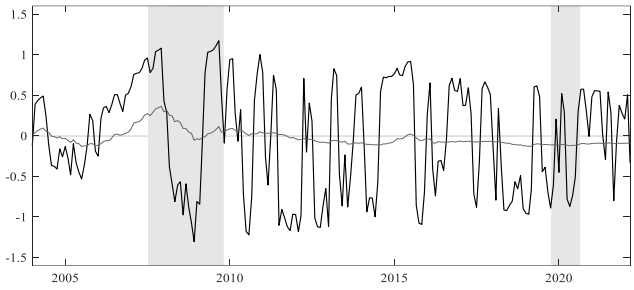

Fig. 5. Out-of-sample forecasting plot of the first principal component forecasting model for technical indicators. The out-of-sample forecasting period was from January 2004 to March 2022. The black curve is the monthly excess return rate of the Shanghai Composite index predicted by the principal component forecasting model, and the gray curve is the monthly excess return rate of the Shanghai Composite index predicted by the historical average forecasting model. Gray columns indicate the decline period of the NBER business cycle.

As can be seen from Fig. 5, the out-of-sample forecasting model of the principal component forecasting model also reflects the characteristics of sharp changes, which is less volatile than the in-sample estimate, but significantly greater than the volatility of the historical average forecasting model. Secondly, in the case of out-of-sample forecasting, the NBER business cycle decline period is still all experienced a sharp rise and decline, and there is no counter-cyclical characteristics.

6. Asset allocation

6.1. Theoretical basis and evaluation method

Campbell and Thompson (2008) proposed an evaluation mechanism that can measure the economic value of a certain yield forecasting method, that is, a mean-variance investor optimally allocates capital to stocks and risk-free bonds according to the forecasting model, and evaluates the merits of this forecasting method by calculating the deterministic equivalent return (CER). The expected utility of mean-variance investors is as follows:

$$U\left(R_p\right)=E\left(R_p\right)-\frac{1}{2}\gamma \operatorname{Var}\left(R_p\right) \tag{22}$$

where R_p is the portfolio return of mean-variance investors, $E(R_p)$ is the expected portfolio return, $Var(R_p)$ is the variance of portfolio return, and γ is the risk aversion coefficient of mean-variance investors. At the end of month *t*, the mean-to-investors investors in order to achieve the maximum utility in month *t*+1 can be expressed as:

$$w_t=\left(\frac{1}{\gamma}\right)\left(\frac{\hat{r}_{t+1}}{\hat{\sigma}_{t+1}^2}\right) \tag{23}$$

where $\hat{r}_{t+1}$ represents the predicted value of excess yield and $\hat{\sigma}_{t+1}^2$ represents its predicted variance 1-w_t is the weight assigned to risk-free bonds. In this way, the portfolio yield at momth *t*+1 can be expressed as:

$$R_{p,t+1}=w_t r_{t+1}+R_{f,t+1} \tag{24}$$

where $R_{f,t+1}$ is the risk-free return rate in month *t*+1. According to the article by Campbell and Thompson (2008), this paper assumes that mean-variance investors use the moving window of monthly earnings over the past five years to estimate the variance of equity risk premium, in order to limit short selling and leverage over 50%, limit wt between 0-1.5.

At this point, the certainty equivalent return (CER) of the portfolio can be calculated by the following equation:

$$\mathrm{CER}_p=\hat{\mu}_p-\frac{1}{2}\gamma\hat{\sigma}_p^2 \tag{25}$$

where $\hat{\mu}_p$ and $\hat{\sigma}_p^2$ represent the mean and variance of the portfolio yield during the forecast evaluation period. The deterministic equivalent return (CER) can be interpreted as a defined risk-free return on a risk-free investment as attractive as a venture capital. This paper will calculate the historical average forecasting model, 20 technical index forecasting model and the certainty of principal component forecasting model for investors (CER), CER gain means the investors using a single technical index or principal component forecasting model and using the historical average forecasting model of the certainty of equivalent return (CER). Finally, by multiplying the CER gain by 1200, the CER gain can be interpreted as the annual percentage management fee that investors are willing to pay to allocate a single technical indicator or principal component forecasting model instead of the historical average forecasting model.

In addition, the Sharpe ratio is also calculated. The Sharpe ratio for the portfolio can be expressed as:

$$SR=\frac{\bar{R}_p^e}{\sigma_p^e} \tag{26}$$

where $\bar{R}_p^e$ and σ_p^e represent the mean and standard deviation of excess yields of the portfolio during the out-of-sample evaluation period.

6.2. Portfolio performance

This paper reports the portfolio performance of a mean-variance investor with a relative risk aversion coefficient of 5 who make monthly allocation between stocks and risk-free bonds using a historical average (HA), technical indicator forecasting model, and principal component forecasting model forecastings. This paper considers not only the deterministic equivalent return (CER) gain without transaction cost, but also the deterministic equivalent return (CER) gain at a transaction cost of 50bps. Relative turnover rate (%) represents the capital turnover rate of the forecasting model

relative to the historical average forecasting model (HA). The specific investment portfolio is shown in Table 5.

Table. 5 Portfolio performance

Indicators	Δ(ann.)	$\Delta(ann.)_{EXP}$	$\Delta(ann.)_{REC}$	*SR*	Relative average turnover rate(%)	$\Delta(ann.)_{cost=50bps}$
HA	0.03			0.00	1.55	2.83%
Panel A: regression based on technical indicators						
MA(1,3)	0.74%	-0.29%	10.06%	0.09	23.52	-1.56%
MA(1,4)	0.25%	-0.68%	8.61%	0.08	19.51	-1.67%
MA(1,5)	0.26%	-0.62%	8.19%	0.07	15.90	-1.27%
MA(1,6)	-0.18%	-0.07%	-1.42%	0.06	13.49	-1.47%
MA(2,3)	-0.88%	-1.00%	-0.14%	0.07	27.81	-3.59%
MA(2,4)	0.65%	-0.56%	11.62%	0.09	22.63	-1.50%
MA(2,5)	0.69%	-0.35%	10.07%	0.09	15.71	-0.78%
MA(2,6)	0.98%	0.00%	9.87%	0.10	13.63	-0.28%
MOM(3)	0.99%	0.36%	6.70%	0.10	17.57	-0.70%
MOM(4)	0.29%	0.28%	0.11%	0.08	17.20	-1.34%
MOM(5)	0.79%	1.06%	-1.77%	0.09	11.09	-0.23%
MOM(6)	0.24%	0.44%	-1.74%	0.07	9.79	-0.65%
VOL(1,3)	-0.16%	0.71%	-5.46%	0.05	23.11	-2.35%
VOL(1,4)	0.42%	1.07%	-2.92%	0.07	13.85	-0.84%
VOL(1,5)	0.10%	0.67%	-2.47%	0.07	15.31	-1.33%
VOL(1,6)	0.01%	0.43%	-1.25%	0.06	12.98	-1.18%
VOL(2,3)	-0.29%	-0.51%	1.55%	0.04	19.35	-2.02%
VOL(2,4)	-0.54%	0.49%	-7.41%	0.06	17.83	-2.20%
VOL(2,5)	0.21%	0.54%	-0.27%	0.08	12.16	-0.90%
VOL(2,6)	-0.30%	-0.20%	1.36%	0.05	9.04	-1.09%
Panel B: regression based on the principal component						
PC-TECH	0.79%	0.17%	6.30%	0.09	17.56	-0.89%

Notes: This table reports the portfolio performance of a mean-variance investor with a relative risk aversion coefficient of 5, who makes a monthly allocation between stocks and risk-free bonds using a historical average (HA), technical indicator forecasting model, and principal component forecasting model forecastings. The sample span ranged from December 1995 to March 2021. Δ(ann.), $\Delta(ann.)_{EXP}$, $\Delta(ann.)_{REC}$ represent the certainty equivalent return (CER) gain of the forecast model, the NBER business cycle expansion period, and the NBER business cycle decline period (HA). The *SR* indicates the Sharpe ratio. $\Delta(ann.)_{cost=50bps}$ indicates full sample deterministic equivalent return (CER) for transaction expense of 50bps.

As can be seen from Table 5, the historical average forecasting model CER is 0.03% without transaction costs, indicating that the historical average forecasting model can produce positive deterministic equivalence returns. Its Sharpe ratio is 0, indicating that the yield rate generated by the historical average forecast model is equal to the market risk-free return rate. As can be seen from panel A: (1) out of the 20 technical indicators, With 14 technical index forecasting models with a CER gain greater than 0, More than the historical average; (2) The Sharpe ratio of the 20 technical indicators is greater than 0, It shows that all technical index forecasting models produce a yield greater than the risk-free return rate, That is, positive excess returns; (3) Looking at the results of the expansion and decline periods of the NBER business cycle, Found a $\Delta(ann.)_{REC}$ greater than $\Delta(ann.)_{EXP}$, This means that only half of the forecasting models have greater CER gains during the NBER business cycle decline; (4) The capital turnover rate of the historical average forecasting model

is 1.55%, It considers the transaction costs of 50 basis points, There are still 283 basis points of CER returns. The capital turnover rate of the 20 technical index forecasting models is greater than that of the historical average forecasting model, among which the capital turnover rate of the moving average index MA (2,3) is the largest, which is 27.81 times that of the historical average level. After considering the transaction costs of 50 basis points, the CER gain of all the technical indicator forecasting models is negative. Even for the 14 technical index forecasting models with positive CER gain without transaction costs, the CER gain turns from positive to negative in the presence of transaction costs.

From panel B in Table 5, the CER of the principal component forecasting model is 79 basis points; the CER gain during the NBER business cycle decline period is 613 (=630-17) basis points more than the expansion period; the Sharpe ratio is 0.09, indicating that the yield of the principal component forecasting model is greater than the risk-free return rate; the principal component forecasting model is 17.56 times the historical average, and the CER gain is changed from 79 basis points to-89 basis points.

Overall, without considering transaction costs, both the principal component forecasting model and most technical index forecasting models can produce greater deterministic equivalent returns than the historical average forecasting model. However, the capital turnover rate of the principal component forecasting model and all the technical index forecasting models is about 9~27 times of the historical average level. After considering the transaction cost, the CER gain of all the forecasting models is negative. Even so, the Sharpe ratio of the principal component forecasting model and all the technical index forecasting models is greater than the historical average and greater than 0, indicating that excess returns can still be generated.

7. Conclusions

In this paper, the closing price and trading volume data of the Shanghai Composite Index from November 1994 to March 2022 are selected, and 20 technical indicators are constructed according to the moving-average (MA) rule, momentum (MOM) rule and volume on balance (VOL) rule. 20 technical index forecasting models and principal component forecasting models are used to estimate in-sample and predict the excess yield of the Shanghai Composite index. Secondly, we also study the average change of the excess return rate of the actual Shanghai Composite Index and that estimated by the principal component forecasting model near the peak and trough of the business cycle. Finally, this paper allocates the mean-variance investors to form a portfolio and compares the combination performance of historical average model, technical index forecasting model and principal component forecasting model. The following conclusions are drawn:

First, technical indicators provide useful information for predicting the market return rate. The technical index forecasting model and the principal component forecasting model constructed in this paper basically have significant forecasting ability for the excess yield rate of the Shanghai Composite index both inside and outside the sample. Compared with the business cycle expansion period, the technical index forecasting model and the principal component forecasting model have more superior forecasting performance in the recession period.

Second, the information provided by the technical indicators can better predict the rise of the peak and the trough front of the business cycle.

Third, the information in the technical indicators is helpful to obtain excess returns. Without transaction costs, the principal component forecasting model and most technical index forecasting models can produce higher CER gains than the historical average. However, considering transaction costs, all forecasting models have CER gain negative. During the business cycle decline period, the principal component forecasting has obvious advantages, but only half of the technical index forecasting models show better performance than the expansion period.

References

[1] Aldin M M, Dehnavi H D, Entezari S. Evaluating the Employment of Technical Indicators in Predicting Stock Price Index Variations Using Artificial Neural Networks (Case Study: Tehran Stock Exchange) [J]. International Journal of Business and Management, 2012, 7(15):25-34.

[2] Banz R W. The relationship between return and market value of common stocks [J]. Journal of Financial Economics, 1981, 9(1):3-18.

[3] Breen W, Glosten L R, Jagannathan R. Economic Significance of Predictable Variations in Stock Index Returns [J]. The Journal of Finance, 1989, 44(5):1177-1189.

[4] Brock W, Lakonishok J, LeBaron B. Simple Technical Trading Rules and the Stochastic Properties of Stock Returns [J]. The Journal of Finance, 1992, 47(5):1731-1764.

[5] Campbell J Y, Thompson S B. Predicting excess stock returns out of sample: Can anything beat the historical average? [J]. Review of Financial Studies, 2008,4(21):1509-1531.

[6] Campbell J Y, Vuolteenaho T. Inflation illusion and stock prices [J]. American Economic Review, 2004, 94(2): 19-23.

[7] Chang Y H, Chan C C, Chiang Y C, Volume information and the profitability of technical trading [J]. Asia-Pacific Journal of Financial Studies, 2014, 43(2):249-272 .

[8] Clark T E, West K D. Approximately normal tests for equal predictive accuracy in nested models [J]. Journal of Econometrics, 2007,1(138):291-311.

[9] Dai Z, Zhu H, Kang J. New technical indicators and stock returns predictability[J]. International Review of Economics and Finance, 2021, 71:127-142.

[10] De Bondt W F M, Thaler R. Does the Stock Market Overreact? [J]. The Journal of Finance, 1985, 40(3):793-805.

[11] Gehrig T, Menkhoff L. Extended evidence on the use of technical analysis in foreign exchange [J]. International Journal of Finance&Economics, 2006, 11(4):327-338.

[12] Granville J E. Granville's New Key to Stock Market Profits [M]. New York: Prentice-Hall, 1963.

[13] Henkel S J, Martin J S, Nardari F. Time-varying short-horizon predictability[J]. Journal of Financial Economics, 2011, 99(3):560-580.

[14] Hsu P H, Taylor M P, Wang Z. Technical trading: Is it still beating the foreign exchange market? [J]. Journal of International Economics, 2016, 102: 188-208 .

[15] Irwin S H. What Do We Know About the Profitability of Technical Analysis? [J]. Journal of Economic Surveys, 2007, 21(4):786-826.

[16] Jegadeesh N, Titman S. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency[J]. The Journal of Finance, 1993, 48(1):65-91.

[17] Lento C, Gradojevic N. The Profitability of Technical Trading Rules: A Combined Signal Approach [J]. Journal of Applied Business Research, 2007, 23(1):13-28.

[18] Lin Q. Technical analysis and stock return predictability: An aligned approach [J]. Journal of Financial Markets, 2018, 38:103-123.

[19] Menkhoff L. The use of technical analysis by fund managers: International evidence [J]. Journal of Banking & Finance, 2010, 34:2573-2586.

[20] Moskowitz T J, Ooi Y H, Pedersen L H. Time series momentum[J]. Journal of Financial Economic, 2012, 104:228–250.

[21] Neely C J, Rapach D E, Tu J, et al. Forecasting the Equity Risk Premium: The Role of Technical Indicators [J]. Management Science, 2014, 60(7):1772-1791.

[22] Panopoulou E, Souropanis I. The role of technical indicators in exchange rate forecasting [J]. Journal of Empirical Finance, 2019, 53:197-221.

[23] Reimganum M R. Misspecification of capital asset pricing: Empirical anomalies based on earnings' yields and market values [J]. Journal of Financial Economics, 1981, 9(1):19-46.

[24] Vajda V. Could a trader using only “old” technical indicator be successful at the Forex market? [J]. Procedia Economics and Finance, 2014, 15:318-325.

[25] Wang Y, Liu L, Wu C. Forecasting commodity prices out-of-sample: Can technical indicators help? [J]. International Journal of Forecasting, 2020, 36:666-683.

[26] Welch I, Goyal A. A comprehensive look at the empirical performance of equity premium prediction [J]. Review of Financial Studies, 2008, 21(4):1455-1508.

[27] Wong W, Du J, Chong T. Do the Technical indicators Reward Chartists?A study on the Stock Markets of China, Hong Kong and Taiwan [J]. Review of Applied Economics, 2005, 1(2):183-205.

[28] Yao Y, Cai S, Wang H. Are technical indicators helpful to investors in china's stock market? A study based on some distribution forecast models and their combinations[J]. Economic Research-Ekonomska Istraživanja, 2021, 35(1):2668-2692.

[29] Yin L, Yang Q, Su Z. Predictability of structural co-movement in commodity prices: the role of technical indicators [J]. Quantitative Finance, 2016, 17:795-812.

[30] Yin L, Yang Q. Predicting the oil prices: Do technical indicators help? [J]. Energy Economics,2016,56:338-350.

[31] Zhang Y, Ma F, Wang Y. Forecasting crude oil prices with a large set of predictors: Can LASSO select powerful predictors?[J]. Journal of Empirical Finance, 2019, 54:97-117.

[32] Zhang Y, Ma F, Shi B, et al. Forecasting the prices of crude oil: An iterated combination approach [J]. Energy Economics, 2018, 70:472-483.