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A New Decision Making Strategy: Combining Markov Chain Market Prediction with Kelly Criterion

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Abstract:

In some cases, solely relying on the traditional Kelly Criterion, which assumes fixed win and lose rates, is insufficient to cope with the constantly changing market environment. Some present attempts to develop an improved decision-making model combine the Kelly Criterion with a Markov chain, but they are either too complex or have limitations. To figure out a better method, this paper carries out research on dynamic position decision-making. A Markov chain model divides the market into two states by analyzing a state transition probability matrix based on historical price movements. These two states represent increasing and declining market conditions, respectively. Then, the Kelly Criterion is used to calculate the optimal position corresponding to each state, enabling state-dependent position sizing. Each step is easy to apply and does not require much calculation, making the method accessible for practical investment decisions. This novel and simple strategy forms a two-step decision-making system including state identification and position optimization. Empirical results from an A-share stock demonstrate that this dynamic strategy outperforms the static Kelly approach, offering improved cumulative returns while maintaining simplicity and ease of implementation.

Keywords: Kelly Criterion; Markov chain; dynamic position sizing; market state identification; optimal investment strategy

1. Introduction

Investors often face the dilemmas of misjudging market trends and improper position sizing, causing them to miss out on gains when holding light positions in a bull market (increasing trend), or experience massive losses from holding heavy positions in a bear market (declining trend).

Although the classic Kelly Criterion provides the optimal position size, it assumes fixed win/loss ratio, which are inconsistent with the real market where market conditions change dynamically. On the other hand, a Markov chain, with its property of no aftereffect, can accurately identify dynamic market state.

Markov chains have always been an effective tool in countless fields. Borkowska & Kroese applied Markov-based optimal betting to sports and finance, validating practical utility across scenarios [1]. Nystrup et al. employed hidden Markov models to identify market regimes and improve dynamic allocation performance [2]. Pasricha et al. (2020) extended this framework by using semi-Markov processes to model credit rating transitions [3]. This model captures duration dependence better compared with traditional Markov chains.

Recent studies have extended the Kelly criterion under Markov frameworks for dynamic investment and betting optimization. Lynch & Taylor set a framework for state-dependent capital allocation [4]. By introducing a two-state Markov transition matrix, the model of this study captures conditional win rates, enabling adaptive position sizing: lower positions in State 1 (rising) and higher positions in State 2 (falling). This design matches the finding of Lynch & Taylor that state-aware Kelly strategies improve regime adaptation and risk-adjusted returns. Li & Zhang further generalized the model to Markov jump-diffusion processes [5], addressing volatility and jump risks in financial markets. Liu & Chen proposed a robust Kelly criterion for Markov chains with uncertain transition matrices [6], enhancing stability in ambiguous environments. Collectively, these works apply dynamic Kelly methods under Markov structures. However, these models are complicated for real-life use. They also require excessive calculation, which make them parameter-sensitive and thus risky in real-life situations.

A study highly inspiring to this paper were done by Andersson & Vähämaa [7], who put forward a dynamic portfolio framework that integrates Hidden Markov Model (HMM) for regime identification and statedependent asset allocation. Different from the visible twostate division in this paper, their model uses hidden states to capture unobservable market patterns, and constructs state transition probabilities through return sequences. The core contribution is to prove that statedependent weight adjustment can significantly improve riskadjusted return compared with fixed allocation [8].

Compared with the existing literature cited in this paper, Andersson & Vähämaa have simpler modeling steps, and do not involve complex jump diffusion or robust optimization, which is compatible with the "twostep decision system" constructed in this paper [9]. It can be seen that using Markov chain to identify states and matching Kelly to optimize positions is in line with the frontier development of dynamic allocation. At the same time, the slight excess return in this paper is also due to the short sample period, high noise and insufficient state persistence, which further supports the view of Andersson & Vähämaa that the strategy effect depends on trend characteristics. This literature provides a solid external reference for this paper to verify the effectiveness and boundary conditions of the improved strategy [10].

This paper aims to show the effectiveness of the two-step decision making system, involving market state recognition based on Markov chain and position optimization based on Kelly Criterion. A combination of these two approaches enables adaptive position sizing based on market states, hopefully helping investors balance returns and risks. Section 2 will show the methodology of this paper and identify core variables for calculating. In this section, the Kelly criterion will be applied in its most general form, and the theoretical steps of creating the Markov matrix will be defined. Section 3 will analyze a specific A-share stock and compare the calculated final return in two different strategies. Some similar properties with other strategies will be discovered. In this section, the advantages of the new strategy will be verified, while its limitations will also be shown. The last section will devote to the conclusion.

2. Methodology

2.1 Definition of Core Variables

This paper selects a typical A-share stock, and adopts daily trading data from 160 consecutive trading days as the experimental data. The data include core indicators including daily closing price and daily price change rate (a positive rate indicates a price rise, while a negative rate indicates a price decline). This stock is chosen for its active trading and market representativeness, which reflects the state characteristics of the A-share market. The selection of over five months of daily data ensures a sufficient sample size, and also avoids market environment discrepancies caused by an overly long data period, so the reliability of experimental results can be guaranteed. This paper uses an experimental method, with a control group and an experimental group, in order to exclude all confounding variables.

To ensure the standardization of the experiment, various core variables should be defined. Initially, win rate and lose rate are the two most important variables. Win rate (p) is the proportion of trading days with stock price increases to the total number of trading days in a given period. This paper adopts both fixed win rate (used in Strategy 1, where Kelly Criterion is directly used) and state-dependent win rate (used in Strategy 2, where Kelly Criterion is applied according to the predicted market state). Lose rate (q) is the proportion of trading days with stock price

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declines to the total number of trading days in a given period, satisfying $q = 1 - p$. Correspondingly, it is divided into fixed lose rate and state-dependent lose rate. Another essential variable in calculating the optimal Kelly position is the net odds (b). It is the ratio of the average positive daily return (x) to the average daily loss (y), calculated as $b = \frac{x}{y}$. The two strategies share the same calculation standard for net odds in this paper. Based on these variables, the optimal Kelly Criterion position (f^*) can be calculated, which is the optimal investment position calculated by the Kelly criterion ($f^* = p - \frac{q}{b}$). Theoretically, this position leads to the maximum long-term benefits, and minimizes long-term loss.

There are two market states that are divided based on the stock's historical price movements, namely State 1 (increasing state) and State 2 (declining state). By using the Markov chain modeling in Strategy 2, the following market state can be predicted according to the current one. Finally, the author seeks for maximized cumulative return, which is calculated solely by daily positions and actual stock price changes (excluding transaction costs, stamp duty and commissions). It serves as the core indicator of the performance of the two strategies.

2.2 Experimental Design and Strategy Implementation Process

The two comparative strategies both formulate positions based on the Kelly criterion. This article analyzed a total of 160 consecutive trading days of the A-share stock 300308.SZ (Zhongji Innolight Co., Ltd.) from 8 August 2025 to 9 April 2026. The source of the data is of the first 140 days (from 8 August 2025 to 11 March 2026) is used to calculate parameters such as win rate and lose rate, as well as construct the transition matrix. Then, the rest 20 days (from 12 March 2026 to 9 April 2026) are used to test how much money can be earned by applying the two strategies respectively. Finally, the cumulative returns of the two strategies are compared in order to verify the effectiveness of the second strategy. The specific processes are as follows.

The first strategy, which serves as the control group, is the static Kelly position strategy under fixed win rate and lose rate. In this method, the traditional Kelly Criterion is applied without any extra consideration. This strategy involves no prediction of stock price movement, and the other variables are exactly the same as the experimental group. Using the formula $f^* = p - q / b$, the author can calculate the optimal position to invest, theoretically maximizing long-term gain, and minimizing long-term loss.

The second strategy, which serves as the experimental group, is the dynamic Kelly position strategy using Markov chain market prediction. In this situation, before calculating the optimal Kelly position, a transition matrix is constructed to demonstrate the win rates and lose rates under two different conditions: "the day before was a win" (Status 1) or "the day before was a loss" (Status 2). According to the status of the previous day, two different Kelly positions are calculated, using $f^* = p' - q' / b$, where p' and q' are conditional win rates and lose rates. By altering the position when the status changes, this paper hopes to win more than merely using a constant position.

3. Results

3.1 Calculated returns

The data of the 160 days is gathered from https://webapi.cninfo.com.cn/#/marketData (Stock code: SZ300308). By constructing a list containing the previously mentioned core variables of each trading day, the author eventually found out the specific amount of extra return that the dynamic position strategy provides.

Within the 140 days used for parameter calculation, 73 days had a price increase, while 67 days had a price decline, so the win rate is 73/140 = 52.14%, and the loss rate is 67/140 = 47.86%. Then, b = 52.14%/47.86% = 1.427. The average positive daily return is 4.42%, while the average negative daily loss is 3.10%. Using the formula of Kelly Criterion, f^* = 18.59%, so a position of 18.59% should be held in the first strategy.

Within the 73 price increases, 35 were followed by another increase, while 38 were followed by a decline; within the 67 price increases, 30 were followed by another decline, while 37 were followed by an increase. Therefore, the following transition matrix can be constructed:

$$P = \begin{bmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{bmatrix} = \begin{bmatrix} \frac{35}{73} & \frac{38}{73} \\ \frac{37}{67} & \frac{30}{67} \end{bmatrix} = \begin{bmatrix} 47.95\% & 52.05\% \\ 55.22\% & 44.78\% \end{bmatrix} \quad (1)$$

This matrix indicates that, when the previous day is in Status 1 (price increase), the win rate of this day is 47.95%, while the lose rate is 52.05%; when the previous day is in Status 2 (price decline), the win rate is 55.22%, while the lose rate is 44.78%. Using the same b as strategy 1, f times Status 1 = 11.45%, and f times Status 2 = 23.83%. Therefore, a position of 11.45% should be held if the previous day was an increase, and a position of 23.83% should be held if the previous day was a decline.

Assume an initial total wealth of $100,000 at 12 March 2026. After calculation, the first strategy ends in $104,505.40 at the end of 9 April 2026, which is an increase of 4.51%. The second strategy ends in $104,992.86, which is an increase of 4.99%. The dynamic strategy outperforms the static strategy by a 0.46 percentage points. The returns of half Kelly and quarter Kelly are also calculated. For half Kelly, the dynamic strategy earns 0.22% more than the fixed one, and for quarter Kelly, the proportion is 0.11%. These results confirm that incorporating Markov chain can generate incremental returns.

3.2 Result Analysis

It is actually surprising to find that the optimal position is lower (11.45%) in price increasing days (up days), while higher (23.83%) in price decreasing days (down days). If the price has just started to increase, investors may believe that it has a bigger chance to continue this trend. Nevertheless, it is not the case for this stock. In the case of this study, it is actually the strategy of "buy on dips, sell on rises". Therefore, the limitations of these two strategies are similar to some extent which helps to explain why this dynamic strategy provides a slight gain in this stock.

There are many periods in the first 140 days that up days and down days alternately frequently, increasing the estimated probability of an up day after a down day, as well as decreasing the estimated probability of an up day followed by another up day. This cause a relatively small win rate (47.95%) when in Status 1, and a relatively larger win rate (55.22%) when in Status 2, so a low position was held in Status 1, and a high position was held in Status 2. As a result, once consecutive up days occur in the last 20 days, strategy 2 would earn less than strategy 1, and once consecutive declining days occur, strategy 2 would lose more. Conversely, if the first 140 days had many consecutive increasing or declining days, several days of alternating appearance of increasing and declining days would cause great decline in the total positive return.

Therefore, it can deduce that the time dimension of investment is also a key factor affecting the strategy effect. This strategy is more suitable for medium and long-term trending markets dominated by sustainable trends, while its performance is relatively limited in short-term volatile markets dominated by random factors, including market noise and sudden policy impacts. In the short-term market, the non-aftereffect property of the Markov chain may fail to effectively capture the irregular price jumps, and the state division based on historical data may lag behind the rapid changes in the market. These factors result in the deviation between the calculated optimal position and the real-time market demand. At the same time, this study does not consider transaction costs, or stamp duties, which have a certain impact on the net returns of the strategy in real investment scenarios. The frequent position adjustments driven by state changes may increase transaction costs and partially offset the excess returns brought by dynamic optimization, which is a factor that needs to be taken into consideration in subsequent research.

Conclusion

Overall, this study empirically tests the performance of a static Kelly criterion and a Markov chain-augmented dynamic Kelly criterion in the context of A-share stock trading, using 160 trading days of data for in-sample estimation and 20 days for out-of-sample testing. However, The Markov chain-augmented dynamic Kelly strategy is not a one-size-fits-all solution, and its effectiveness is dependent on the stock's price trend characteristics.

The strategy performs best for trending stocks with strong auto-correlation (i.e., long consecutive up/down days, low frequency of alternating days). The strategy cannot work effectively for stocks with frequent alternating up/down days. For such stocks, the state transition probabilities are rather unstable and non-predictive, leading to misguided position sizing that erodes the dynamic strategy's advantage. Furthermore, the strategy is more effective in long-term trending markets rather than short-term volatile markets, where price movements are highly dominated by noise rather than persistent trends.

This paper emphasizes the balance between simplicity and effectiveness, so the results should be viewed dialectically. According to its constraints, future research can take more factors such as transaction costs and market noises into account. The results can also be extended to multi-state hidden Markov models, or fractional Kelly for risk control. These attempts may increase the gain by monitoring the market state more specifically. Still, specification in data analysis would make the calculation more complicated, and excess amount of math makes it more difficult for normal investors to use. Thus, it is also important to figure out a balance between preciseness and simplicity. When this equilibrium is achieved, a state-dependent dynamic method that can fully adapt to daily use would be found.

To improve the accuracy of market state recognition, future studies can apply hidden Markov models, semi-Markov processes or multi-state division. Future studies can also try optimizing the position adjustment rules to reduce unnecessary transactions and improve the net return of the strategy. The combination of macroeconomic indicators, market sentiment, and other factors with the Markov-Kelly framework can also build a multi-factor decision-making system, thus improving the prediction accuracy and return performance.

References

[1] BORKOWSKA A O, KROESE D P. Optimal betting under

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Markov chain dynamics with application to sports & finance. arXiv preprint, arXiv:2403.08719, 2024. https://arxiv.org/abs/2403.08719.
[2] NYSTRUP P, MADSEN H, LINDSTRÖM E. Dynamic portfolio optimization across hidden market regimes. Quantitative Finance, 2018, 18(1): 1-13.
[3] PASRICHA P, SELVAMUTHU D, D'AMICO G, et al. Portfolio optimization of credit risky bonds: a semi-Markov process approach. Financial Innovation, 2020, 6(1): 51.
[4] LYNCH R, TAYLOR M P. Optimal Kelly strategies for hidden Markov models. Quantitative Finance, 2022, 22(10): 1689-1706.
[5] LI Y, ZHANG X. Kelly criterion for Markovian switching jump-diffusion models. Insurance: Mathematics and Economics, 2023, 111: 212-227.
[6] LIU J, CHEN Y. Robust Kelly criterion for Markov chains with uncertain transition matrices. European Journal of Operational Research, 2025, 302(2): 568-582.
[7] ANDERSSON M, VÄHÄMAA S. Hidden Markov model-based regime switching and dynamic portfolio management. Journal of Banking & Finance, 2014, 48: 213-226.
[8] ZHAO Y, MACLEAN L C. Kelly investing with downside risk control in a regime-switching market. Quantitative Finance, 2022, 22(1): 75-94.
[9] KULL A. A novel derivation and interpretation of the Kelly criterion. Journal of Risk, 2025, 27(3). LILLO F, MAZZARISI P, TSAKNAKI I Y. Tackling estimation risk in Kelly investing using options. arXiv preprint, arXiv:2508.18868, 2025.
[10] ZHAO Y, MACLEAN L C. Kelly investing with downside risk control in a regime-switching market. Quantitative Finance, 2022, 22(1): 75-94.