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CONSTRUCTION AND EMPIRICAL STUDY OF A HIDDEN MARKOV MODEL-BASED STOCK PRICE PREDICTION PROCEDURE UNDER SHAREHOLDER DISENFRANCHISEMENT

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Abstract: Shareholder disenfranchisement events due to shareholders' failure to pay their contributions in full and on time not only bring significant adjustments to the corporate governance structure, but also lead to unfavorable shocks to a company's stock price. By studying the impact of shareholder disenfranchisement on stock price volatility, this paper highlights the significant impact of shareholder disenfranchisement events on stock price volatility, which results in the difficulty of manually forecasting a company's stock price. To solve this problem, this paper adopts the Hidden Markov Algorithm to construct a stock price prediction model for shareholder disenfranchisement companies. By learning the historical stock price data of shareholder disenfranchisement companies, the model predicts the future trend of the company's stock price. The accuracy of the HMM model in predicting the stock price of three shareholder disenfranchisement companies, X1, X2 and X3, is higher, and the model's MAPE value in stock price prediction is significantly lower than that of other models such as LSTM. Using the model in this paper can fully grasp the movement of the company's stock price after shareholder disenfranchisement, and realize the accurate prediction of the stock price of shareholder disenfranchised companies.

Keywords: Hidden Markov Model; MAPE; LSTM; Shareholder disenfranchisement; Stock price prediction

INTRODUCTION

Since the reform and opening-up, China’s economy has developed at a remarkable pace; however, the market economy system remains imperfect. As an integral part of the financial market, the stock market plays a pivotal role in ensuring the stability of China’s economic growth (Pan & Mishra, 2018; Guru & Yadav, 2019). Fluctuations in the Chinese stock market in recent years have triggered significant volatility in the broader financial system, directly affecting market stability and the sustainable development of the economy. Accurate forecasting of stock market movements enables timely regulatory interventions and policy guidance, thereby providing strong support for long-term economic sustainability (Durusu-Ciftci et al., 2017; Kutan et al., 2018).

The stock market is often described as the “barometer” of the economy, a role recognized not only by the government but also by investors. Broadly, two motivations underpin this interest: (1) investors seek to understand the dynamics of stock price movements to make accurate predictions and achieve profits, and (2) regulators aim to uncover the internal mechanisms of price fluctuations to anticipate sharp market oscillations and implement stabilizing measures (Bustos & Pomares-Quimbaya, 2020; Lu et al., 2020; Kumbure et al., 2022).

Currently, the Chinese stock market faces a multifaceted systemic crisis shaped by long-standing structural deficiencies. Over time, these institutional weaknesses have been neglected or tolerated, allowing negative market factors to accumulate and intertwine, while positive forces have gradually weakened, ultimately evolving into a comprehensive existential challenge (Zhang & Hamori, 2021; Zhou et al., 2020; Paramati et al., 2017). Nevertheless, whether in expansionary or contractionary phases, the market has contributed significantly to China's economic reform, dismantling elements of the traditional system and fostering the establishment of a modern economic framework (Huy et al., 2020; Ashraf, 2020).

The stock market holds an irreplaceable position in the modern market economy, particularly for a country undergoing systemic transformation. A robust stock market underpins the development of the banking sector, the financial system, and, by extension, the broader economy (Baker et al., 2020; Ho, 2019). In this context, stock price forecasting not only guides investors toward profitable decisions but also contributes to national economic growth (Kumar et al., 2021; Xiao et al., 2020).

Globally, the stock market is a critical component of the financial system, with price fluctuations influencing investor behavior, corporate strategy, and macroeconomic performance. Accurate price prediction is therefore essential for investment decisions, corporate planning, and policymaking (Shahi et al., 2020; Kurani et al., 2023). Increasing globalization and market liberalization have amplified the complexity and volatility of stock markets, as they are influenced by diverse factors including macroeconomic indicators, political events, firm performance, and investor sentiment (Berradi & Lazaar, 2019; Singh & Srivastava, 2017). The interaction of these variables poses significant challenges for predictive modeling. While traditional stock forecasting relies on linear models, recent advancements in artificial intelligence and machine learning offer the capacity to address nonlinear relationships and extract patterns from complex datasets, thereby improving predictive accuracy (Liang et al., 2020; Wang & Song, 2024).

This study first examines the theoretical link between shareholder disenfranchisement and stock price volatility, analyzing the potential market impacts of such governance events. Using panel regression models, we empirically investigate the synchronicity between disenfranchisement events and stock price volatility for Chinese listed companies between 2020 and 2023. Our findings reveal that disenfranchisement events negatively affect the performance of traditional stock price forecasting methods. To address this limitation, we construct a forecasting model based on the Hidden Markov Model (HMM) tailored to companies experiencing shareholder disenfranchisement. Leveraging the HMM's objectivity and learning capacity, the model aims to enhance predictive accuracy for this specific market context.

The empirical analysis draws on trading data from three companies—X1, X2, and X3—with shareholder disenfranchisement events during the 2020–2023 period. Taking Company X1 as an example, we examine data characteristics and apply a sliding-window approach to train the HMM parameters. Predictions from the proposed model are benchmarked against Long Short-Term Memory (LSTM), Random Forest, and Support Vector Machine (SVM) models, with forecasting accuracy evaluated using the mean absolute percentage error (MAPE).

2. A Study of the Impact of Shareholder Disenfranchisement on Stock Price Volatility

This section integrates theoretical analysis and empirical investigation to examine the impact of shareholder disenfranchisement on stock price volatility. The objective is to comprehensively reveal the transmission mechanisms through which shareholder disenfranchisement affects stock price dynamics, thereby providing dual guidance for academic research and practical decision-making in capital markets

2.1 Loss of Shareholder Rights

Loss of shareholder rights refers to the partial or complete deprivation of corporate rights when shareholders fail to fulfill their obligations under statutory provisions or the company's articles of association. With the revised Company Law of the People's Republic of China taking effect on July 1, 2024, the shareholder disqualification regime has emerged as a critical legal instrument to safeguard corporate capital adequacy and protect creditor rights. This system stipulates that if a shareholder in a limited liability company fails to pay the subscribed capital in full and on time, and subsequently neglects to fulfill this obligation after a formal demand from the company, the company may, through written notice, revoke the shareholder's equity rights.

In the context of China's rapidly developing capital markets, instances of shareholder disenfranchisement have occurred with increasing frequency, drawing public and academic attention to their implications for corporate governance and investor confidence. For instance, in a recent case, a listed company deprived a shareholder of voting and profit rights due to non-payment of capital contributions, directly influencing both the firm's decision-making processes and its stock price performance. This underscores the necessity of studying the relationship between shareholder disenfranchisement and stock price volatility.

2.1.1 Legal Basis of the Shareholder Disqualification Regime

The shareholder forfeiture mechanism is an important provision of the amended Company Law, designed to enforce capital contribution responsibilities and maintain stability in corporate capital structures. Article 52 of the new law specifies that when a shareholder fails to meet the capital contribution obligation on time, and does not remedy the situation within a reasonable period after a company-issued demand, the board of directors may, by resolution, initiate the disenfranchisement process through formal written notice.

The law further defines the procedural and substantive requirements for such actions. The demand notice must be issued in writing, granting shareholders a statutory grace period—typically no less than 60 days. Only upon expiry of this grace period without payment can disenfranchisement be executed. Importantly, forfeiture of rights does not automatically annul the shareholder's equity; instead, equity must be transferred in accordance with the law or cancelled through a reduction in registered capital. These provisions clarify the legal consequences of disenfranchisement while ensuring procedural fairness and enforceability.

2.1.2 Shareholder Disenfranchisement and Corporate Governance

The loss of shareholder rights has both legal and governance implications. From a corporate governance perspective, disenfranchisement represents a significant restructuring of shareholder entitlements. On one hand, it reinforces the responsibility of shareholders to contribute capital, thereby enhancing the adequacy and transparency of the firm's financial base. On the other hand, by removing "non-compliant" shareholders who fail to meet capital obligations, the mechanism can improve shareholder composition and strengthen governance efficiency.

2.1.3 Relationship Between Shareholder Disenfranchisement and Stock Price Volatility

The impact of shareholder disenfranchisement on stock price volatility is complex and multidimensional (Wang & Song, 2024). Theoretically, disenfranchisement alters the firm's ownership structure and may increase perceived legal and operational risks, leading to heightened market uncertainty. When a company announces the loss of rights of a shareholder, investors often interpret it as a signal of underlying governance deficiencies or weaknesses in the firm's capital position. This negative perception can erode investor confidence, prompting stock price declines.

Empirical evidence supports this link: disenfranchisement events are frequently followed by significant price swings. For example, as shown in Figure 1, the share price of a listed company fell sharply following an October 25 announcement of shareholder disenfranchisement, reflecting investor concerns about operational stability and legal exposure.

Moreover, the subsequent handling of forfeited shares can further influence volatility. If these shares are acquired by another major shareholder, the resulting shift in control may alter market expectations and affect valuation. Conversely, if the company opts to cancel the forfeited equity through a capital reduction, short-term improvements in capital structure may be offset by longer-term market apprehension regarding the firm's financial resilience and growth prospects.

Figure 1 A company's stock volatility

2.2 Impact analysis

2.2.1 Data sources and sample selection

The empirical research part of this section mainly relies on the public data of China's capital market, focusing on the analysis of listed companies with shareholder disenfranchisement events during the period from 2020 to 2023. The data sources include Vantage Information, Wind database and annual reports and announcements of listed companies. In order to ensure the representativeness and reliability of the data, the following types of companies are selected as research samples:

(1) Listed companies with shareholder disenfranchisement events.

(2) Listed companies that have not experienced shareholder disenfranchisement during the same period but have similar industries and sizes as the control group.

(3) All sample companies need to have complete records of financial data and transaction data.

After screening through the above criteria, a sample set containing 50 companies with shareholder disenfranchisement events and 50 control companies is finally obtained. These companies are diversified and representative in terms of industry distribution, enterprise size and shareholding structure, which can reflect the impact of shareholders' disenfranchisement on share price volatility in a more comprehensive way.

2.2.2 Variable Definition and Data Handling

(1) Explained variable: stock price volatility (SPV)

Stock price volatility is an important measure of the magnitude of stock price changes. In order to accurately calculate the stock price volatility, this paper adopts the standard deviation of daily returns as the measure of stock price volatility. The specific calculation formula is as follows:

$$SPV = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(R_i - \bar{R})^2} \quad (1)$$

where R_i is the daily return of the stock on day i, $\bar{R}$ is the average daily return over the sample period, N is the number of trading days, and the daily return is calculated by the formula:

$$R_i = \frac{P_i - P_{i-1}}{P_{i-1}} \quad (2)$$

where P_i and P_{i-1} are the closing prices on day i and day $i-1$, respectively.

(2) Explanatory variables: shareholder disenfranchisement (SLR)

The explanatory variable is a dummy variable for whether shareholders are disenfranchised. It takes the value of 1 if the firm has a shareholder disenfranchisement event in a given year and 0 otherwise.This variable is used to capture the effect of shareholder disenfranchisement events on stock price volatility.

(3) Control Variables

The factors affecting the formation and volatility of stock prices in the stock market are very complex. In addition to the shareholder disenfranchisement factor, the main factors at the macro level are monetary policy, fiscal policy, industrial policy, regulatory policy, trading system, etc., and the main factors at the micro level are growth expectations, asset acquisitions, and industry life cycle. For the uniqueness and scale characteristics of listed companies, four indicators, namely, the level of economic development, company size, fixed asset turnover, and return on invested capital, are selected as control variables. On the basis of organizing the data of the selected indicators, in order to ensure the accuracy of the empirical analysis results, further logarithmic treatment is done to eliminate the influence of heteroskedasticity. The types, names and codes of the variables after logarization are shown in Table 1.

Table 1 Variable type, name and code

Variable type	Variable name	Variable code
Explained variable	Stock price volatility	SPV
Interpretation variable	Shareholders lose rights	SLR
Control variable	Level of economic development	GDP
	Company size	$Scale$
	Fixed asset turnover	FAT
	Return on invested capital	$ROIC$

2.2.3 Model construction

In this paper, a panel model is used to explore the relationship between shareholder disenfranchisement and stock price volatility and the impact effect. The set panel model is specifically denoted as:

$$SPV_{i,t} = \alpha + \beta_1 SLR_{i,t} + \beta_2 Controls_{i,t} + \gamma_i + \delta_t + \varepsilon_{it} \qquad (3)$$

Where, $_1$, and $_2$ are the ending terms, the coefficients to be estimated for the explanatory variables and the control variables, respectively, SPV denotes the stock price volatility, SLR denotes the shareholder disenfranchisement, and $Controls$ represents the set of control variables. $_i$ and $_t$ represent the existence of individual fixed effects and time fixed effects of the model, respectively, and $_{it}$ is the random disturbance term.

The Hausman test of the model shows that the original hypothesis of random effects is rejected, so the panel fixed effects model is chosen for regression. If the regression coefficient of SLR is positive, it indicates that shareholders' disenfranchisement leads to an increase in share price volatility, i.e., shareholders' disenfranchisement causes significant volatility in share price.

2.2.4 Empirical results and analysis

(1) Descriptive statistics of variables

Table 2 shows the descriptive statistics of the variables. From the data in the table, it can be seen that the share price volatility of listed companies as a whole performs well, but from the value of standard deviation, there is a huge difference in the share price volatility of listed companies, and the variability of return on invested capital is also more significant, and the standard deviation of the shareholders' disenfranchisement and the level of economic development is relatively close to each other, which suggests that the two indexes may have the same fluctuation amplitude.

Table 2 Descriptive statistical results of variables

Variable	Observed value	Mean	Standard deviation	Minimum value	Maximum value
SPV	100	1.836	208.732	0.837	3.486
SLR	100	1.243	0.953	0.000	1.000
LnGDP	100	12.837	0.874	10.845	14.938
LnScale	100	22.685	2.481	19.876	28.943
FAT	100	3.374	3.476	0.124	14.738
ROIC	100	11.238	11.658	-27.462	54.853

(2) Analysis of benchmark regression results

Table 3 shows the benchmark regression results of the model, where *, **, and *** indicate that they are significant at the 10%, 5%, and 1% levels, respectively. Analyzing the data in the table, it can be seen that the regression results of individual fixed effects, point-in-time fixed effects and panel interaction fixed effects show that shareholders' disenfranchisement is positively correlated with stock price volatility at the 1% level, which indicates that shareholders' disenfranchisement can significantly lead to an increase in stock price volatility. From the regression coefficient value, every 1% increase in shareholder disenfranchisement increases stock price volatility by an average of %. The empirical results also reasonably explain the significant impact of company size on reducing share price volatility, investors will choose large-scale, strong assets of the company to invest in order to maintain the stability of the share price of large-scale listed companies and reduce the volatility of the company's share price, so the company size is negatively correlated with the volatility of the share price. Fixed asset turnover, return on invested capital have a significant negative impact on the share price volatility of listed companies, the level of economic development has a negative but not significant impact on the share price volatility after controlling for individual effects, and after controlling for the point-in-time and panel interaction effects, it has a significant negative impact on the share price volatility. This reflects, on the one hand, the impact of macroeconomic policy changes on stock price volatility, and on the other hand, it shows that the value of a company's stock is based on market expectations of future returns, and if the market does not have enough information related to the company's true prospects, the market expectations will deviate from its intrinsic value, and after determining the listing price, the returns that shareholders obtain depend more on the changes in expectations of the future performance of the company than on the company's actual performance.

Table 3 Benchmark regression results

Variable	*SPV*		
	Individual effect	Time effect	Mixed effects
SLR	169.837*** (7.831)	172.483*** (6.274)	178.964*** (15.862)
LnGDP	-5.481 (1.073)	-60.857*** (-6.793)	-66.472*** (-3.541)
LnScale	-9.574** (-2.387)	-133.836*** (-11.697)	-152.478*** (-8.297)
FAT	-15.416*** (-5.396)	-7.064*** (-2.348)	-10.582*** (-3.051)
ROIC	-3.926*** (-4.087)	-3.983*** (-12.876)	-5.035*** (-6.764)
_cons	-487.124 (-1.062)	-2698.373*** (-12.306)	-2984.527*** (-8.294)
N	100	100	100
R^2	0.631	0.726	0.778

(3) Robustness Analysis

To further enhance the robustness of the paper's findings, the paper conducts a counterfactual test by changing the timing of shareholder disenfranchisement announcements. The implementation time of shareholder disenfranchisement is artificially adjusted forward by two periods. The regression results are shown in Table 4, and the regression coefficients are not significant. The results indicate that the hypothesized implementation time of shareholder disenfranchisement does not have a significant effect on stock price volatility, which on the other hand suggests that the increase in stock price volatility is not due to other factors, but rather from the implementation of the shareholder disenfranchisement policy. It further indicates the significant effect of shareholder disenfranchisement on stock price volatility.

Table 4 Robustness test results

Variable	*SPV*
SLR	12.384 (4.283)
LnGDP	-22.651 (-7.864)
LnScale	-21.732 (-8.457)
FAT	-9.476 (-6.875)
ROIC	-2.896 (-7.064)
Time effect	Yes
Individual effect	Yes

(4) Comparative analysis

In this paper, 50 listed companies without shareholder disenfranchisement events are selected as the control group to highlight the impact of shareholder disenfranchisement on the company's share price volatility through the comparison with the share price volatility of listed companies with shareholder disenfranchisement events. Fig. 2 shows the results of the comparison of share price volatility of the two types of listed companies, and the shaded portion of the chart is the difference in the share price volatility between the two types of companies. From the figure, it can be seen that the share price volatility of listed companies without shareholder disenfranchisement events is significantly lower than that of listed companies with shareholder disenfranchisement events, whose share price volatility are all in the range of 0-0.5. The share price volatility of listed companies with shareholder disenfranchisement events can be up to 2.298, which verifies the conclusion that shareholder disenfranchisement significantly affects the share price volatility in this paper.

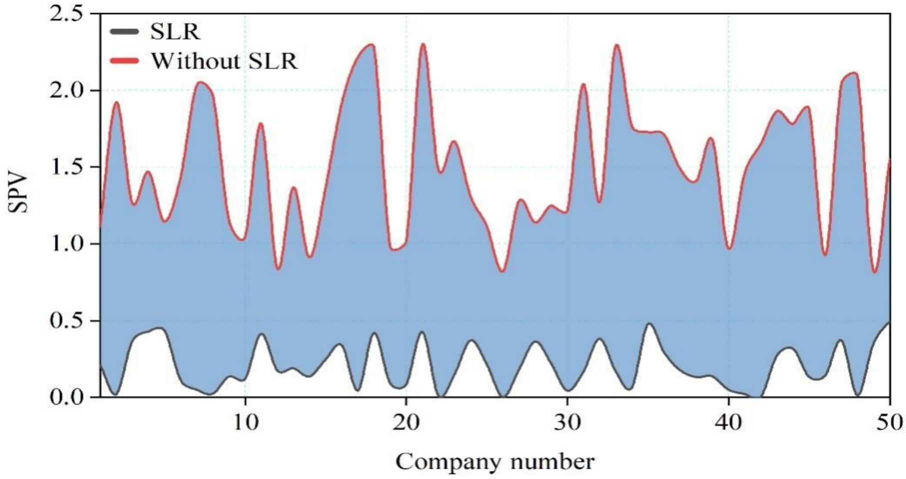
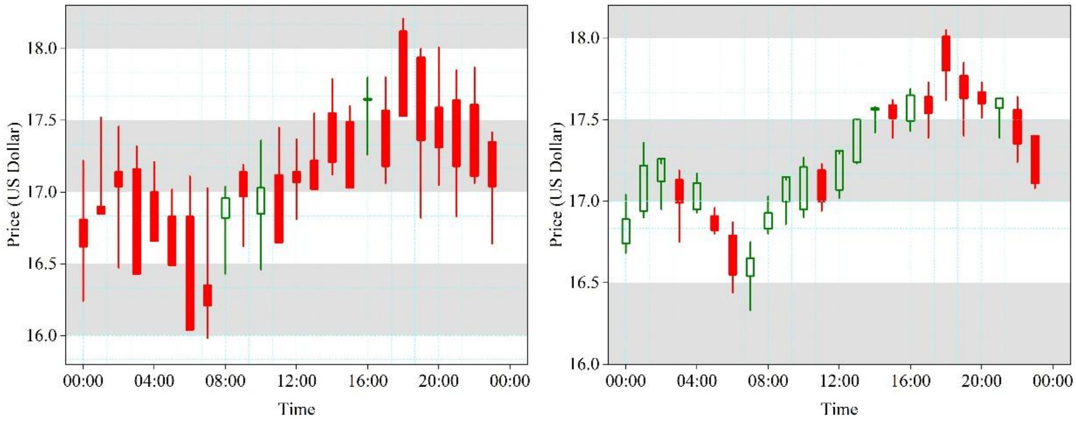


Figure 2 Stock price volatility contrast

Figure 3 shows the stock price movements of two listed companies (A and B) selected in this paper on a particular day, (a) represents the stock price of Company A and (b) represents the stock price of Company B, where Company A had a shareholder disenfranchisement event, while Company B did not have a shareholder disenfranchisement event. As can be seen from the figure, the stock price volatility of Company A is significantly higher than that of Company B on that day. At the same time, the closing price of Company A's stock was lower than the opening price in nine time periods, including 04:00, 05:00, and 06:00, and Company A's closing price was lower than Company B's closing price in all time periods on that day. This visualizes the impact of shareholders' disenfranchisement on the company's stock price and stock price volatility.



(a)Company A (b)Company B

Figure 3 Stock price contrast of different companies

3. Hidden Markov model-based stock price prediction

From the analysis in the previous section, it can be seen that when a company experiences a shareholder disenfranchisement event, it can lead to significant fluctuations in the company's stock price. At this point, it will become extremely difficult to predict the company's stock price artificially. Identifying small changes in the stock price through the model and thus objectively predicting the stock price trend will greatly improve the accuracy of predicting the stock price of a company with a shareholder disenfranchisement event. Therefore, in this section, the Hidden Markov Model will be used as the basis for constructing the Arch Bottom Stock Price Prediction Model, so as to realize the prediction of the stock price of a company with a shareholder disenfranchisement event, and to help investors correctly judge the market trend.

3.1 Hidden Markov Models

Hidden Markov models are theoretically different from models that are trained independently on sample data [23], Hidden Markov models are meant to assume discrete bi-stochastic processes with hidden variables, whose samples have hidden time-series relationships within them, including the unobservable, hidden stochastic process and another stochastic process, which is the source of the word hidden in Hidden Markov Models. The opposite of this is the observable, displayed observed variables. Based on this, Hidden Markov Models are able to dig deeper into the data for potential, time-series related phenomena, outputting a sequence of hidden variables that can be used to make reasonable speculations about future events that will occur based on the potential relationship of the sequence. For example, in the case of an input method used in keyboarding, the input of pinyin or letters is an observable observable variable, and the input method will predict the words or phrases that will be typed, and will give the possible outcomes, and then the person who inputs the words will decide which outcome to choose. Therefore, Hidden Markov Models can be very useful in many situations, such as speech recognition, map matching, natural language processing or predictive finance.

It is known from Bayesian formula [24]:

$$p(x_1, x_2, \cdots, x_N) = \prod p(x_n \mid x_{n-1}, \cdots, x_1) \tag{4}$$

N random variables whose joint probability distribution can be expressed as the product of the consecutive products of conditional probability distributions.

The Markov model means that the variables are related only to the current state and not to the previous state of the variables or to the distribution of the state before that. The joint distribution of the variables is then:

$$p(x_1, x_2, \cdots, x_N) = p(x_1)\prod p(x_n \mid x_{n-1}) \tag{5}$$

Consider higher-order Markovianity and construct the state-space model shown in Fig. 4 by adding hidden variables with the aim of solving the problem of controlling the exponential explosion in the presence of higher-order Markovianity. Where z_n is a hidden variable, x_n is an observed variable, and $z_n - 1$ and $z_n + 1$ are independent of each other when z_n is given.

At this point Eq. (5) transforms to:

$$p(x_1, x_2, \cdots, x_N, z_1, \cdots, z_N) = p(z_1)\left[\prod_{n=2}^{N} p(z_N \mid z_{n-1})\right]\left[\prod_{n=1}^{N} p(x_n \mid z_N)\right] \tag{6}$$

At this point, the original complex model is converted to Eq. (6), which consists of only three parts: $p(z_1), p(z_N \mid z_{n-1}), p(x_n \mid z_N)$. The initial problem can be solved by solving these three parts separately. These three parts are called: the initial probability model, the state transfer probability model, and the observation probability model.

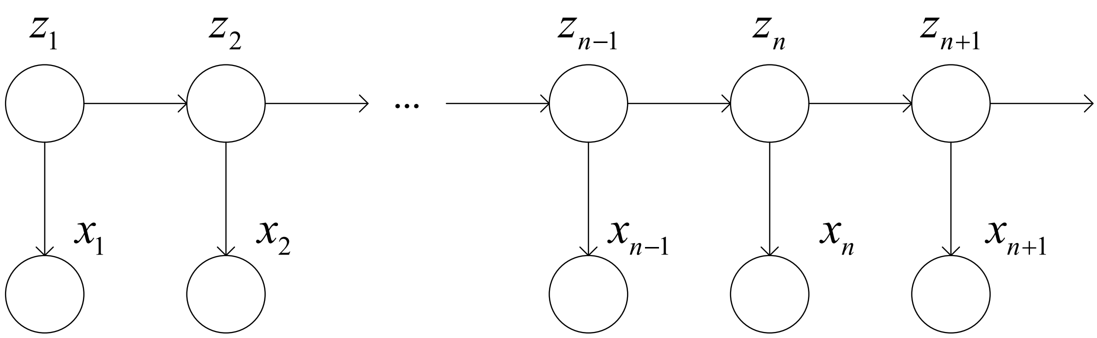


Figure 4 State space model

The state shift probability model: z_n is a discrete hidden variable, and if there are K states, then z_n denotes a K-dimensional random variable that takes only 0 or 1 in each dimension, and only one dimension has a value equal to 1. For example, if there are four independently undisturbed states of a discrete variable z_n that $z_n = [0,0,0,1]^T$ exists, then this equation denotes that the variable z_n is in state four at this time in its form. In this way $p(z_N \mid z_{n-1})$ in the three parts can be transformed into the following form:

$$p(z_N \mid z_{n-1}, A) = \prod_{j=1}^{K}\prod_{k=1}^{K} A_{j,k}^{z_{n-1,j} z_{nk}} \tag{7}$$

Initial probability matrix model: the distribution of the first hidden variable z_1 can be expressed in terms of a vector π representing the probabilities, and the k rd factor under the sequence represents the probability of z_1 being in the k th state if the normalization condition is satisfied, then $p(z_1)$ of the three parts can be transformed into the following form:

$$p(z_1 \mid \pi) = \prod_{k=1}^{K} \pi_k^{z_{1k}} \tag{8}$$

The observed probability model: $p(x_n \mid z_N)$ can be similarly represented as $p(x_n \mid z_N, \phi)$, where ϕ denotes the parameters under the current model. Then the observation probability model $p(x_n \mid z_N)$ transforms into the following form:

$$p(x_n \mid z_N, \phi) = \prod_{k=1}^{K} p(x_n \mid \phi_k)^{z_{nk}} \tag{9}$$

With the above analysis, Equation (3), the joint probability distribution of all variables, can be expressed as follows:

$$p(X, Z \mid \theta) = p(z_1 \mid \pi)\left[\prod_{n=2}^{N} p(z_N \mid z_{n-1}, A)\right]\left[\prod_{n=1}^{N} p(x_n \mid z_N, \phi)\right] \tag{10}$$

In Equation (7) X is $x_1, x_2, \cdots, x_N$, which is the whole observed random sequence, Z is $z_1, \cdots, z_N$, which is the whole hidden random sequence, and θ denotes all the remaining parameters.

In machine learning, the above parameters are learned by the great likelihood method, but due to the addition of hidden variables, the great likelihood method used by the general model is not accepted, and then the EM algorithm is chosen to solve the unknown hidden parameters by gradual and iterative convergence, which often does not require too many rounds to converge due to the fast convergence speed.

The model parameters are obtained by forward and backward computation of M-step and E-step. When predicting, if you consider predicting the next set of observed variables for a given observed variable, the results can be obtained by using the conditional independence of the model with forward calculations, as shown in Equation (11). If we consider to find out the hidden sequence corresponding to a given observed variable, it can be obtained by using the Viterbi algorithm.

$$p(x_{N+1} \mid X) = \frac{1}{p(X)} \sum_{Z_{N+1}} p(x_{N+1} \mid z_{N+1}) \sum_{Z_N} \alpha(z_N) p(z_{N+1} \mid z_N) \tag{11}$$

3.2 Stock price forecasting under shareholder disenfranchisement

3.2.1 Sample Selection and Characterization

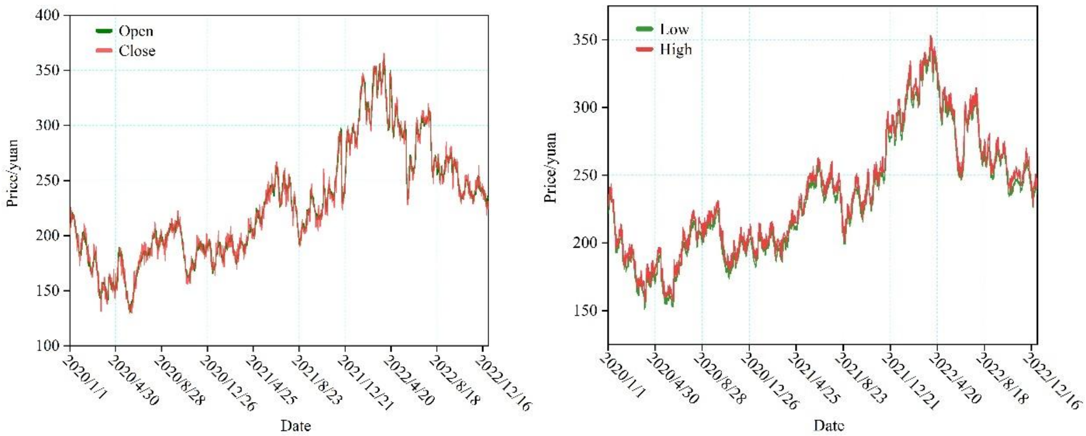
In order to measure the performance of the HMM model proposed in this paper in stock price prediction on individual stocks with different occurrence of shareholder disenfranchisement events, three individual stocks of listed companies with occurrence of shareholder disenfranchisement events, X1, X2, and X3, are selected as the samples for empirical analysis in this paper. Python is used to crawl the valid data of the three companies from Yahoo Finance website from January 1, 2020 to December 31, 2023 as the sample data, and the sample data is divided into two parts, the first part is the stock opening, high, low, and closing price data from January 1, 2020 to December 31, 2022, which is used as the training set to train the model parameters. The second part is the stock closing price data from January 1, 2023 to December 31, 2023 as a test set to test the prediction accuracy of the model.

Firstly, the sample data of company X1 is used as an example to illustrate the basic characteristics of the data in the training and test sets of company X1 as shown in Table 5. From the table, it can be seen that the mean values of the highest price, lowest price, opening price and closing price of the stock of X1 company during these three years are in the range of the interval (167,206), the standard deviation is around 60, the maximum value is in the range of the interval (158,338), and the minimum value is in the range of the interval (108,146).

Table 5 Stocks characteristic of X1 company

	High	Low	Open	Close
Mean	205.84	167.43	182.58	179.65
Std	58.74	58.28	59.03	58.96
Max	337.85	158.26	296.39	287.48
Min	145.73	108.94	125.26	117.31

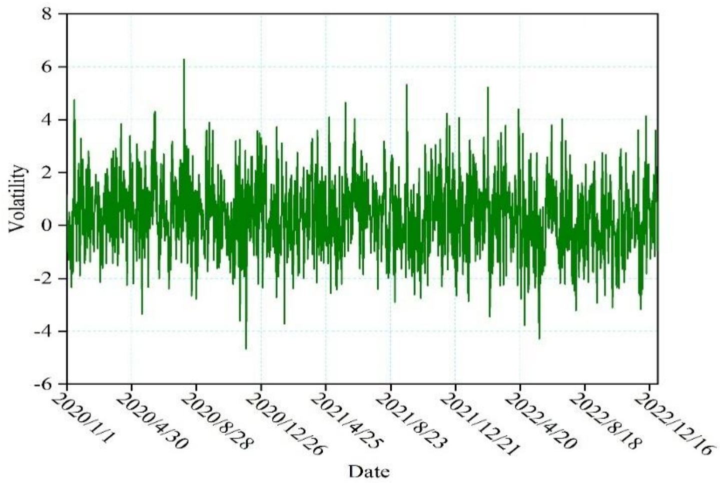
Using python software through the plot function of matplotlib, the charts of the opening price, closing price, high price and low price of the stock of company X1 during the sample period are obtained as shown in Fig. 5, where (a) denotes the trend of the opening price and closing price, and (b) denotes the trend of the high price and low price. As can be seen from the figure, the trend of opening price, closing price, high price and low price are consistent. During the time period from January 2020 to December 31, 2022, the opening price, closing price, high price, and low price all wave up and down within a certain range, and the stock price generally remains stable.



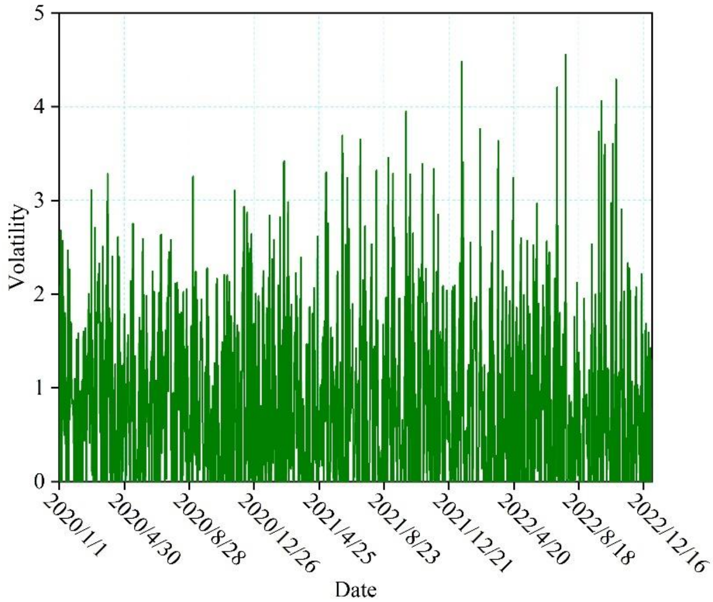
(a) Open and Close (b)High and Low

Figure 5 Stock price trend

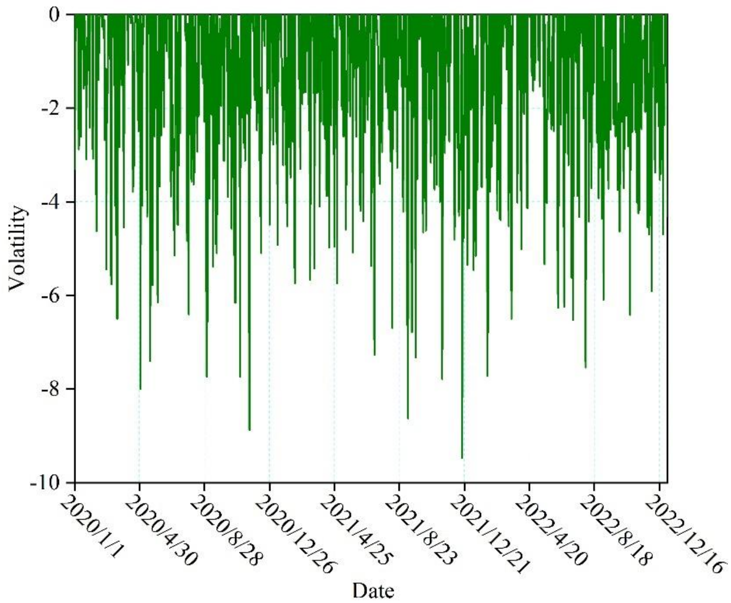
The original opening price, closing price, maximum price and minimum price data are processed according to the formula, in order to differentiate the maximum price volatility from the minimum price volatility obtained from the graph, this section of the formula on the right side of the equals sign plus a negative sign for processing, the resulting closing price volatility, maximum price volatility and minimum price volatility over time is shown in Figure 6, (a), (b), (c) represent the stock's closing price, respectively, volatility curves of the maximum and minimum prices. From the figure, it can be seen that although the stock data price of Company X1 does not show obvious regularity, and its stock price data varies in a large range, after converting the stock price data into volatility data, its closing, maximum, and minimum price volatility shows the corresponding normal distribution characteristics.The daily stock returns of Company X1 from January 1, 2020 to December 31, 2022 are mostly concentrated in the range between -6 and 8. It can also be noticed that at certain moments of the sample period, the values of the three types of volatility take prominence, indicating that historically, the stock price on that day has been more volatile.



(a) Stock close price volatility



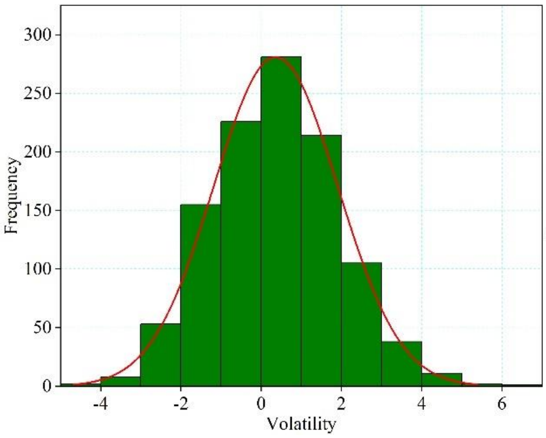
(b) Stock high price volatility

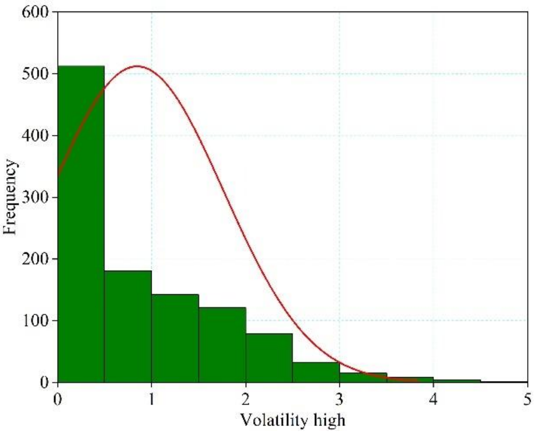


(c) Stock low price volatility

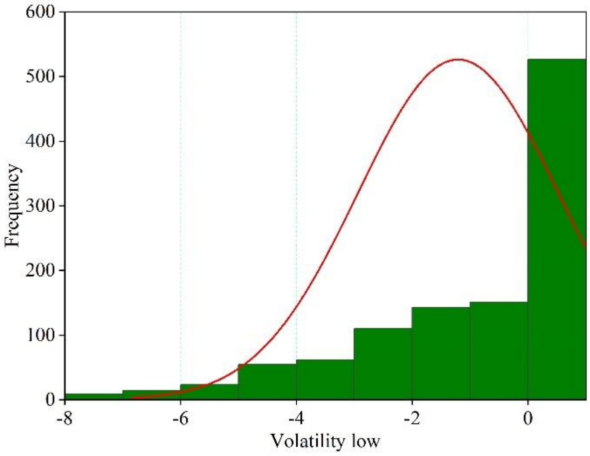
Figure 6 Stock price volatility

Figure 7 shows the interval distribution of volatility statistics in this paper, (a), (b) and (c) represent the frequency distribution of closing price, maximum price and minimum price volatility intervals, respectively. From the figure, it can be seen that the closing price, maximum price and minimum price volatility of X1 stock basically obeys a normal distribution. Statistics on the number of days that all volatility values appear in each subdivided interval reveal that the closer the value of the interval is taken to zero, the greater the corresponding number of days of volatility. When the absolute value of positive and negative volatility exceeds 4, the corresponding number of days are in single digits. At the same time, it can be seen that the mean value of closing price volatility is close to 0, and the frequency distribution graph of volatility fluctuation intervals has a sharp peak and short tail, indicating that the overall volatility is relatively stable.





(a) X1 volatility distribution (b) X1 volatility high distribution

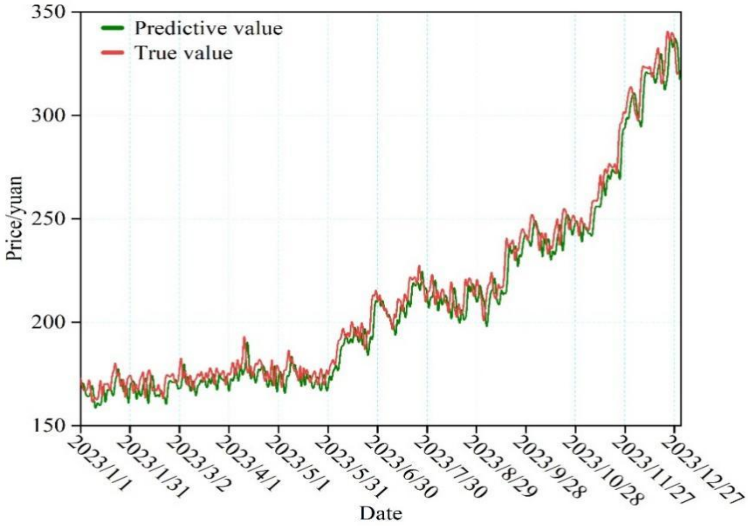


(c)X1 volatility low distribution

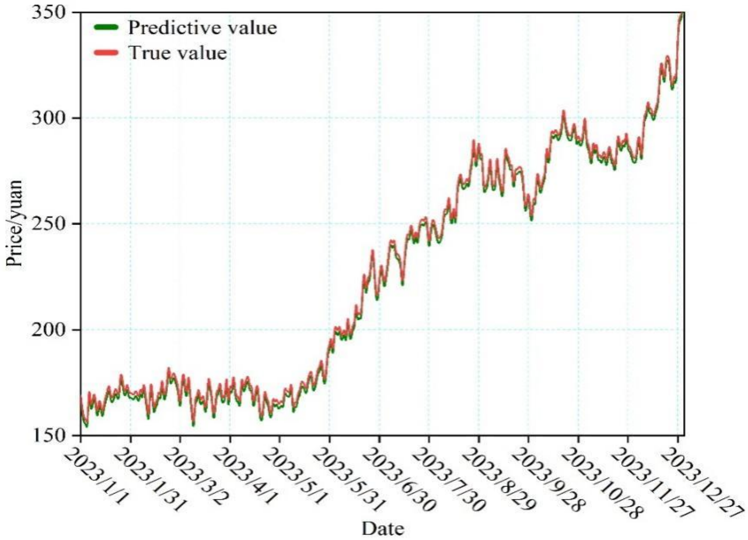
Figure 7 Distribution of variable range of stock price

3.2.2 Projected results

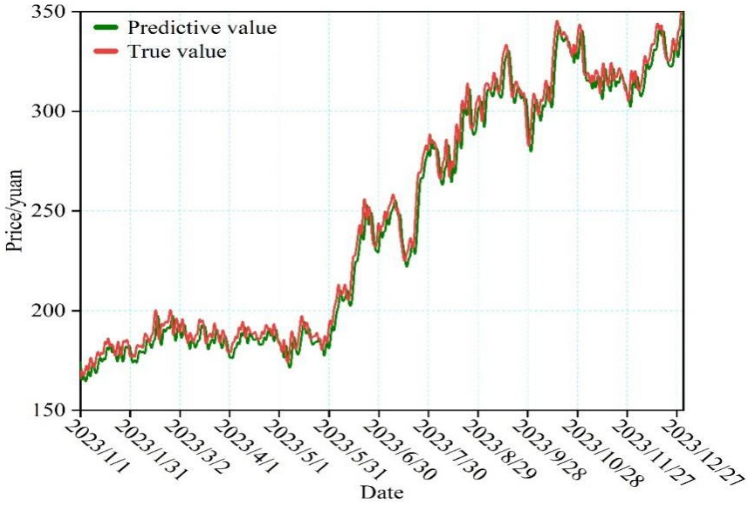
In the prediction experiment, a sliding window approach is used to train the HMM parameters and make predictions in order to ensure the accuracy as well as the reasonableness of the prediction results. Specifically, the data from January 1, 2020 to December 31, 2022 is considered to be used to train the model parameters and predict the closing price on January 1, 2023. Then data from January 2, 2020 to January 2, 2023 is used to train the model parameters and predict the closing price on January 2, 2023, and so on until December 31, 2023. Finally, all the prediction results for 2023 are obtained as shown in Fig. 8, with (a), (b), and (c) denoting the 2023 stock price prediction results for three listed companies with shareholder disenfranchisement events, X1, X2, and X3, respectively. From the figure, it can be intuitively seen that the gap between the prediction results obtained from the stock price prediction model constructed by the HMM algorithm in this paper and the real results is relatively small, and the predicted value of the stock price for X2 company is the closest to the real value, which is a strong indication of the accuracy of this paper's model for the prediction of the stock price after the occurrence of shareholder disenfranchisement events.



(a) Company X1



(b)Company X2



(c)Company X3

Figure 8 2023 stock price prediction and true value comparison of three companies

In order to verify the effectiveness of the models, LSTM, Random Forest, and SVM models were selected as comparison models. And a common prediction assessment index, i.e., the average of absolute relative error $MAPE$, was used to evaluate the validity of the prediction results of different models. $MAPE$ is defined as:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|\, y_{prediction} - y_{true}\,|}{y_{true}} \tag{12}$$

The prediction errors of each model are shown in Table 6. From the table, it can be seen that the prediction errors of this paper's model for different complimentary stock prices are lower than those of the other three models, indicating that the Hidden Markov Model has a higher accuracy and stability in stock price prediction than other methods. Moreover, the stock price prediction error of the HMM model for company X2 is less than 0.01, which matches the results obtained from the test dataset of this paper, highlighting the applicability of the HMM model of this paper in the research scenario of this paper.

Table 6 Prediction error of different models

Company	Date	Models			
		HMM	LSTM	RF	SVM
X1	2023-01	0.0102	0.0482	0.0594	0.0571
	2023-03	0.0113	0.0471	0.0635	0.0582
	2023-07	0.0103	0.0436	0.0668	0.0539
	2023-10	0.0106	0.0458	0.0629	0.0564
	2023-12	0.0109	0.0496	0.0684	0.0538
X2	2023-01	0.0001	0.0432	0.0657	0.0552
	2023-03	0.0008	0.0459	0.0694	0.0603
	2023-07	0.0006	0.0416	0.0663	0.0569
	2023-10	0.0009	0.0428	0.0685	0.0533
	2023-12	0.0003	0.0437	0.0648	0.0541
X3	2023-01	0.0117	0.0531	0.0702	0.0592
	2023-03	0.0126	0.0498	0.0713	0.0633
	2023-07	0.0134	0.0502	0.0711	0.0624
	2023-10	0.0103	0.0497	0.0724	0.0619
	2023-12	0.0109	0.0486	0.0719	0.0628

CONCLUSION

This study focuses on developing an effective stock price forecasting method for companies experiencing shareholder disenfranchisement. First, a panel regression model was employed to empirically confirm that shareholder disenfranchisement events exert a significant positive impact on stock price volatility. Building on this finding, a Hidden Markov Model (HMM)-based forecasting framework was proposed to address the limitations of manual prediction methods, enabling accurate and efficient forecasting of stock prices for affected companies.

The empirical evaluation, conducted on three listed companies (X1, X2, and X3) with shareholder disenfranchisement events, demonstrates the high predictive accuracy of the proposed model. Across all three cases, the gap between the predicted and actual stock prices was minimal. Company X2 achieved the closest alignment with observed values, with a Mean Absolute Percentage Error (MAPE) of less than 0.01. Overall, the MAPE values for all three companies clustered around 0.01, indicating exceptional predictive precision.

By contrast, benchmark models—including Long Short-Term Memory (LSTM), Random Forest, and Support Vector Machine (SVM)—exhibited substantially higher prediction errors. The LSTM model, while performing best among the three benchmarks, produced a MAPE close to 0.05 for Company X3. The Random Forest model's MAPE exceeded 0.07 for the same company, and all three alternative models recorded MAPE values above 0.04 across the board.

These results confirm that the HMM-based approach proposed in this study significantly outperforms traditional machine learning models in forecasting stock prices for companies undergoing shareholder disenfranchisement. The model offers reliable technical support for investors, analysts, and policymakers, enabling them to more accurately anticipate price trends, make informed investment decisions, and enhance overall market confidence.

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