Proceedings of CONF-APMM 2025 Symposium: Simulation and Theory of Differential-Integral Equation in Applied Physics
DOI: 10.54254/2753-8818/2025.DL27621

MA200 and HMM in Regime - Specific Stock Markets Prediction

Mengrui Wei

Institute of Financial Technology, The University of Hong Kong, Hong Kong, China
u3655669@connect.hku.hk

Abstract. This study investigates how using regime-dependent forecasting in stock market prediction will affect the prediction accuracy compared with traditional methods that ignore market states. In this paper, we are interested in predicting the rise and fall of stock prices and using the log return for each day as a criterion for this. We assume there are two regimes: Bull and Bear, and two methods are used for including them in forecasting. The MA200 method directly classifies each day into bull or bear regimes and estimates separate transition matrices to calculate the probability for the next day being up or down. While the Hidden Markov Model (HMM) uses the Expectation–Maximisation(EM) algorithm to estimate regime transitions and assumes regime-dependent normal distributions for log returns to find the probability. Afterwards, we make a prediction to label each day as "Up" or "Down" and compare with the actual data to find the hitting rate as accuracy. This paper has used 3 different stock markets and found out that both methods perform better than the traditional one. Additionally, HMM outperforms in one-step forecasts, while due to the complexity of this method, MA200 will be good to perform N-step forecasts by getting the nth power of P until n = 10.

Keywords: Stock Market Regimes, Hidden Markov Chain, MA200, Transition Matrix, Stock Market Prediction

1. Introduction

Forecasting of the financial markets has long been a popular but challenging topic in modern society. Accurate prediction of market behaviour is important in the investment decision-making process. However, the non-stationarity and complex autocorrelation structure make the modelling very hard. This paper will then focus on setting an approach to predict the rise and fall of the stock prices, which can be useful in the risk management and decision-making for both individual and institutional investors.

In 1965, Fama suggested that stock prices follow a random walk model, the price for today is the sum of the price for the previous day plus some white noise [1]. Therefore, we can see that it follows the Markov property: the distribution of the next price depends only on the current state, with past history providing no additional information.

In the stock market, there are different types of regimes indicating the status of the market. For simplification, this paper will focus on two of them: Bull (Period of rising price) and Bear (Period of

© 2026 The Authors. This is an open access article distributed under the terms of the Creative Commons Attribution License 4.0 (https://creativecommons.org/licenses/by/4.0/).

DOI: 10.54254/2753-8818/2025.DL27621

falling price) [2]. In 2022, a finding indicated that bull markets in China's A-share market exhibit stronger connectivity and a small-world effect. While bear markets display distinct structural patterns, which reflect the big difference in different market behaviour and the persistence within regimes [3]. Therefore, analysing the transition probabilities with or without regime differentiation might lead to different predictive accuracies. This is what this paper is focusing on: to check whether considering differences in regimes to adjust the transition matrix will improve the predictive accuracy [4].

In the previous research, MA200 (200-day moving average) and HMM (Hidden Markov Model) are 2 ways to involve the regimes into the consideration. Therefore, this paper will use both to give a different approach to the transition matrix and compare with the one that has no difference in regime to evaluate whether regime-aware models provide greater predictive power than a direct application of Markov chain alone. This paper will conduct an experiment in 3 stocks: Apple (more bull markets than bear), Nokia (more bear markets than bull), and S&P 500 (mixed bull and bear patterns) to check the overall behaviour of those methods.

2. Research method

First, for the choice of stocks, Apple's consistent innovation and strong financial performance have kept it in bull markets more often, while Nokia has experienced a long decline after the rise of luxury brands (e.g., HUAWEI, Apple), kept it at a bear market for a while. S&P 500, on the other hand, is an index stock, consisting of 500 of the largest publicly traded companies in the United States; it has a more balanced pattern between bear and bull markets. The experiments of these 3 markets are to make the conclusion more generalised under different situations.

For the length of the data, to avoid the effect within the COVID-19 period and make the results more generalised, this paper chooses to use the data from 2023-01-01 to 2025-01-01 and uses the first 80% data as training data, and the remaining 20% as testing data for accuracy checking. Here, as we care about the accuracy for prediction, we will use the testing data for out –of- sample accuracy to check if the model is adequate for future prediction.

We first compute the log daily return using the adjusted closing price. Using logarithms will make the distribution more like a normal distribution to benefit future permutations. The log return is defined as below, where P_t^{adj} denotes the adjusted closing price on day t [5],

$$r_t = ln(\frac{P_t^{adj}}{P_{t-1}^{adj}}) \tag{1}$$

For labelling, each day is assigned a binary term "Up" or "Down" based on the log return. Specifically,

$$Label_t = \begin{cases} Up, r_t > 0 \\ Down, r_t \leq 0 \end{cases} \tag{2}$$

Thus, whether the price goes up or down forms the target variable that we aim to predict in our modelling framework.

2.1. Traditional transition matrix without indicating regimes

For the traditional transaction matrix, we name it A here. We define the transition probability as:

DOI: 10.54254/2753-8818/2025.DL27621

$$P_{i\to j} = \frac{N_{i\to j}}{N_{i\to Down}+N_{i\to Up}} \tag{3}$$

where $N_{i\to j}$ is the number of transitions from state i to state j, with $i, j \in \{\text{Down}, \text{Up}\}$. So, the full matrix is:

$$A = \begin{pmatrix} P_{Down\to Down} & P_{Down\to Up} \\ P_{Up\to Down} & P_{Up\to Up} \end{pmatrix} \tag{4}$$

Afterwards, for each day in the test sample, we first check whether the previous day was classified as Up or Down and locate the corresponding row of the transition matrix. Then we have a stochastic process to randomly choose the next state (Up or Down) according to the probabilities specified in that row to get the prediction for that day. Finally, we evaluate the model by computing the hitting rate, i.e., the proportion of days in the test data for which the predicted state matches the actual observed state (means correctly predicted).

2.2. MA200 prediction

The MA200 prediction is a widely used indicator that uses the equation as below:

$$MA_{200}(t) = \frac{1}{200}\sum_{i=0}^{199} P_{t-i} \tag{5}$$

If the current price is lower than MA200, then we say we are in the bear market, and oppositely, if the current price is higher than MA200, then we are in the bull market [6]. Unlike the traditional approach in 2.2, we first construct separate transition matrices for bull and bear markets. Specifically, we group the days belonging to each regime and then apply the same method as in Section 2.2 to obtain two distinct transition matrices, denoted as $\mathrm{A}^{(\mathrm{Bull})}$ and $A^{(Bear)}$. Then, we will conduct a Chi-square check on those matrices to check if there is a significant difference between these 2 markets by checking if the p - value is smaller than 0.05. If so, then for each day in the test sample, we determine whether it falls into a bull or bear regime and select the corresponding transition matrix accordingly. Figure 1 shows the transition matrix for both sections 2.2 and 2.3 and the Chi-square test in AAPL stock. Using the same procedure as in Section 2.2, we then generate predictions and compute the hitting rate. Finally, the predictive accuracy is compared with that of the traditional approach, and the comparison will be reported in the Results section.

```
[1] "All data transition matrix:"
      nst
st       Down    Up
  Down 0.473 0.527
  Up   0.483 0.517
[1] "Bull market transition matrix:"
      nst
st       Down    Up
  Down 0.469 0.531
  Up   0.464 0.536
```

```
[1] "Bear market transition matrix:"
      nst
st       Down    Up
  Down 0.484 0.516
  Up   0.544 0.456

        Pearson's Chi-squared test

data:  counts
X-squared = 33.748, df = 3, p-value = 2.239e-07
```

Figure 1. AAPL transition matrix and Chi square result

DOI: 10.54254/2753-8818/2025.DL27621

2.3. Hidden Markov Model

Hidden Markov Model (HMM) is one of the Bayesian states–space approaches that was used to capture how a system changes in discrete time, with the governing states being hidden from direct observation [7]. In this case, we denote the hidden state as S_t and we have $i, j \in \{\text{Bull}, \text{Bear}\}$ and then denote the prediction state as $\mathrm{X_t} \in \{\text{Up}, \text{Down}\}$.

Here, instead of directly labelling the dates as Bull or Bear, we form a transition matrix B to give out the possibility of transferring from state i to j to reflect the persistence in the bull and bear market:

$$P(S_{t+1} = j \mid S_t = i) = b_{ij}, \ \sum_j b_{ij} = 1 \tag{6}$$

Afterwards, we assume that the log return $\mathrm{X_t}$ given $S_t = k$ follows a normal distribution with mean u_k and standard deviation σ_k , where $\mathrm{k} \in \{\text{Bull}, \text{Bear}\}$ [8]:

$$X_t \mid (S_t = k) \sim N(\mu_k, \sigma_k^2), \ P(X_t \mid S_t = k) = N(\mu_k, \sigma_k^2) \tag{7}$$

For the terms B and u_k , σ_k , we use the EM algorithm to find an estimation. We first find the posterior probabilities of hidden states given the current parameter estimates and update B and u_k , σ_k to maximise the log-likelihood until we reach a convergence [9]. Afterwards, we first use today's state (Bull or Bear) to compute the probability for being in each regime tomorrow by our transition matrix B, and then give these probabilities into the normal distribution to get $\mathrm{P\,(X_{t+1} > 0 S_{t+1} = k)}$ .Then, by law of total probability [10], we have:

$$P(Upatt + 1) = \sum_k P(S_{t+1} = k \mid S_t) \, P(X_{t+1} > 0 \mid S_{t+1} = k) \tag{8}$$

So $\mathrm{P\,(Down\ at\ t + 1)}$ is just 1 - $\mathrm{P\,(Up\ at\ t + 1)}$, and we will use the same stochastic process as in Section 2.2 or 2.3 to choose a label for that day and calculate the hitting rate afterwards for comparison.

3. Results

3.1. One-step forecast

We first use the one-step forecast as a basic and vital indicator of how the models performed. This means that given real status and characters of day t, we predict the status of day t+1. Figure 2 shows the one-step forecast result as follows:

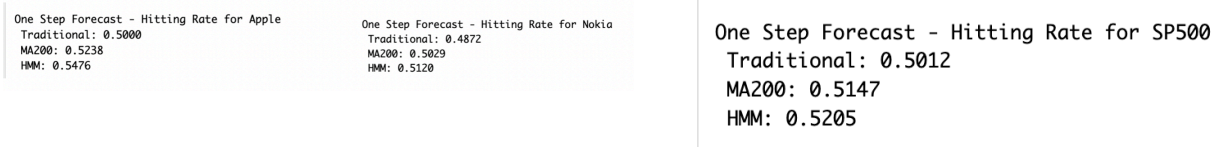

Figure 2. Hitting rate for 3 stocks

Here, we can see that all the hitting rates are close to 0.5, especially for the traditional method (without considering regimes). This is because the financial market can be considered as a random

DOI: 10.54254/2753-8818/2025.DL27621

walk process, in which we have 1/2 possibilities to give the correct prediction [1]. While the traditional methods give almost no improvement from the random walk cases, because very little information is included, and we only have rough and overall possibilities for each transition.

3.1.1. MA200 vs HMM - Why HMM works better than MA200

As we can see from the results, in all 3 stocks, both methods work better than the traditional method, which means that the difference in regimes gives a positive outcome. Additionally, HMM always works better than MA200. This is because MA200 applies a rigid threshold to distinguish bull and bear markets, then when the market is in a sideways pattern or when the differences are marginal. The label might be inaccurate. By contrast, HMM uses the Expectation–Maximisation (EM) algorithm to iteratively learn from the data, which has a greater flexibility in adapting to changes. Instead of assigning a deterministic label, HMM produces probabilistic estimates for both bull and bear states, which will model the markets more comprehensively.

3.1.2. Overall comparison in all 3 markets

As we can see, overall, Apple gives the highest hitting rate. This is because that, in the Apple, we are always in the bull markets, which have a very strong persistence. Additionally, Apple is a mature and strong company which have a very clear trend in its return, so it is relatively easy for predicting. While Nokia as a comparison, gives the lowest accuracy, because it is a poorly performing stock, which is easy to be affected by noise and other market oscillations. Therefore, it is hard to be predicted. Finally, S&P 500 mixes lots of companies, which performs in between the previous 2 stocks. The overall market tends to alternate between bull and bear phases in a more balanced manner, so the prediction is a little more challenging than Apple.

3.2. N–step forecast

Even though MA200 does not perform as well as the HMM one, we have certain transition matrices for Up and Down under both regimes. It is easy to conduct the N-step forecasting in this case. By the Markov Property, we have [11]:

$$P(X_{t+n} \mid X_t) = P^n \tag{9}$$

We will then apply this to our matrix A, $A^{(\mathrm{Bull})}$ and $A^{(\mathrm{Bear})}$, the hitting rate for using MA200 and the traditional matrix from 1 to 10 step forecast is shown in Figure 3.

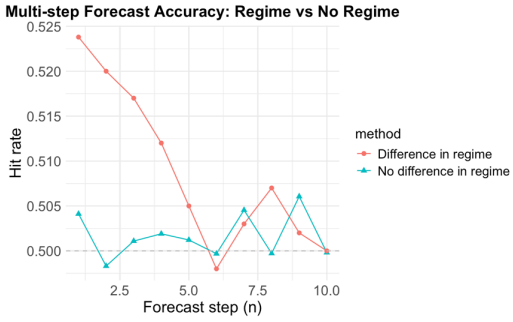

Figure 3. The N-Step hitting rate

DOI: 10.54254/2753-8818/2025.DL27621

As we can see, the results in using MA200(red line) have decreased significantly after the 6th step and oscillated around 0.5 afterwards. The difference between it and the traditional method has decreased significantly as the step increases. This is because, after the prediction step has increased, the information becomes less relevant, and there will be more information missing during that process. and finally, at step 10, both hitting rates have reached 0.5, which aligns with the random walk assumption, and the information for regime or previous states becomes not useful after 10 steps.

4. Shortcoming and limitations

Here, we only rely on the hitting rate to assess our model. However, it can only reflect the proportion of correct directional forecasts without considering the confidence of the prediction. Therefore, in this case, future studies can focus on involving probability-based loss functions such as log loss (cross-entropy loss) and the Brier score [12]. This can give a more comprehensive assessment. Additionally, consecutive misclassifications might give some serious consequence; this can be added in the modelling of future studies.

In addition, the labelling of future states (Up or Down) in this study was from a stochastic process, where the next state was randomly drawn from the estimated. The additional randomness has been involved during this process. Therefore, future machine learning methods can be applied in this section.

Moreover, this study includes assumptions on Markov Properties, which might not be general enough in the financial markets. Future studies could improve this by incorporating richer state dynamics to relax the Markov assumptions and give more generalized results.

5. Conclusion

This paper has introduced 2 different methods for considering how differences in regimes will affect the prediction accuracy. The MA200 is a relatively straightforward method for classifying each day into either bull or bear, based on the moving average data. This allows distinct transition matrices to be estimated for 2 regimes and will be particularly suitable when considering an N-step forecast, as the transition matrix for N-step is just the nth power of the one-step transition matrix. The one-step forecast result is better than the traditional one, which indicates that the difference in regime will improve the performance of the prediction. However, when the step is greater than 10, due to the lack of recent information, there will be no advantage considering the difference in regimes. HMM is a more sophisticated method, using the EM algorithm to converge to a transition matrix that captures the dynamics between bull and bear regimes. This paper assumes the log return conditional on either regime follows a normal distribution. This method performs better than MA200 for a one-step forecast, making it a suitable choice in that context, while it is complex when extended to an N-step forecast. This paper gives a direction for researchers and practitioners, when facing different forecasting objectives, can select the most appropriate modelling method to improve the accuracy (MA200 for long and medium term, HMM for short term).

References

[1] Fama, E.F. (1965) The Behavior of Stock-Market Prices. Journal of Business, 38(1), 34–105.Bootorabi, F.
[2] Gonzalez, L., Hoang, P., Powell, J. G., & Shi, J. (2006). Defining and dating bull and bear markets: Two centuries of evidence. Multinational Finance Journal, 10(1/2), 81–116.

DOI: 10.54254/2753-8818/2025.DL27621

[3] Chen, M., Li, N., Zheng, L., Huang, D., & Wu, B. (2022). Dynamic correlation of market connectivity, risk spillover and abnormal volatility in stock price. Physica A: Statistical Mechanics and its Applications, 587, 126506.
[4] Öztürk, C. (2025). Bear and Bull Regimes in Financial Markets: Insights from Markov Regime-Switching Models. SSRN.
[5] Fan, J., & Yao, Q. (2017). The elements of financial econometrics. Cambridge University Press.
[6] Larkin, P., & Warachka, M. (2017). Leverage for the long run: A systematic approach to managing risk and magnifying returns in stocks (SSRN Scholarly Paper No. 2741701). Social Science Research Network.
[7] Christensen, H., Godsill, S., & Turner, R. E. (2020). Hidden Markov models applied to intraday momentum trading with side information. arXiv. https: //doi.org/10.48550/arXiv.2006.08307
[8] Nystrup, Peter; Madsen, Henrik; Lindström, Erik. (2016). Long Memory of Financial Time Series and Hidden Markov Models with Time-Varying Parameters. Journal of Forecasting, 36(8), 989–1002. DOI: 10.1002/for.2447.
[9] Churbanov, A., & Winters-Hilt, S. (2008). Implementing EM and Viterbi algorithms for hidden Markov model in linear memory. BMC Bioinformatics, 9, 224.
[10] Ross, S. M. (2014). Introduction to probability models (11th ed.). Academic Press.
[11] Hamilton, J. D. (1994). Time series analysis. Princeton University Press
[12] Gneiting, T., & Raftery, A. E. (2007). Strictly proper scoring rules, prediction, and estimation. Journal of the American Statistical Association, 102(477), 359–378.