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# Are technical indicators helpful to investors in china's stock market? A study based on some distribution forecast models and their combinations

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## ABSTRACT

Can investors use technical analysis to generate positive risk-adjusted returns by observing historical transaction data? The study investigates whether technical indicators (TIs) are beneficial to the returns and risk management of China's stock market investors. It is conducted from the perspective of a distribution forecast rather than a traditional point forecast. The study investigates the TIs' predictability on the distribution of returns. It also examines the TIs' impact on risk management. A high-dimensional-same-frequency information distribution forecasting model, the LASSO-EGARCH model, is built. The LASSO regression's results show that the TIs have limited 'explanatory power' for the return prediction. However, the adaptive moving average and turnover rate show significant and robust effects. The statistical evaluation and economic evaluation show that the TIs information's integration cannot improve the direction forecast's accuracy, nor does it have excess profitability. However, it enables the return distribution to have a better calibration. The above conclusion reveals that the usefulness of the analysis for China's stock market lies in its risk management when the stock price plunges, rather than in excess profits. This may provide a reference for investors who prefer the TIs' analysis.

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## 1. Introduction

Forecasting stock prices is a classic problem. However, non-linear and non-stationary characteristics make the stock market a complex system. Forecasting has thus become a difficult task. The efficient market hypothesis (EMH) proposed by Fama (1995) states that in an efficient information market, it is not possible to predict the stock prices and that stocks behave in a random walk manner. However, the scientific community has proposed various methods for forecasting the stock market (Cavalcante

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et al., 2016). These methods can be divided into fundamental and technical analyses. The fundamental analysis uses potential factors, such as macroeconomic variables that affect a company or industry, as forecasting factors. The technical analysis relies on the historical price and trading volume information to forecast stock market trends, such as technical indicators (TIs). Wang and Li (2020) empirically found breakdowns in the link between China's stock market and the macroeconomy. They noted that the real economy could not predict the stock markets' booms or busts. Therefore, this study focuses on technical analysis. Technical analysts believe that most of the stock's information is reflected in the recent prices and volumes. They also believe that the movement trends are hidden in them. Many participants in the financial market use technical analysis (Park & Irwin, 2009). Technical traders have a larger fraction than the fundamentalists and arbitrageurs in the equilibrium of the financial markets (Gong et al., 2021). The technical analysis has been the most common method used in the literature (Atsalakis & Valavanis, 2009; Cavalcante et al., 2016). Furthermore, as Nazário et al. (2017) and Bustos and Pomares-Quimbaya (2020) introduced in their articles, TIs have been the most popular forecasting information. They have been used as signals to indicate when to buy and sell stocks.

## 2. Literature review

Many aspects of the literature have been researched regarding the TIs' significance and usefulness. Many studies have found that technical analysis methods have predictive power or can generate profits. For example, Zhu and Pan (2003) concluded that the money flow index (MFI) has a high predictive accuracy for China's stock prices. Park and Irwin (2007) found that 56 of 95 selected modern technical analysis studies produced supporting evidence for its profitability. Ko et al. (2014) showed that applying a moving average time strategy to a portfolio classified by a book-to-market ratio in the Taiwan stock market can generate higher returns than a buy-and-hold strategy. Lin (2018) proposed a new TI that exhibits statistically and economically significant in-sample and out-of-sample predictive power. It outperforms the well-known TIs and macroeconomic variables. Mohanty et al. (2020) believe that TIs under a deep learning framework can improve financial market forecasts' quality. However, there is no consensus on whether the TI analysis is effective in the literature. Dong (2011) concludes that basic TIs have a weaker impact on the Chinese small and medium-sized companies' stock prices. This is far inferior to financial information. Fang et al. (2014) studied the profitability of 93 market indicators and found no evidence that they could predict the stock market returns. Nazário et al. (2017) classified and coded the technical analysis documents of the past 55 years, focusing on the stock analysis. They found that the research results 'supporting technical analysis' and 'not supporting technical analysis' account for almost equal proportions. A more detailed overview of the technical analysis can be found in Bustos and Pomares-Quimbaya (2020), Fang et al. (2014), Gandhmal and Kumar (2019), and Nazário et al. (2017). This is where the role and influence of the stock markets' TIs are systematically reviewed.

The related documents mainly focus on point forecasts. Therefore, they only study the impact on the stock market's mean returns. However, the return is always accompanied by risk. TIs may also have an impact on risk. However, there is little research on this aspect. In contrast, this study researches the distribution forecasting's perspective. As compared with a point forecast, a distribution forecast provides a more complete information description. The return is examined from the two aspects of the mean and median of the distribution. The risk is characterised by the conditional heteroscedasticity to realise the dual study of the TIs' impact on the return and risk. With the help of the distribution forecast's overall evaluation, the combinations of models are considered. The statistical and economic significance of TIs is further explored.

This study uses the GARCH family framework. The conditional mean of the returns is described by three models: constant, ARMA process, and LASSO regression with high-dimensional-same-frequency TI information. The GARCH process is used to characterise conditional volatility. The GARCH model proposed by Bollerslev (1986) has shown good empirical effects in the literature, as described by Milosevic et al. (2019). However, a large number of scholars believe that it is necessary to consider the leverage effect of the returns. Models with leverage include the TARCH model (GJR-GARCH model) and the EGARCH model. The EGARCH model proposed by Nelson (1991) is widely used. Wang and Wang (2008) believed that the skewed Student's t-distribution provides the best choice for the characterisation and prediction of the actual volatility of China's stock market. The volatility described by the conditional variance adopts the EGARCH model with skewed Student's t-distribution residuals. The return distribution forecast is hereby realised under the GARCH framework. The direction predictability and excess profitability based on the mean and median forecasts can be tested. The risk characteristics can also be investigated based on the Value at Risk (VaR). Furthermore, based on the distribution forecast's overall statistical evaluation, the TI information's significance and usefulness can be revealed through the model combination and comparison.

### **3. Models and methods**

#### **3.1. Model selection and construction**

The TIs considered in this study were high-dimensional and had the same frequency of information. Three models were established and analysed by comparison: (1) EGARCH, which only models conditional variance; (2) ARMA-EGARCH, which models conditional mean and EGARCH model's conditional variance; and (3) the conditional mean and EGARCH model's conditional variance. The residuals are all set to obey the skewed Student's t-distribution.

##### **3.1.1. EGARCH model**

The EGARCH model is selected for three reasons: (1) It relieves the non-negative constraints of the parameters to be estimated. This is more flexible. (2) It allows the return innovation to throw asymmetric shocks on the volatility. This is a leverage effect, which is consistent with the investors' experience. It is manifested as a strong

increase in the volatility caused by negative windfall returns. The impact is greater than the positive windfall returns. (3) Many empirical studies show that for China’s stock market, the EGARCH model has better performance. The EGARCH model with a skewed Student’s t-distribution error was selected as the base model. It is represented as:

$$\left\{ \begin{array}{l} Y_t = \mu + \varepsilon_t, \\ \ln h_t = \omega + \beta \ln h_{t-1} + \alpha \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}, \\ \varepsilon_t | I_{t-1} \sim \text{iid} \frac{2}{(\lambda + \lambda^{-1})\sqrt{h_t}} \left[ f_v \left( \frac{\varepsilon_t}{\lambda\sqrt{h_t}} \right) I(\varepsilon_t \geq 0) + f_v \left( \frac{\lambda\varepsilon_t}{\sqrt{h_t}} \right) I(\varepsilon_t < 0) \right]. \end{array} \right. \quad (1)$$

In Model (1),  $Y_t$  is the return at moment  $t$ ,  $\varepsilon_t$  is the residual, and  $h_t$  is the heteroscedasticity of  $Y_t$ .  $\mu$  is the constant conditional mean of  $Y_t$ , and  $\gamma$  is the leverage coefficient.  $I_{t-1}$  represents the information set at moment  $t-1$ , and  $f_v(\cdot)$  is the density function of the students’ t-distribution with a freedom degree of  $v$ .

**3.1.2. ARMA-EGARCH model**

In Model (1), the conditional mean is set as a constant. However, the conditional mean of returns may be time-variant. To describe the return series’ autocorrelation characteristics, the ARMA model of the conditional mean is considered based on Model (1). This is recorded as the ARMA-EGARCH model, expressed as:

$$\left\{ \begin{array}{l} Y_t = \phi_0 + \phi_1 Y_{t-1} + \dots + \phi_p Y_{t-p} + \theta_1 \varepsilon_{t-1} + \dots + \theta_q \varepsilon_{t-q} + \varepsilon_t, \\ \ln h_t = \omega + \beta \ln h_{t-1} + \alpha \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}, \\ \varepsilon_t | I_{t-1} \sim \text{iid} \frac{2}{(\lambda + \lambda^{-1})\sqrt{h_t}} \left[ f_v \left( \frac{\varepsilon_t}{\lambda\sqrt{h_t}} \right) I(\varepsilon_t \geq 0) + f_v \left( \frac{\lambda\varepsilon_t}{\sqrt{h_t}} \right) I(\varepsilon_t < 0) \right]. \end{array} \right. \quad (2)$$

Model (2)’s first equation implies that the conditional mean of  $Y_t$  obeys the ARMA(p, q) process. Suppose the unconditional expectation of  $Y_t$  is  $\mu$  then,  $\phi_0 = (1 - \phi_1 - \dots - \phi_p)\mu$  here. With the expression of the lag operator  $B$ , Model (2)’s first equation can be written as:

$\phi(B)(Y_t - \mu) = \theta(B)\varepsilon_t$ , where  $\phi(B) = 1 - \phi_1 B - \dots - \phi_p B^p$  and  $\theta(B) = 1 + \theta_1 B + \dots + \theta_q B^q$ . To stabilise the ARMA (p, q) process, the values of  $\{\phi_i\}$  should satisfy that the roots of  $\phi(B) = 0$  are outside the unit circle. To make the process reversible, the values of  $\{\theta_i\}$  should satisfy that the roots of  $\theta(B) = 0$  are outside the unit circle.

**3.1.3. LASSO-EGARCH model**

The intention is to analyse the TIs’ impact on the returns by examining the dynamic evolution process of the return series itself. The rational choice would be to add the TIs as exogenous variables to the conditional mean equation to construct a new model based on Model (1) or Model (2). We have tried to add TIs to the ARMA-

EGARCH (Model (2)). However, for many return samples, the model is not identifiable. The optimisation cannot converge. Therefore, we only add the TIs to Model (1) to build Model (3), which is shown as:

$$\left\{ \begin{array}{l} Y_t = \delta_0 + \delta_1 X_{1,t-1} + \dots + \delta_m X_{m,t-1} + \varepsilon_t, \\ \ln h_t = \omega + \beta \ln h_{t-1} + \alpha \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}, \\ \varepsilon_t | I_{t-1} \sim \text{iid} \frac{2}{(\lambda + \lambda^{-1})\sqrt{h_t}} \left[ f_v \left( \frac{\varepsilon_t}{\lambda\sqrt{h_t}} \right) I(\varepsilon_t \geq 0) + f_v \left( \frac{\lambda\varepsilon_t}{\sqrt{h_t}} \right) I(\varepsilon_t < 0) \right]. \end{array} \right. \quad (3)$$

In Model (3),  $X_{1,t-1}, X_{2,t-1}, \dots, X_{m,t-1}$  are the values of the TIs at moment t-1. What we want to study is the TIs' predictive effect on the returns. The value of TIs lags behind the returns by one period. The subscript of  $Y_t$  is t, and the subscripts of the TI variables are t-1. When many TIs are used, this is a high-dimensional problem. The direct parameter estimation of Model (3) is likely to face the 'dimension disaster'. Since TIs are mainly derived from the price and volume information, there may be multicollinearity problems. Before realising the entire model's parameter estimation, the TIs' multicollinearity diagnosis and dimensionality reduction were performed. Hong et al. (2016) indicated that in the past two decades, dimensionality reduction methods have made considerable progress. Among them, the LASSO regression has many good properties. It can perform parameter estimation while selecting variables, solve the incalculable problem of the traditional model selection methods when the number of variables is large and reduces the model selection's uncertainty. Therefore, Model (3)'s dimensionality reduction will be realised by the LASSO regression, called the LASSO-EGARCH model. This is a high-dimensional same-frequency information model.

According to the three models' construction, the comparison between Model (1) and Model (2) can test whether the conditional mean of the return has dynamic evolution characteristics. A comparison between Model (1) and Model (3) shows the TIs gain information. With the help of the quantitative results of the statistical evaluation when comparing Models (2) and (3), we can examine the relative importance of the TI information embedded within the fluctuation of the return itself. This serves to verify whether the historical information is reflected in the price at a given time.

**3.2. Models' parameter estimation and forecasting**

Model (1) uses the maximum likelihood method closely related to the Kullback-Leibler distance loss for the parameter estimation. Model (2) involves the problem of ARMA (p, q) order determination. The maximum possible values of p and q are set to pmax and qmax (in the following calculation: pmax = 5, qmax = 2). The order is determined by the Akaike information criterion (AIC). It is realised by the auto.arima () function of the R software package: forecast. Model (3) involves high-dimensional TIs. If the maximum likelihood estimation is directly used, it will encounter the 'dimension disaster'. Before realising the entire model's

parameter estimation, a multicollinearity diagnosis and LASSO regression on TIs to achieve ‘dimensionality reduction’ are performed. Model (3)’s estimation process is discussed below.

### 3.2.1. Multicollinearity diagnosis

In multiple linear regression, multicollinearity may occur when there is a strong correlation between the explanatory variables. At this time, a small change in the model or data may cause large changes in the coefficient estimates. This makes the results unstable and difficult to explain.

The variance inflation factor (*VIF*) is an important measure of multicollinearity, defined as

$$VIF_j = \frac{1}{1 - R_j^2}, \quad (4)$$

where  $R_j^2$  represents the R-square when the  $j$ th variable regresses on all the other variables.

The condition number is another indicator for measuring the total multicollinearity. It is often expressed by  $\kappa$ , and is defined as

$$\kappa = \sqrt{\frac{\lambda_{max}}{\lambda_{min}}}. \quad (5)$$

This is where  $\lambda$  is the eigenvalue of the matrix  $X^T X$  and  $X$  represents an explanatory variables’ data matrix. When the matrix  $X$  is orthogonal, the condition number is  $\kappa = 1$ .

Generally, if the *VIF* is too large (greater than five or 10), there is multicollinearity. Empirically, when  $\kappa > 15$ , there is multicollinearity. When  $\kappa > 30$ , the multicollinearity is serious.

### 3.2.2. LASSO regression

The methods to address the multicollinearity include eliminating unimportant explanatory variables and increasing the sample size. Eliminating the influence of the multicollinearity on the regression models has been a priority for statisticians over the past decades. Statisticians are also committed to improving the classical least squares method and proposing methods to improve the estimator’s stability at the cost of biased estimates. The common methods include principal component regression, partial least squares regression, ridge regression, and LASSO regression.

The concepts of principal component regression and partial least squares regression are to linearly combine the original independent variables through the variables’ correlation. Many independent variables are transformed to a smaller number of ‘comprehensive variables’ to achieve the purpose of ‘dimensionality reduction’. However, such methods do not essentially achieve dimensionality reduction and cannot intuitively analyse the original variables’ relative importance. The ridge regression

increases the coefficient sum of squares' penalty term based on the square loss. Therefore, the coefficient must make the residual sum of squares small but not inflate the coefficient. In principle, the LASSO regression is similar to the ridge regression. However, the LASSO regression's penalty term is not the coefficients' sum of squares. It is the sum of the coefficients' absolute values. Due to the absolute value's characteristics, the LASSO regression does not reduce the coefficient values, such as ridge regression. It filters out some coefficients to realise the variable selection while estimating the parameters. LASSO was iproposed by Tibshirani (1996). It is a compressed estimation, retains the advantages of subset shrinkage, and is an effective estimation for processing data with multicollinearity.

Suppose there are random samples  $(x_i, y_i)$ ,  $i = 1, 2, \dots, n$ , where  $x_i = (x_{i1}, x_{i2}, \dots, x_{ip})^T$  is a  $p$ -dimensional independent variable and  $y_i$  is the response variable for the  $i$ th observation. Assuming that  $y_i$  is independent of the observations, the corresponding LASSO estimate can be expressed as:

$$\begin{aligned}
 (\hat{\alpha}, \hat{\beta}) = \operatorname{argmin} & \left\{ \sum_{i=1}^n \left( y_i - \alpha_i - \sum_{j=1}^p \beta_j x_{ij} \right)^2 \right\}, \\
 \text{s.t. } & \sum_{j=1}^p |\beta_j| \leq t.
 \end{aligned} \tag{6}$$

In Model (6),  $t$  is a harmonic parameter and  $t \geq 0$ . By controlling  $t$ , the sum of the absolute values of the regression coefficients becomes smaller. As  $t$  gradually decreases, some regression coefficients shrink and move toward or equal 0. When the corresponding regression coefficient was 0, the independent variable was removed from the model.

Model (6) can be solved by using the least angle regression (LAR) algorithm by Effron et al. (2004). The Mallows (1973) criterion  $C_p$  was used for the model selection.

Model (3)'s conditional mean equation is solved by the LASSO regression. The coefficient  $\delta_i$  corresponding to the TI variable  $X_{i, t-1}$  can be obtained.

**3.2.3. Forecasting of the return distribution**

For a given return sample  $\{Y_t\}$ , assuming that the parameters of the one-step-ahead prediction remain unchanged, the conditional mean prediction of  $Y_{t+1}$  is  $\hat{\mu}_{t+1}$ . In Model (1),  $\hat{\mu}_{t+1} = \mu$ , in Model (2),  $\hat{\mu}_{t+1} = \phi_0 + \phi_1 Y_t + \dots + \phi_p Y_{t-p+1} + \theta_1 \hat{\epsilon}_t + \dots + \theta_q \hat{\epsilon}_{t-q+1}$ , and in Model (3),  $\hat{\mu}_{t+1} = \delta_0 + \delta_1 X_{1,t} + \delta_2 X_{2,t} + \dots + \delta_m X_{m,t}$ . Let the conditional variance prediction of  $Y_{t+1}$  be  $\hat{h}_{t+1}$ , thereafter

$$\hat{h}_{t+1} = \exp \left( \omega + \beta \ln \hat{h}_t + \alpha \left| \frac{\hat{\epsilon}_t}{\sqrt{\hat{h}_t}} \right| \right) + \gamma \frac{\hat{\epsilon}_t}{\sqrt{\hat{h}_t}}.$$



Therefore, the distribution function of  $Y_{t+1}$  is predicted as

$$\begin{aligned} \hat{F}_{t+1|t}(y) &= P(Y_{t+1} \leq y) = P\left(\hat{\mu}_{t+1} + \sqrt{\hat{h}_{t+1}}z_{t+1} \leq y\right) = zP\left(z_{t+1} \leq \frac{y - \hat{\mu}_{t+1}}{\sqrt{\hat{h}_{t+1}}}\right) \\ &= F_{z_{t+1}}\left(\frac{y - \hat{\mu}_{t+1}}{\sqrt{\hat{h}_{t+1}}}\right), \end{aligned} \tag{7}$$

where  $z_{t+1} = \frac{\varepsilon_{t+1}}{\sqrt{\hat{h}_{t+1}}}$  is the standardised residual. This obeys a skewed Student's t-distribution with a mean of 0 and a variance of 1.  $F_{z_{t+1}}(\cdot)$  is the cumulative distribution function of  $z_{t+1}$ . Thus, the density function of  $Y_{t+1}$  is

$$f_{t+1|t}(y) = \frac{1}{\sqrt{\hat{h}_{t+1}}}f_{z_{t+1}}\left(\frac{y - \hat{\mu}_{t+1}}{\sqrt{\hat{h}_{t+1}}}\right), \tag{8}$$

wherein  $f_{z_{t+1}}(\cdot)$  is the density function of  $z_{t+1}$ .

## 4. Empirical study

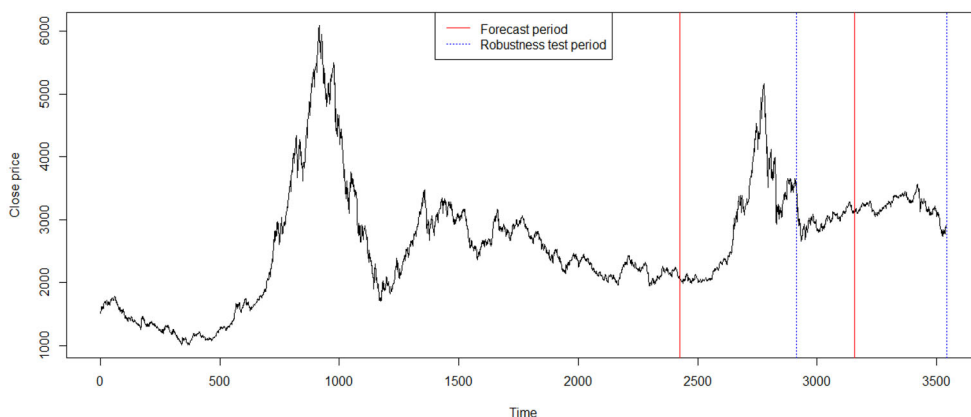
### 4.1. Data description

#### 4.1.1. Research object and time span

The Shanghai Composite Index (SHCI) is often used to represent China's stock market and was selected as the research object. The empirical study's period is from January 2, 2004 to December 30, 2016. This is a total of 13 years of returns. The sample size of returns is  $T = 3158$ . The data for 10 years from January 2, 2004 to December 31, 2013 is the initial fitting sample. Therefore, the in-sample size is  $T_0 = 2425$ . The period from January 2, 2014 to December 30, 2016 is the out-of-sample forecast period: the out-of-sample size is  $n = 733$ . The robustness test uses the returns from January 4, 2012 to July 31, 2018, and  $T = 1599$ . The data for four years from January 4, 2012 to December 31, 2015 is the initial fitting sample, i.e.  $T_0 = 970$ . January 4, 2016 to July 31, 2018 is the out-of-sample prediction interval, i.e.  $n = 629$ . The daily closing price data comes from 'Securities Investment Software: Big Wisdom 365'. The return is calculated as the closing price's logarithmic return percentage. Figure 1 shows the closing price data of the Shanghai Composite Index from January 2, 2004 to July 31, 2018. The period between the solid red lines is the empirical forecast time interval. This covers three market states of 'consolidation', 'bull', and 'bear'. The blue dotted lines are the robustness test's forecast periods, including two market states of 'consolidation' and 'bear'.

#### 4.1.2. Selection of TIs

Investors who prefer technical analysis often try to mine information through historical prices and volumes. Technical analysis mainly includes graphic strategies and TI strategies. TIs are popular because of their quantitative characteristics. There are



**Figure 1.** The SHCI's daily closing price and forecast period.

Source: compiled by authors with the help of R software.

many types of TIs, and their construction origins and ideas are very different. They are based on historical prices and volumes. We select 39 TIs that are commonly used in securities' practice. These are specially calibrated as the 'most commonly used' TIs by the securities investment software, 'Big Wisdom 365'. They can be divided into five types: volume type, containing four indicators; trend type, containing 12 indicators; energy type, containing seven indicators; overbought and oversold type, containing 11 TIs. The remaining five are classified as 'others'. See Table 1 for further details. The TIs' data are gathered from the securities investment software: 'Big Wisdom 365'. The parameters are the default software system's ones.

#### 4.2. Multicollinearity diagnosis and LASSO regression

For the empirical study's period, the multicollinearity diagnosis was performed on 39 TIs and the calculated condition number  $\kappa = 485709.5$ . The overall multicollinearity problem is thus serious. The VIFs were calculated and are listed in Table 2. Except for the four indicators: ADX, PSY, VHF, and VR, all VIFs exceed five. Among them, VOL and turnover rate (HSL) reach greater than 10, and the VIF values of K, D, and J even attain  $10^9$ . Thus, a relatively high-level multicollinearity problem among the indicators exists. It is unsuitable to use OLS to estimate the multiple linear regression models. Instead, the LASSO regression was adopted to reduce the risk of multicollinearity.

For Model (3), we first perform a LASSO regression of the return on TIs. For each fitting sample  $C_p$ , the TI that has a significant impact on the return can be selected through the compression of the harmonic parameter and the criterion's application. As a rolling sample for estimation was used, there are different significant variables selected each time. Modelling is required to measure the TIs' impact on the overall returns. Here, a significance index  $Im_{1,i}$  is defined as

$$Im_{1,i} = \frac{\sum_{t=1}^n I(\delta_i^{(t)})}{n} \times 100, \quad (9)$$

**Table 1.** The TIs selected.

Type (Number)	Symbol	Meaning	Parameter setting	Principle or algorithm
Volume (4)	VOL	Trading volume	–	The total number of lots traded on a certain day
	AMO	Transaction amount	–	The total number of transactions on a certain day
	HSL	Turnover rate	–	Trading volume/total number of shares issued*100
	OBV	On balance volume	–	Starting from the first day of the listing, the total stock trading volume has been accumulated daily. If the day's closing price is higher than yesterday's, the previous OBV plus the day's trading volume will be the day's OBV, otherwise, the day's trading volume will be less the day's OBV.
Trend (12)	DDD	The adjustable moving average line	10,50,10	The difference between the closing price's short-term average and the long-term average is divided by the number of short-term days to obtain DDD.
	AMA			The M-day average of DDD is AMA.
	PDI	DMI trend indicator	14, 6	An important indicator in the Welda trading system can generate a buying and selling signal that crosses the indicator. This can identify whether the market has been launched. Numerous TIs on the market must be used with DMI.
	MDI			
	ADX			
	ADXR			
	VHF	Vertical horizontal filter	28	The function is similar to DMI. This is used to determine the type of stock price movement: trend or range oscillation. First, calculate the difference between the highest closing price and the lowest closing price in N days. Calculate the cumulative sum of the difference between today's closing and yesterday's closing in N days. The ratio of the two is VHF.
	MA1	5-day average price	5	The average of the closing prices of the previous five days
	MA2	10-day average price	10	The average of the closing prices of the previous 10 days
	MACD	Moving average convergence and divergence	26,12,9	Use two long-term and short-term smoothing averages to calculate the difference between the two as the basis for studying and judging the market transactions.
DPO	Detrended price oscillator	20, 11, 6	The difference between the stock price and the moving average of the previous period can more truly describe the current stock price's degree of deviation.	
TRIX	Triple exponential smoothing average	12, 20	It is a long-term indicator. The indicator's signal can be used in long-term operations to filter out some short-term fluctuations and to avoid too frequent transactions. This would result in partial unprofitable transactions and the loss of handling fees.	
Energy (7)	AR	ARBR Popularity willingness index	26	Use the opening price's relative position to express popularity.
	BR		26	Express the willingness with today's fluctuation range, relative to yesterday's closing price.
	CR	Energy index	26, 5, 10, 20	In N days, if the highest price on a certain day is higher than the previous day's mid-price, add the difference between the two to the strong sum. If the

*(continued)*

**Table 1.** Continued.

Type (Number)	Symbol	Meaning	Parameter setting	Principle or algorithm
				lowest price on a certain day is lower than the previous mid-price, add the difference between the previous mid-price and the lowest price to the weak sum in. Divide the strong sum by the weak sum and multiply by 100 to get the CR.
	PSY	Psychological line	12	It is a quantitative scale that reflects the people's market mentality. It uses the ratio curve of the time when the market momentum rises over some time, to study the market's tendency to be long or short. In N days, if a day closes in yang, the daily trading volume is added to the strong sum. When the yin is closed, it is added to the weak sum. If the market is flat, half of the day's trading volume will add up to a strong sum. Furthermore, half will add up to a weak sum. Finally, calculate the ratio of the strong sum to the weak sum and zoom in 100 times.
	VR	Volume ratio	26	It is a quantitative scale that reflects people's market mentality. It uses the ratio curve of the time when the market momentum rises over some time to study the market's tendency to be long or short. In N days, if a day closes in yang, the daily trading volume is added to the strong sum. When the yin is closed, it is added to the weak sum. If the market is flat, half of the day's trading volume will add up to a strong sum. Thereafter, half will total a weak sum. Finally, calculate the strong sum's ratio to the weak sum and zoom in 100 times.
	PVI	Positive volume indicator	72	When the statistical increase in price increases, the funds' flow. If the price drops and the volume shrinks, it means that the big players dominate the market for the day's market conditions.
	NVI	Negative volume indicator	72	This is the main analytical tool to detect the large market and treat the shrinking trading volume as funds for the intervention of large investors.
Overbought and oversold (11)	BIAS	Bias	6	This is the gap between the day's closing price and the moving average.
	CCI	Commodity channel index	14	Use the current stock price's volatility to compare with the normal distribution range to draw the conclusion of overbought or oversold. This is used to capture the trend reversal points.
	K D J	KDJ stochastics index	9, 3, 3	Use the relative position of the current stock price in the recent stock price's distribution to predict a possible trend reversal.
	RSI	Relative strength index	6, 12, 24	Use the ratio of the upward volatility to the total volatility to describe the trend's strength.
	MFI	Money flow index	14	It is an extended indicator of RSI. This is the ratio of the sum of the rising

*(continued)*

**Table 1.** Continued.

Type (Number)	Symbol	Meaning	Parameter setting	Principle or algorithm
	MTM	Momentum index	6,6	volume to the sum of the falling volume in a certain period. This is the difference between the day's closing price and the closing price before N
	ROC	Rate of change	12, 6	This is the difference between the day's closing price and the closing price of n days ago
	ATR	Average true range	14	This is the maximum value of today's amplitude, today's highest and yesterday's closing price, today's lowest, and yesterday's closing price
	W&R	Williams index	14, 28	Use the day's closing price's relative position in the recent stock price distribution to describe the degree of the overbought and oversold.
Others (5)	JCS JCM JCL	ZLJC Main force in and out	12, 26	This is a volume and price/trend indicator. The trend change signal sometimes lags and is often used in conjunction with the main trading indicators. JCS is the short-term main operating trajectory. JCM is the medium-term main operating trajectory. JCL is the long-term main operating trajectory.
	MID	The middle line of the BOLL band	26, 2	This is the BOLL band's midline and it is the moving average.
	SAR	Stop and reverses	10, 2, 20	This is an analysis tool that pays equal attention to the price and time. First, select a period and calculate the changing stop-loss price for each period.

Note: The indicators' symbol, meaning, principle, or algorithm originate from the securities investment software: 'Big Wisdom 365' and the parameters are set to be the software's default. In this software, the TIs in Table 1 are called 'Investors' Common Indicators'.

Source: compiled by authors based on the data obtained.

where  $I(\delta_i^{(t)}) = \begin{cases} 1, & \delta_i^{(t)} \neq 0 \\ 0, & \delta_i^{(t)} = 0 \end{cases}$ .  $\delta_i^{(t)}$  represents the coefficient of the  $i$ -th TI in the  $t$ -th LASSO regression, and  $n = 733$  is the total number of the LASSO regressions. Formula (9)'s numerator calculates the total number of times that  $X_i$  is selected as a significant variable by the LASSO regression. It can thus be regarded as a measurement of the explanatory variables' importance.  $Im_{1,i}$  is a percentage, and the range is  $[0, 100]$ . The greater the value of  $Im_{1,i}$ , the greater the significance of  $X_i$ .

Suppose the standardised coefficient of the LASSO regression is  $\delta'_i$ . The relative magnitude of the absolute value of  $\delta'_i$  indicates the relative influence degree of the  $i$ -th TI on the return. The greater the absolute value of  $\delta'_i$ , the greater the degree of influence of the explanatory variable  $X_i$ . Thus, the relative impact importance index  $Im_{2,i}$  is defined as the proportion of the top ten impacts, namely:

$$Im_{2,i} = \frac{\sum_{t=1}^n I(\text{rank}(\delta'_i{}^{(t)}))}{n} \times 100, \quad (10)$$

**Table 2.** The multicollinearity diagnosis of TIs.

No	TI	VIF	No	TI	VIF	No	TI	VIF
1	VOL	1.07e + 06	14	D	1.97e + 09	27	MA2	9332.05
2	AMOUNT	38.24	15	J	1.27e + 09	28	MID	5333.50
3	HSL	1.07e + 06	16	MACD	91.26	29	MFI	5.17
4	AR	5.75	17	OBV	372.82	30	MTM	14.49
5	BR	19.60	18	PSY	3.97	31	TRIX	27.07
6	BIAS	16.39	19	RSI	23.37	32	DPO	113.11
7	CCI	13.11	20	W&R	19.63	33	VHF	3.49
8	CR	26.75	21	JCS	29669.76	34	ROC	13.01
9	PDI	6.04	22	JCM	79253.37	35	PVI	46.04
10	MDI	6.20	23	JCL	29924.26	36	NVI	7.07
11	ADX	4.08	24	DDD	326.66	37	VR	4.10
12	ADXR	5.60	25	AMA	311.10	38	ATR	7.74
13	K	5.42e + 09	26	MA1	8495.52	39	SAR	162.90

Note: The values are accurate for two decimal places. 1.07e + 06 means  $1.07 \times 10^6$ . The others are similar.

Source: calculated by authors via R software.

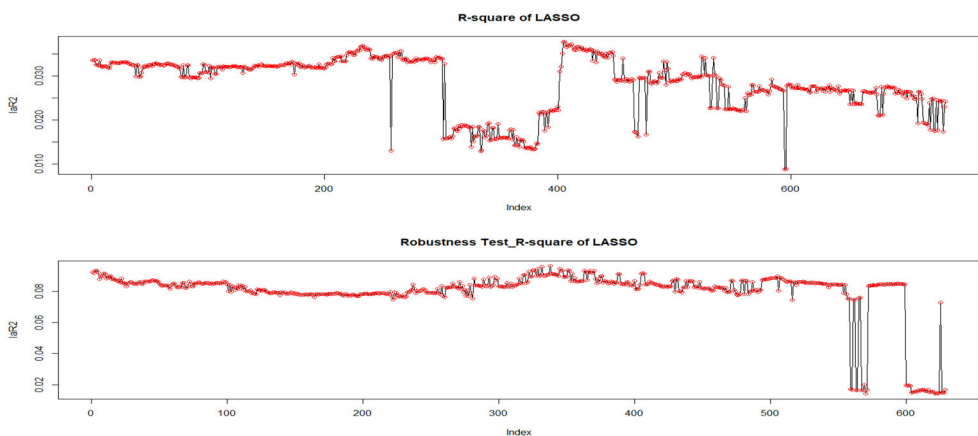
This is where  $rank(\cdot)$  represents the rank of sorting from the largest to the smallest. If  $\delta_i^{(t)}$  is the largest value of  $\delta_k^{(t)}$ ,  $1 \leq k \leq p$ , then  $rank(\delta_i^{(t)}) = 1$ . The larger the value of  $Im_{2,i}$ , the more time  $X_i$  has the ability to make an important influence (top 10). Under the definition of Formula (10),  $Im_{2,i}$  represents a percentage, and the range is  $[0, 100]$ . The statistical results for  $Im_{1,i}$  and  $Im_{2,i}$  are presented in Table 3. Many TIs have a significant impact at most moments in the sample. There were 11 TIs with a greater  $Im_{1,i}$  value than 0.9. They are arranged in descending order as CCI, adjustable moving average (AMA), ADX, J, MTM, NVI, MFI, ROC, SAR, HSL, and PSY. The top 11  $Im_{2,i}$  value rankings from largest to smallest were AMA, HSL, DDD, JCL, AMO, SAR, OBV, MID, CCI, MACD, and NVI. Such importance is marked in bold in Table 3. Both  $Im_{1,i}$  and  $Im_{2,i}$  rank in the top 11, with five TIs. They are HSL, CCI, AMA, NVI, and SAR. We consider them to be relatively ‘important’ TIs. Among them, the values of  $Im_{1,i}$  and  $Im_{2,i}$  of AMA and HSL have reached more than 90%. AMA and HSL are significant for over 90% of the times, as compared to other TIs. AMA reflects the difference between the long-term and short-term dynamic moving averages. The difference between the long-term and short-term moving averages contains some information about future returns. The HSL also has a certain predictive effect on the returns. The importance of AMA may be attributed to its adaptive characteristics. The HSL is often regarded as a market liquidity indicator and sometimes reflects the investor sentiment. From a behavioural finance perspective, the investor sentiment influences stock market fluctuations (Lopez-Cabarcos et al., 2020). The HSL will have an impact on the returns, for example the value CCI’s  $Im_{1,i}$ , which is the homeopathic indicator. For every LASSO regression, it is selected as an important variable. However, its influence ranks only 51.71% of the top 10 times for  $Im_{2,i} = 51.71\%$ .

However, how much explanatory power do such TIs have? We calculated the LASSO’s regression coefficient and concurrently achieved the fitting R-square. The R-square’s maximum value was 3.78%. The minimum was 0.88%. Each LASSO regression’s results appear in the upper part of Figure 2. Despite the large number of TIs, their explanatory power for return forecasts is limited.

**Table 3.** The importance measurement of TIs (Unit: %).

No	TI	$lm_1$	$lm_2$	No	TI	$lm_1$	$lm_2$	No	TI	$lm_1$	$lm_2$
1	VOL	8.19	8.19	14	D	2.18	0	27	MA2	42.16	41.34
2	AMO	87.86	<b>67.12</b>	15	J	<b>99.73</b>	47.75	28	MID	52.66	<b>57.03</b>
3	HSL	<b>92.09</b>	<b>91.13</b>	16	MACD	89.90	<b>50.48</b>	29	MFI	<b>95.91</b>	4.91
4	AR	76.26	2.05	17	OBV	63.03	<b>57.03</b>	30	MTM	<b>98.09</b>	26.33
5	BR	76.53	0.27	18	PSY	<b>91.13</b>	2.32	31	TRIX	85.54	2.18
6	BIAS	59.48	0	19	RSI	73.53	0	32	DPO	39.02	0
7	CCI	<b>100</b>	<b>51.71</b>	20	W&R	81.04	0	33	VHF	74.90	7.23
8	CR	80.76	0	21	JCS	48.70	48.70	34	ROC	<b>94.54</b>	16.37
9	PDI	45.57	0	22	JCM	11.73	11.60	35	PVI	71.62	11.87
10	MDI	72.17	0	23	JCL	87.59	<b>78.04</b>	36	NVI	<b>97.82</b>	<b>49.66</b>
11	ADX	<b>99.73</b>	7.23	24	DDD	80.63	<b>80.63</b>	37	VR	89.63	0
12	ADXR	81.58	0	25	AMA	<b>99.86</b>	<b>97.54</b>	38	ATR	87.45	0.68
13	K	75.17	7.09	26	MA1	25.92	19.65	39	SAR	<b>93.86</b>	<b>58.39</b>

Source: compiled by authors with the help of R software.



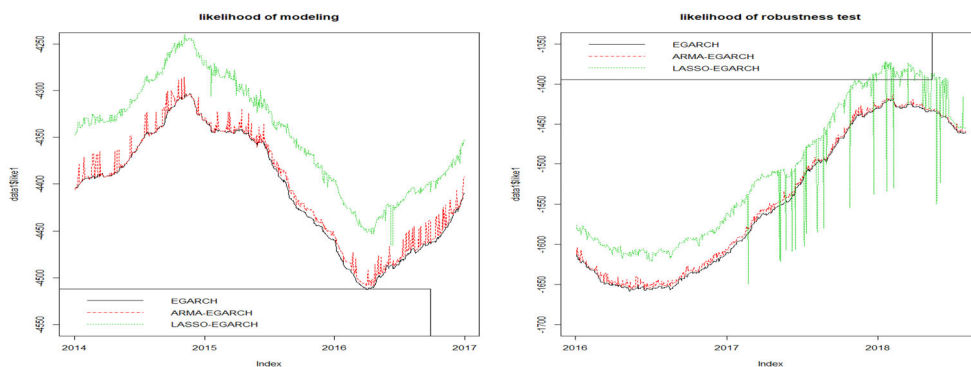
**Figure 2.** The R-square of the LASSO regression.  
: drawn by authors with the help of R software.

### 4.3. Fitting effect of model in-sample

The models are solved by a maximum likelihood estimation, where the objective functions are the average log-likelihood functions. Referring to Ghalanos (2020), the package, Rugarch R software, was employed to implement the programming. The in-sample average log-likelihood function values of the EGARCH, ARMA-EGARCH, and LASSO-EGARCH models of SHCI from 2004 to 2016 were obtained (see the left part of Figure 3). The larger the average log-likelihood function value, the better the model fits the data. Figure 3 indicates that the LASSO-EGARCH model (green line) has the best fitting effect, ARMA-EGARCH (red line) has the second, and EGARCH (black line) has the worst. The ARMA modelling of the conditional mean has a good effect on the distribution of returns. The TI information's integration has improved the conditional return distribution's fitting.

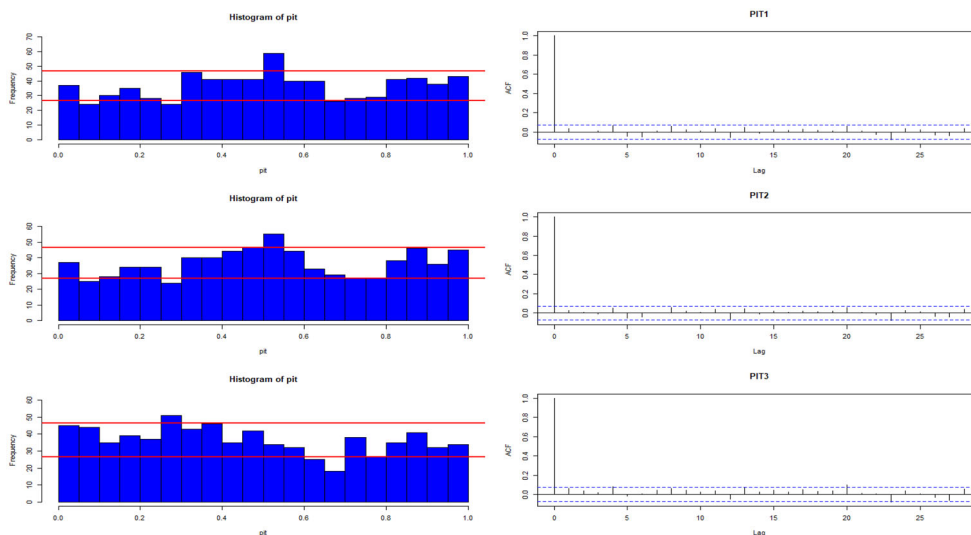
### 4.4. Statistical evaluation of distribution forecast

Models (1), (2), and (3) perform rolling sample estimations and predictions with a total time of 733. Given the forecast of the return distribution  $\hat{F}_{t+1|t}(y)$  and the



**Figure 3.** The comparison of the average log-likelihood function in-sample.

Source: drawn by authors with the help of R software.



**Figure 4.** The PITs' histogram and autocorrelation graph.

: drawn by authors with the help of R software.

observation of out-of-sample returns  $\{y_t\}$ , the probability integral transform (PIT) sequence can be calculated as  $PIT_t = \hat{F}_{t+1|t}(y_t)$ . The statistical histogram and PIT sequence's autocorrelation graph are shown in Figure 4. The area between the two solid red lines in the histogram indicates the confidence interval that the PIT sequence obeys a uniform distribution  $U(0, 1)$ . The area between the two blue dotted lines in the autocorrelation graph represents the interval's range, where the autocorrelation is zero. From Figure 4, the three models' PITs are close to  $U(0, 1)$ . There is no significant autocorrelation overall. However, visual observation cannot identify which of the three models is better.

Thereafter, the non-parametric omnibus test of Hong and Li (2005) (HL test) was used to determine the predictive effect of the conditional return distribution and the lag order  $p = 4$ . The empirical period's statistics appear in the upper half of Table 4. The  $W$  and  $M(i, j)$ 's statistics asymptotic distributions were standard normal distributions  $N(0, 1)$ . The right tail test was performed. Given the significance level



**Table 4.** The results of the HL test.

Period	Model	M(1,1)	M(2,2)	M(3,3)	M(4,4)	M(1,2)	M(2,1)	W
Empirical	EGARCH	-0.5612	0.5300	1.7098	2.3341	2.6123	-1.2473	7.6999
	ARMA-EGARCH	-1.1247	-0.3910	0.5152	1.0403	1.7920	-1.8873	8.7766
	LASSO-EGARCH	3.8890	2.5677	1.8042	1.2975	6.2786	1.5053	4.3522
Robustness test	EGARCH	-2.1990	-1.3395	-0.3483	0.5204	-2.0149	-0.7875	2.3557
	ARMA-EGARCH	-1.6294	-1.3160	-0.4084	0.5270	-2.1721	-0.0120	1.3609
	LASSO-EGARCH	-1.8886	-1.4181	-0.6873	-0.1871	-1.5112	-1.9141	5.4996

Source: calculated by authors via R software.

$\alpha = 0.05$ , the corresponding quantile value is 1.645. The statistics that reject the null hypothesis (cases greater than 1.645) are in bold. None of the three models is sufficient to forecast the returns' distribution. From the W statistics, LASSO-EGARCH is the best, followed by EGARCH, and thereafter, ARMA-EGARCH. The M (i, j) statistics can be used to explore possible sources of unsatisfactory return distribution forecasts. According to M (i, j), LASSO-EGARCH performs the worst: only M (4, 4) (reflecting kurtosis modelling) and M (2, 1) (reflecting the leverage effect) do not reject the null hypothesis. ARMA-EGARCH is relatively better: the value of M (1, 2) that rejected the null hypothesis is 1.7920. This is only slightly larger than the judged quantile value of 1.645. Relying only on the first four moments is insufficient to describe the predicted distribution.

Three score evaluations: the times of Bayesian winner, average logarithmic score, and average CRPS were performed according to Yao et al. (2020) (see Table 5). LASSO-EGARCH is the best Bayesian winner. The rank is consistent with that of the HL test. The average logarithmic score and average CRPS both show that LASSO-EGARCH is the worst model and that the ARMA-EGARCH model is not as good as the EGARCH model. The ARMA modelling of the conditional mean and the impact modelling of TIs introduce 'noise'. This makes the return distribution more unsatisfactory.

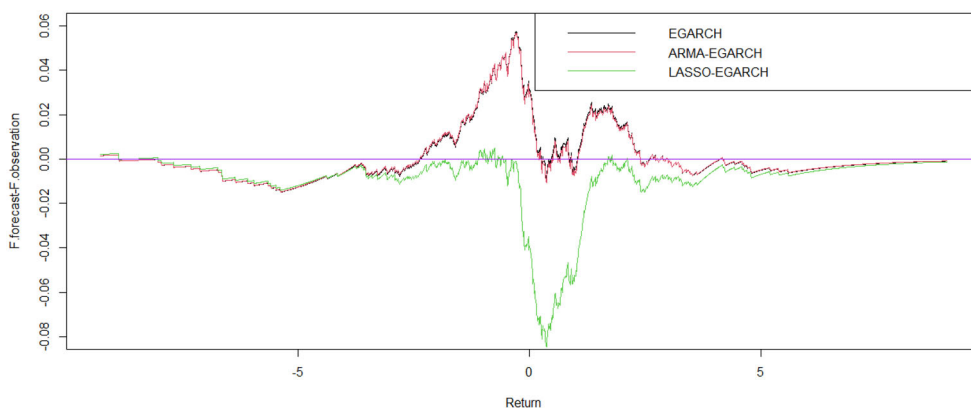
Gneiting et al. (2010) noted that the model should be calibrated for distribution prediction, and especially for marginal calibration. Figure 5 shows the three models' marginal calibration diagrams. The return was discretised from the minimum to the maximum, and one grid point was taken for each step of 0.01. The three models have good calibration results: the vertical values range from -0.08 to 0.06, and the tail calibration is good. The EGARCH model's (black line) and the ARMA-EGARCH model's graphs (red line) are almost aligned and cannot be identified. This means they have similar marginal calibration effects. LASSO-EGARCH shows very different calibration characteristics. The left side calibration is better than the other two. The negative returns have a significantly superior calibration. However, LASSO-EGARCH shows an abnormally poor calibration effect in the 0%–1% return range. Although the LASSO-EGARCH model cannot completely achieve a calibration effect that is superior to the other two, the characteristic of 'non-synchronisation' of marginal calibration is reflected. This inspired us to improve the model through a combination.

Gneiting et al. (2010) noted that the distribution prediction should seek better sharpness after the model calibration. The average widths of the 50% and 90% confidence intervals were used to examine the sharpness. The smaller the values, the better the sharpness. The results are listed in Table 6. LASSO-EGARCH is the best sharpness.

**Table 5.** The results of the score and ranking.

Period	Model	Bayesian winner	Rank 1	Average Log-score	Rank 2	Average CRPS	Rank 3
Empirical	EGARCH	236	2	1.7026	1	0.8489	1
	ARMA-EGARCH	165	3	1.7079	2	0.8521	2
	LASSO-EGARCH	332	1	1.7318	3	0.8656	3
Robustness test	EGARCH	146	3	1.2272	1	0.5182	1
	ARMA-EGARCH	177	2	1.2355	2	0.5245	2
	LASSO-EGARCH	306	1	1.2711	3	0.5260	3

Source: calculated by authors via R software.



**Figure 5.** The marginal calibration during the empirical period. Note: The EGARCH and ARMA-EGARCH models' graphs almost overlap.

Source: drawn by authors with the help of R software.

**Table 6.** Sharpness analysis.

Period	Model	50% interval average width	Rank 4	90% interval average width	Rank 5
Empirical	EGARCH	1.8007	3	4.9320	2
	ARMA-EGARCH	1.7983	2	4.9335	3
	LASSO-EGARCH	1.7380	1	4.8858	1
Robustness test	EGARCH	1.1055	3	3.1581	3
	ARMA-EGARCH	1.0983	2	3.1372	2
	LASSO-EGARCH	1.0390	1	3.0520	1

Source: calculated by authors via R software.

#### 4.5. VaR back-test

Investors note the risks while pursuing profits. VaR is widely used as a measure of financial risk. The distribution forecast of the returns' performance is evaluated from the VaR's perspective (VaR back-test). Since the rolling sample is used to estimate and predict, the return distribution is time-varying. The corresponding VaR has time-varying characteristics. We define VaR at moment  $t$  as

$$VaR_t(\alpha) = \inf\{x \in R : F_t(x) \leq \alpha\}, \quad (11)$$

where  $VaR_t(\alpha)$  is the  $\alpha$ -quantile of the cumulative distribution function. For  $F_t(x)$ ,  $\alpha = 0.01$  or  $\alpha = 0.05$ , it was negative. To evaluate the VaR's validity, risk managers

**Table 7.** VaR of unconditional coverage and conditional coverage test.

Period	Model	VaR(0.01)		VaR(0.05)	
		$LR_{prop}(UC)$	$LR_{joint}(CC)$	$LR_{prop}(UC)$	$LR_{joint}(CC)$
Empirical	EGARCH	4.8398 [0.0278]	5.3858 [0.0677]	0.0035 [0.9528]	0.6547 [0.7208]
	ARMA-EGARCH	4.8398 [0.0278]	5.3858 [0.0677]	0.0035 [0.9528]	2.0963 [0.3506]
	LASSO-EGARCH	1.6088 [0.2047]	1.9445 [0.3782]	1.8729 [0.1711]	2.4309 [0.2966]
Robustness test	EGARCH	2.9123 [0.0879]	3.2686 [0.1951]	0.0714 [0.7893]	0.3386 [0.8442]
	ARMA-EGARCH	2.9123 [0.0879]	3.2686 [0.1951]	0.4130 [0.5205]	0.9010 [0.6373]
	LASSO-EGARCH	0.4324 [0.5108]	0.6129 [0.7361]	0.4130 [0.5205]	0.9010 [0.6373]

Note: The values in square brackets indicate the P-value of the corresponding statistics.

Source: calculated by authors via R software.

must perform back-testing. The methods used here include Kupiec's (1995) unconditional coverage test and Christoffersen (1998)'s conditional coverage test.

Kupiec (1995) constructed a log-likelihood ratio test statistic ' $LR_{prop}$ ', according to the VaR abnormalities' proportion. When the sample size  $T \rightarrow \infty$ ,  $LR_{prop} \sim \chi^2(1)$ . Christoffersen (1998) proposed  $LR_{joint}$ . When  $T \rightarrow \infty$ ,  $LR_{joint} \sim \chi^2(2)$ . The VaR back-test results of the unconditional coverage test and conditional coverage test when  $\alpha = 0.01$  and  $\alpha = 0.05$  appear in Table 7.

In the empirical period, from the P-value of the statistic  $LR_{prop}$ , when  $\alpha = 0.01$ , the EGARCH and ARMA-EGARCH models reject the null hypothesis at the 5% significance level. The number of breakdowns does not match the real return at the 1% tail. The EGARCH and ARMA-EGARCH models' expected breakdown times were seven. The actual was 14. These models underestimate the 1% tail risk. The LASSO-EGARCH's P-value of  $LR_{prop}$  is 0.2047. It does not reject the null hypothesis at the 5% significance level. LASSO-EGARCH's expected number of breakdowns is seven. The actual is 11. Compared with EGARCH and ARMA-EGARCH, LASSO-EGARCH improves the underestimation of the 1% tail risk. When  $\alpha = 0.05$ , EGARCH, ARMA-EGARCH, and LASSO-EGARCH do not reject the null hypothesis at the 5% significance level. They all have a good assessment of the 5% tail risk.

From the values of  $LR_{joint}$  and its P-value, regardless of whether  $\alpha = 0.01$  or  $\alpha = 0.05$ , the null hypothesis is not rejected at the 5% significance level. From Christoffersen (1998)'s evaluation, all three models perform a good tail risk assessment. However, when  $\alpha = 0.01$ , the P values of EGARCH and ARMA-EGARCH are 0.0677, and LASSO-EGARCH is 0.3782. LASSO-EGARCH is better than EGARCH and ARMA-EGARCH. This is consistent with the marginal calibration's conclusion that LASSO-EGARCH has better left-tail calibration.

## 5. Robustness test

### 5.1. Multicollinearity diagnosis of TI and LASSO regression's results

The robustness test was performed from January 4, 2012 to July 31, 2018. January 4, 2016 to July 31, 2018 is the out-of-sample prediction interval. A multicollinearity

**Table 8.** The multicollinearity diagnosis of TI in the robustness test period.

No	TI	VIF	No	TI	VIF	No	TI	VIF
1	VOL	1.40e + 06	14	D	1.75e + 09	27	MA2	5012.15
2	AMOUNT	102.65	15	J	1.21e + 09	28	MID	4014.26
3	HSL	1.40e + 06	16	MACD	119.26	29	MFI	4.6323
4	AR	5.28	17	OBV	473.23	30	MTM	14.95
5	BR	21.23	18	PSY	4.07	31	TRIX	69.97
6	BIAS	24.93	19	RSI	23.61	32	DPO	165.47
7	CCI	10.75	20	W&R	18.95	33	VHF	4.21
8	CR	31.72	21	JCS	42777.14	34	ROC	16.44
9	PDI	5.44	22	JCM	99890.94	35	PVI	185.68
10	MDI	6.68	23	JCL	52142.82	36	NVI	32.36
11	ADX	4.42	24	DDD	356.16	37	VR	5.61
12	ADXR	6.58	25	AMA	328.23	38	ATR	17.89
13	K	4.94e + 09	26	MA1	6444.54	39	SAR	110.53

Source: calculated by authors via R software.

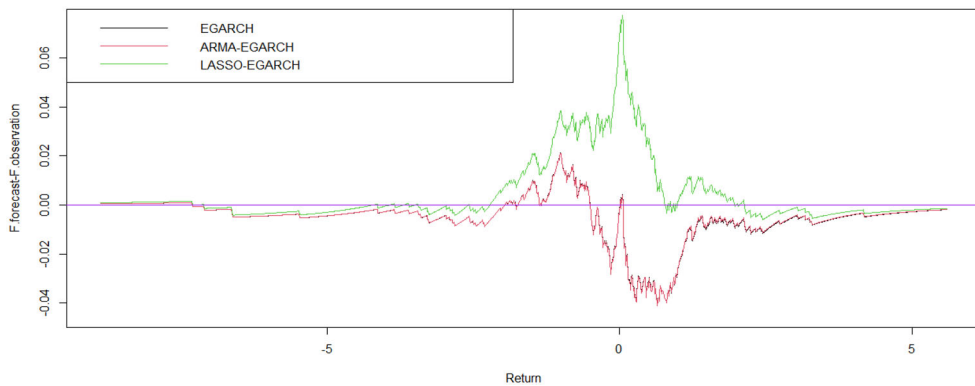
**Table 9.** The importance measurement of TI in the robustness test period (Unit: %).

No	TI	$Im_1$	$Im_2$	No	TI	$Im_1$	$Im_2$	No	TI	$Im_1$	$Im_2$
1	VOL	25.28	31.32	14	D	75.52	21.94	27	MA2	<b>93.96</b>	<b>93.96</b>
2	AMO	<b>91.89</b>	6.04	15	J	<b>93.80</b>	21.94	28	MID	79.97	41.18
3	HSL	<b>93.96</b>	<b>52.94</b>	16	MACD	<b>93.96</b>	5.72	29	MFI	<b>91.10</b>	0
4	AR	<b>94.12</b>	0.16	17	OBV	89.51	<b>55.64</b>	30	MTM	<b>93.96</b>	10.02
5	BR	<b>100</b>	6.04	18	PSY	88.24	1.91	31	TRIX	<b>93.96</b>	7.15
6	BIAS	<b>94.12</b>	0.16	19	RSI	74.72	0	32	DPO	<b>93.96</b>	0.16
7	CCI	<b>93.96</b>	0	20	W&R	<b>93.96</b>	0	33	VHF	79.81	3.97
8	CR	<b>93.96</b>	0	21	JCS	<b>93.96</b>	<b>93.96</b>	34	ROC	<b>93.96</b>	0
9	PDI	79.01	0	22	JCM	<b>93.96</b>	<b>93.96</b>	35	PVI	<b>94.75</b>	<b>72.81</b>
10	MDI	83.94	0	23	JCL	<b>93.96</b>	<b>90.30</b>	36	NVI	<b>91.10</b>	31.96
11	ADX	82.19	2.23	24	DDD	<b>93.96</b>	<b>62.00</b>	37	VR	88.24	0
12	ADXR	86.96	0	25	AMA	<b>93.96</b>	<b>70.43</b>	38	ATR	<b>93.16</b>	0
13	K	31.80	22.10	26	MA1	<b>93.96</b>	<b>93.96</b>	39	SAR	<b>100</b>	6.04

Source: calculated by authors via R software.

diagnosis is performed on 39 TIs, and the condition number  $\kappa = 460677.7$  is calculated. TIs have serious multicollinearity overall. Simultaneously, VIFs were calculated (see Table 8). Except for ADX, PSY, MFI, and VHF, all VIFs exceed five. Among them, VOL and HSL reach  $10^6$ , and K, D and J's VIF values reach  $10^9$ . The TIs' multicollinearity characteristics are consistent with the empirical period's conclusions.

The significance  $Im_1$ 's calculated results and importance indices  $Im_2$  appear in Table 9. There are 26 values of  $Im_1$ : more than 90% where the SAR's and BR's values were one. There are 10 values of  $Im_2$  at more than 50%. The corresponding TIs are JCS, JCM, MA1, MA2, JCL, PVI, AMA, DDD, OBV, and HSL. Considering  $Im_1$  and  $Im_2$  we believe that the nine TIs of JCS, JCM, MA1, MA2, JCL, PVI, AMA, DDD, and HSL are important indicators that affect the returns during the robustness test period. Among them, the AMA's and HSL's results are consistent with those of the empirical period. This means that when analysing TIs, regardless of market conditions, AMA and HSL must be noted. According to the securities investment technical analysis theory, AMA is a classic TI. The long-term moving average is relatively reliable but it often lags. This 'adjustable' feature of AMA makes it an important impact indicator of the returns, regardless of the market conditions. The AMA's predictability for financial returns has attracted attention. HSL refers to the frequency of the stocks changing hands in a certain period. It is one of the indicators reflecting the



**Figure 6.** The marginal calibration chart for the robustness test. *Note:* The EGARCH and ARMA-EGARCH models' graphs almost overlap.

*Source:* drawn by authors with the help of R software.

stocks' liquidity and one of the most important TIs reflecting the market transactions' activity. From a behavioural finance perspective, it also reflects investor sentiment to a certain extent. This should be one of the reasons why it has become an important indicator of the returns. The various TIs' focus is different, and the effective TIs are unrealistic. There is a significant difference in the results of the significance and importance indexes between the robustness test period and the empirical period. This is not only related to the market conditions but also the macro-political and economic environment. Therefore, the TIs' 'explanatory power' is different in different periods.

What is the explanatory power of TIs during the robustness test period? The R-square of the LASSO regression has a maximum of 9.63% and a minimum of 1.42%. This is a slight increase from the empirical period. As shown in the lower part of [Figure 2](#) for each LASSO regression, the TIs' impact on the returns during this period is the same as that of the empirical period, with only weak explanatory power.

## **5.2. Fitting effect in-sample and statistical evaluation out-of-sample**

The sample of the robustness test period's fitting effect is also characterised by the average log-likelihood function, as shown in the right half of [Figure 3](#). Cumulatively, as in the empirical period, LASSO-EGARCH (green line) has the best fitting effect, followed by ARMA-EGARCH (red line), and thereafter EGARCH (black line). However, after 2017, the LASSO-EGARCH's average log-likelihood function at many moments is much lower than that of EGARCH and ARMA-EGARCH. This means that the TIs at such time points are no longer 'information' but 'noise'. Their introduction reduces the fitting effect. TIs represent historical information. They have explanatory power and can be used as 'information', meaning that the market is 'ineffective'. Conversely, the TI predictions' failure may indicate an increase in China's stock market's effectiveness.

Thereafter, the robustness test period's out-of-sample statistical evaluation is conducted. This includes the PIT evaluation, score evaluation, marginal calibration, sharpness evaluation, and VaR evaluation. The HL test was adopted for the PIT evaluation. The results appear in the lower part of [Table 4](#). During this period, the

forecasting effect on returns was generally better than that of the empirical period. The statistics of  $M(i, j)$  cannot reject the null hypothesis at the 5% significance level. The first four moments obtained good prediction results. For the  $W$  statistic, the ARMA-EGARCH model is the best and does not reject the null hypothesis. This means that the corresponding PITs can be regarded as independent and identically distributed in a uniform distribution  $U(0, 1)$ . This is followed by the EGARCH model, and finally, the LASSO-EGARCH model. However, EGARCH and LASSO-EGARCH rejected the null hypothesis.

The score evaluation and sharpness analysis results appear in the lower parts of [Tables 5 and 6](#). LASSO-EGARCH is still the best Bayesian winner. However, its rankings on the average logarithmic score and average CRPS are both the worst. Both the 50% and 90% prediction intervals of LASSO-EGARCH have the smallest average width. This indicates that it has the best sharpness. This conclusion is consistent with the empirical results. The marginal calibration effect is illustrated in [Figure 6](#). Although the graph's fluctuation characteristics are quite different from the marginal calibration graph ([Figure 5](#)) in the empirical period, there are still common points. There is thus no significant difference between EGARCH and ARMA-EGARCH. However, LASSO-EGARCH is quite different from them. It has great 'non-synchronisation' with the other two models and shows a better left-tail calibration. During this period, LASSO-EGARCH shows good right-tail calibration.

As for the VaR back-test, we can form a conclusion as per the bottom half of [Table 7](#). The robustness test period's conclusion is consistent with that of the empirical period. For the 1% and 5% tail risk, all three models provided a good description at a 5% significance level. However, for the 1% tail risk, at the 10% significance level, the EGARCH and ARMA-EGARCH models reject the null hypothesis, while the LASSO-EGARCH model cannot reject the null hypothesis. Further exploration revealed that the LASSO-EGARCH model has improved its risk underestimation compared with the EGARCH and ARMA-EGARCH models.

## 6. Model combination and economic evaluation

As Kim and Upneja (2021) stated, an individual model may not be able to capture the data's different features because of the time series' complex nature. However, using a combination of methods may reduce the variance of the estimated error and improve the recognition performance. Furthermore, being inspired by the marginal calibration's results, we examine the distribution prediction's linear combination obtained from the three models. We then conduct an economic evaluation. Referring to Yao et al. (2020), three combinations were considered as equal weight combination (EW), logarithmic score combination (SW), and CRPS combination (CW). Two-point forecasts are derived from the forecasted distribution of the returns. These are the mean and median values. Thereafter, the mean and median's direction accuracies were calculated. These were denoted as  $DA_1$  and  $DA_2$ . Furthermore, a simulated trading strategy was designed based on the returns' direction forecast. The transaction is divided into two situations: short and non-short selling. The state of holding at a maximum of one unit of the asset at hand is always maintained. In the short-selling

**Table 10.** The directional prediction accuracy and economic evaluation (unit: %).

Period	Model	Mean			Median		
		$DA_1$	$Rate^{(1)}$	$Rate^{(2)}$	$DA_2$	$Rate^{(1)}$	$Rate^{(2)}$
Empirical	EGARCH	<b>54.98</b>	3.26	7.47	<b>55.66</b>	4.54	8.69
	ARMA-EGARCH	53.07	4.03	8.20	55.39	5.23	8.54
	LASSO-EGARCH	53.75	2.67	6.89	54.30	1.69	5.96
	EW	54.57	6.41	10.47	54.57	1.61	5.88
	SW	54.57	<b>7.36</b>	<b>11.39</b>	<b>55.66</b>	<b>5.48</b>	<b>9.59</b>
	CW	<b>55.12</b>	<b>7.03</b>	<b>10.54</b>	<b>55.53</b>	<b>5.36</b>	<b>7.01</b>
Robustness test	EGARCH	52.78	-3.30	-8.42	54.37	-4.72	-9.92
	ARMA-EGARCH	52.62	0.21	-4.74	51.99	-1.13	-6.14
	LASSO-EGARCH	47.85	8.31	3.76	49.44	-0.49	-5.49
	EW	49.28	5.92	1.26	51.83	-0.81	-5.81
	SW	<b>56.44</b> ***	<b>21.16</b> ***	<b>17.25</b>	<b>57.87</b> ***	<b>11.71</b> ***	<b>7.33</b>
	CW	<b>56.28</b> ***	<b>14.92</b> **	<b>10.70</b>	<b>58.82</b> ***	<b>7.71</b> **	<b>3.13</b>

Notes: \*\* represents the significant results at the 5% confidence level. \*\*\* represents the significant results at the 1% confidence level.

Source: calculated by authors via R software.

situation, if the forecast direction is positive, then buy; otherwise, sell. In the non-short-selling situation, if the forecast direction is positive, buy if there is no asset at hand. Continue to hold the position if there is a unit of the asset at hand. Otherwise, when the forecast direction is non-negative, continue to be short if there is no asset at hand, and sell if there is a unit of the asset at hand. Similarly to Yao et al. (2020), the ratio of the strategic mean transaction return to the ideal mean transaction return is calculated. This is the strategy-ideal ratio. It is recorded as  $Rate^{(1)}$  in the short-selling and  $Rate^{(2)}$  in non-short-selling situations. Finally, Pesaran and Timmermann (1992) PT test was used to perform the directional accuracy test on  $DA_1$  and  $DA_2$ . Anatolyev and Gerko (2005) EP test was employed to perform the excess profit test on  $Rate^{(1)}$ .

The direction accuracies and strategy-ideal ratios of the three individual models and the three combined models during the empirical period and the robustness test period are listed in Table 10. The two best values in each column are shown in bold. The PT and EP tests' results that are significant at the 5% and 1% levels are marked with \*\* and \*\*\*, respectively. During the empirical period, LASSO-EGARCH does not have the best performance regarding the direction accuracy nor the strategy-ideal ratio. The combined models SW and CW are relatively better, and those  $Rate^{(2)}$  of EW under the mean forecast have the best performance. However, both the PT and EP tests did not show their significance during the empirical period. Therefore, although the combined models show relatively good economic evaluation effects, the degree is unclear. During the robustness test period, the mean forecast of LASSO-EGARCH has a higher positive strategy-ideal ratio than EGARCH and ARMA-EGARCH. The strategy-ideal ratio of the median forecast of LASSO-EGARCH is negative. However, it is better than the other two individual models. The combined models' SW and CW show an 'absolute' leading effect. They have significant directional accuracy and excess profitability through the PT and EP tests.

## 7. Conclusions

Three individual models are established, namely EGARCH, ARMA-EGARCH, and LASSO-EGARCH. Their residuals are set to obey the skewed Student's t-distribution.

The LASSO-EGARCH model contains high-dimensional-same-frequency TI information. The results show that there is serious multicollinearity in TIs and that the LASSO regression is suitable. The LASSO regression's results show that the TIs for the return forecasts' 'explanatory power' is limited. The TIs' significance and importance have changed in different periods. However, the AMA and HSL have shown a higher significance and greater importance than other TIs. The AMA's importance may be related to its own 'adjustable' characteristics. HSL may also be related to its ability to reflect the market trading activity and investor sentiment.

The distribution forecast's PIT evaluation shows that during the empirical period, the three models are inadequate to predict the return distribution. However, LASSO-EGARCH is better than the other two models. During the robustness test period, LASSO-EGARCH is the worst. This may indicate that TIs have a certain predictive effect on the returns in the 'bull' market. However, in the state of 'consolidation' and 'bear', they have no predictive effect. LASSO-EGARCH is the best Bayesian winner and has the best sharpness. However, it performs the worst regarding the average logarithmic score and average CRPS. Regarding the marginal calibration, EGARCH and ARMA-EGARCH have almost the same effect. LASSO-EGARCH behaves differently: It has better left-tail calibration and is clearly 'asynchronous' with the two other models. VaR back-tests show that LASSO-EGARCH has a better 1% left-tail risk assessment. This means that the TI information is beneficial to the management when the stock market crashes. Furthermore, three combinations of the individual models: the EW, SW, and CRPS combination (CW) were examined. The economic evaluation was conducted on the individual and combined models. Overall, only SW and CW have a better direction accuracy and excess profitability. However, they are not significant during the empirical period but are significant during the robustness test period.

Comprehensively, it can be concluded that the TI information will not enable investors to obtain more economic profit, but in the 'consolidation' and 'bear' market conditions, it will be beneficial to risk management. After adding the TI information into the model, investigating the model combination based on the logarithmic score and CRPS can improve the economic benefits based on the return distribution. However, its significance is related to the market state. Therefore, in the state of the 'consolidation' and 'bear' markets, investors should notice the TI information to help risk management. When an individual TI information embedding model cannot provide the predictability of returns and excess profitability, it cannot be discouraged. The combination of several individual models can be considered based on the distribution forecast evaluation to increase profitability.

This study may have some limitations, such as no integration of the ARMA and TI information for the mean value modelling of returns. Furthermore, there was no addition of the TI information to the conditional volatility modelling. The model is limited to the GARCH framework, and rationality is subject to further discussion. The samples have been subjectively selected according to the natural year, and its rationality is also to be discussed, although Zaremba and Nikorowski (2019) noted that transaction costs impact the abnormal performance of the stock market. We fail to consider transaction costs in the simulated trading strategy. Overcoming the above limitations will also be our future research direction.



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