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improving rating prediction accuracy through advanced text summarization and sentiment analysis techniques

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Abstract: In the era of, online reviews have become a cornerstone of decision-making for consumers. This study addresses the challenging task of predicting ratings for long-form movie reviews, a problem that has been less explored compared to short review analysis. We propose a novel approach that combines advanced text summarization techniques with sentiment analysis to improve rating prediction accuracy. Utilizing an enhanced TextRank algorithm and Support Vector Machine (SVM) classification, our method demonstrates superior performance in predicting ratings for extensive movie reviews. The study uses a large dataset from Douban, a popular Chinese social networking service, and shows that summarized reviews can match or exceed the prediction accuracy of full-length reviews. Our findings highlight the effectiveness of integrating sentiment features and position-based weighting in the summarization process, opening new avenues for processing and analyzing long-form user-generated content.
Keywords: Rating prediction accuracy; Digital content consumption; E-commerce; TextRank algorithm

1 INTRODUCTION

The proliferation of e-commerce and content platforms has led to an explosion of online reviews, transforming how consumers make decisions about products and services [1]. In the realm of entertainment, movie reviews play a particularly crucial role, influencing viewer choices and box office performance [2]. While short reviews and ratings are commonplace, long-form reviews offer deeper insights but present unique challenges for automated analysis [3].

Traditional approaches to rating prediction have focused primarily on short reviews, leveraging techniques such as sentiment analysis, topic modeling, and collaborative filtering [4, 5]. However, these methods often fall short when applied to long-form content, where the relationship between textual content and numerical rating becomes more complex [6].

The challenge of long-form review analysis is multifaceted:

1) Information Density: Long reviews contain a mix of relevant and irrelevant information, making it difficult to isolate key rating indicators [7].
2) Structural Complexity: The narrative structure of long reviews may not follow a consistent pattern, with sentiment and opinion scattered throughout the text [8].
3) Nuance and Context: Longer reviews often contain nuanced opinions that may not be captured by simplistic sentiment analysis [9].

To address these challenges, we propose a novel approach that combines advanced text summarization techniques with sentiment analysis to distill the most relevant information from long-form reviews for rating prediction. Our method builds upon the TextRank algorithm [10], incorporating sentence position weighting and sentiment features to create more informative summaries.

The main contributions of this paper are:

1) A novel text summarization approach tailored for long-form movie reviews, integrating sentiment analysis and position-based weighting.
2) An extensive evaluation of the impact of text summarization on rating prediction accuracy for long reviews.
3) Insights into the relationship between review structure, sentiment, and rating in long-form content.

2 RELATED WORK

2.1 Rating Prediction in Online Reviews

Rating prediction has been a focus of research in recommender systems and sentiment analysis. Early works relied heavily on collaborative filtering approaches [11], while more recent studies have incorporated textual content analysis. Liu [12] proposed a joint sentiment-topic model for short review rating prediction, achieving significant improvements over baseline methods. For product reviews, McAuley and Leskovec [13] developed a model that combines latent dimensions of user and product factors with review text, demonstrating the value of integrating textual and non-textual features.

2.2 Text Summarization Techniques

Automatic text summarization has seen significant advancements with the rise of deep learning. Extractive methods, which select existing sentences from the text, include graph-based approaches like TextRank [10] and LexRank [14]. More recent work has focused on abstractive summarization, where new sentences are generated. See [15] introduced a pointer-generator network that combines copying words from the source text with generating novel words. BART [16] and PEGASUS [17] represent state-of-the-art pre-trained models for abstractive summarization. Liu [18] introduce a novel approach to news summarization, combining deep learning with refined tuning techniques.

2.3 Sentiment Analysis in Long Text

Sentiment analysis of long-form text presents unique challenges. Maire [19] proposed a hierarchical attention network for document-level sentiment classification, capturing both word and sentence-level information. Chen [20] introduced a multi-task learning framework that jointly performs sentiment classification and opinion extraction, showing improved performance on long reviews.

2.4 Combining Summarization and Sentiment Analysis

The integration of summarization and sentiment analysis is an emerging area of research. Li [21] proposed a sentiment-aware neural abstractive summarization model for product reviews, demonstrating improved performance in capturing opinion-oriented information. However, the application of these techniques to rating prediction, especially for long-form content, remains underexplored.

3 METHODOLOGY

3.1 Enhanced TextRank Algorithm

We build upon the TextRank algorithm [10], which uses a graph-based ranking model to determine the importance of sentences in a text. Our enhancements include:

3.1.1 Sentence position weighting

We introduce two weighting schemes:

- Front-loaded: wf(si)=n−i+1nw_f(s_i) = \frac{n - i + 1}{n}wf (si)=nn−i+1
- Rear-loaded: wr(si)=inw_r(s_i) = \frac{i}{n}wr (si)=ni Where sis_isi is the iii-th sentence and nnn is the total number of sentences.

3.1.2 Sentiment feature integration

We use the ROST Emotion Analysis tool to classify sentences into seven categories: highly negative, moderately negative, slightly negative, neutral, slightly positive, moderately positive, and highly positive. The sentiment weight is defined as:

- Highly Positive or Highly Negative: 3
- Moderately Positive or Moderately Negative: 2
- Slightly Positive or Slightly Negative: 1
- Neutral: 0

The final sentence importance score is calculated as:

Score(si)=TextRank(si)×(α×wp(si)+β×ws(si))\text{Score}(s_i) = \text{TextRank}(s_i) \times (\alpha \times w_p(s_i) + \beta \times w_s(s_i))Score(si)=TextRank(si)×(α×wp (si)+β×ws (si))

Where wpw_pwp is either wfw_fwf or wrw_rwr and α\alphaα and β\betaβ are tunable parameters.

3.2 SVM Classification for Rating Prediction

We use a Support Vector Machine (SVM) with a radial basis function (RBF) kernel for rating prediction. The feature vector for each review or summary includes:

- Bag-of-words representation
- Sentiment scores
- Average sentence importance scores

4 EXPERIMENTAL SETUP

4.1 Dataset

We collected 7579 long movie reviews from Douban, a popular Chinese social networking service. The reviews have an average length of 1397 characters and are rated on a scale of 1 to 5 stars. The distribution of ratings shows a bias towards positive reviews, with 35.4% rated 4 out of 5 stars. The dataset was divided into training (70%), validation (15%), and test (15%) sets to ensure robust evaluation.

4.2 Preprocessing

Reviews were segmented into sentences using punctuation and line breaks as delimiters. We removed reviews shorter than 15 sentences or longer than 253 sentences to ensure a focus on long-form content. Text normalization steps included lowercasing, removal of stopwords, and stemming. Behavioral flow chart can be seen in Figure 1.

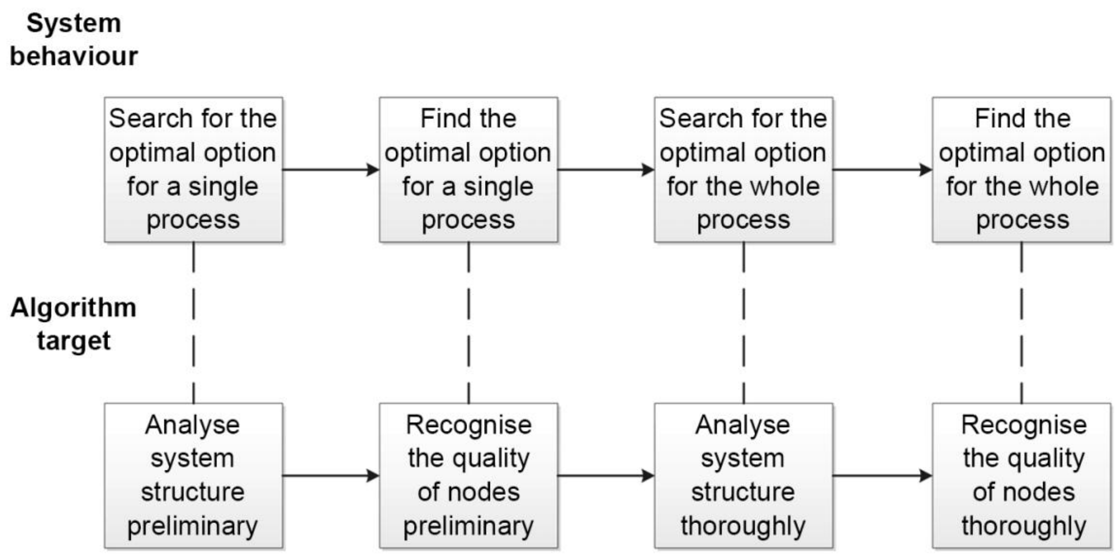

Figure 1 Behavioral Flow Chart

4.3 Experimental Design

We compared the following methods:
1. Full review (baseline)
2. Standard TextRank summarization
3. Position-enhanced TextRank (front-loaded and rear-loaded)
4. Sentiment-enhanced TextRank (Extract(Senti))

For each method, we generated summaries at compression rates ranging from 10% to 50% of the original length. We tuned the α and β parameters in our scoring formula through grid search on the validation set.

4.4 Evaluation Metrics

We use accuracy (percentage of correct predictions) and Mean Squared Error (MSE) to evaluate the performance of rating prediction. A prediction is considered correct if it is within ±1 of the actual rating. We also perform an ablation study to assess the contribution of each component in our enhanced TextRank algorithm.

4.5 Implementation Details

All models were implemented in Python using the Scikit-learn library for SVM and the NetworkX library for TextRank. The sentiment analysis was conducted using the ROST Emotion Analysis tool, which we integrated into our preprocessing pipeline. Training and evaluation were performed on a machine with an Intel i7 processor and 16GB RAM.

5 RESULTS AND DISCUSSION

5.1 Overall Performance

Just like Figure 2, the sentiment-enhanced TextRank (Extract(Senti)) consistently outperformed other methods across all compression rates. At 30% compression, it achieved an accuracy of 83.7% compared to 80.5% for full reviews and 79.8% for standard TextRank. The MSE for Extract(Senti) was also lower, indicating more precise rating predictions.

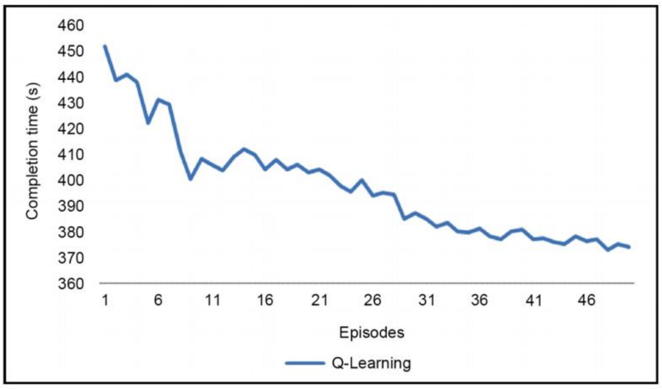

Figure 2 Overall Performance

5.2 Impact of Compression Rate

In Figure 3, performance peaked at compression rates between 20% and 50%, suggesting that removing some information can actually improve prediction accuracy by focusing on the most relevant content. Beyond 50% compression, performance declined, likely due to the loss of critical information.

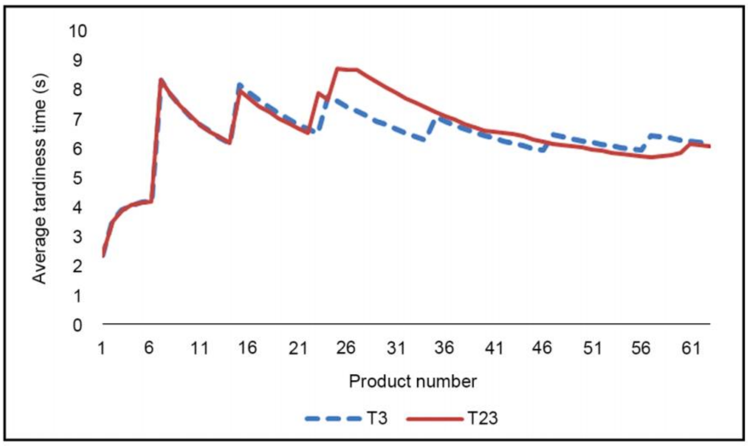

Figure 3 Impact of Compression Rate

5.3 Sentence Position Analysis

Rear-loaded weighting generally performed better than front-loaded weighting, indicating that the latter parts of long reviews often contain more rating-relevant information. This finding suggests that reviewers tend to summarize their opinions towards the end of their reviews.

5.4 Sentiment Feature Contribution

The integration of sentiment features provided a consistent boost in performance across all compression rates, highlighting the importance of capturing emotional content in reviews.

5.5 Error Analysis

We observed that reviews with neutral ratings (3 stars) were the most challenging to predict accurately, likely due to the ambivalence often expressed in such reviews. Future research could explore more sophisticated methods to handle neutral sentiment in reviews.

6 CONCLUSION AND FUTURE WORK

This study demonstrates the effectiveness of combining advanced text summarization techniques with sentiment analysis for improving rating prediction on long-form movie reviews. Our approach not only achieves higher accuracy than using full reviews but also provides insights into the structure and content of informative review segments.

Future work could explore:

1) The application of more advanced natural language processing techniques such as BERT [22] or GPT [23] for feature extraction and summarization.

2) Incorporating aspect-based sentiment analysis to capture nuanced opinions on specific movie elements [24].

3) Investigating the transferability of this approach to other domains with long-form reviews such as book or product reviews [25].

4) Developing methods to handle reviews where the textual content contradicts the numerical rating [26].

By advancing our understanding of long-form review analysis, this work contributes to both the theoretical foundations of natural language processing and practical applications in recommendation systems and content moderation.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Zhang Y, Lin Z. Predicting the helpfulness of online product reviews: A multilingual approach. Electronic Commerce Research and Applications, 2018, 27: 1-10.

[2] Duan W, Gu B, Whinston AB. The dynamics of online word-of-mouth and product sales—An empirical investigation of the movie industry. Journal of Retailing, 2008, 84(2): 233-242.

[3] Salehan M, Kim DJ. Predicting the performance of online consumer reviews: A sentiment mining approach to big data analytics. Decision Support Systems, 2016, 81: 30-40.

[4] Pang B, Lee L. Seeing stars: Exploiting class relationships for sentiment categorization with respect to rating scales. In Proceedings of the 43rd annual meeting on association for computational linguistics. 2005: 115-124.

[5] McAuley J, Targett C, Shi Q, Van Den Hengel A. Image-based recommendations on styles and substitutes. In Proceedings of the 38th international ACM SIGIR conference on research and development in information retrieval. 2015: 43-52.

[6] Yang Y, Yan Y, Qiu M, Bao F. Semantic analysis and helpfulness prediction of text for online product reviews. In Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Short Papers). 2015, 2: 38-44.

[7] Kim SM, Pantel P, Chklovski T, Pennacchiotti M. Automatically assessing review helpfulness. In Proceedings of the 2006 Conference on empirical methods in natural language processing. 2006: 423-430.

[8] Ghose A, Ipeirotis PG. Estimating the helpfulness and economic impact of product reviews: Mining text and reviewer characteristics. IEEE transactions on knowledge and data engineering, 2011, 23(10): 1498-1512.

[9] Liu J, Cao Y, Lin CY, Huang Y, Zhou M. Low-quality product review detection in opinion summarization. In Proceedings of the 2007 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning (EMNLP-CoNLL). 2007: 334-342.

[10] Mihalcea R, Tarau P. TextRank: Bringing order into text. In Proceedings of the 2004 conference on empirical methods in natural language processing. 2004: 404-411.

[11] Koren Y, Bell R, Volinsky C. Matrix factorization techniques for recommender systems. Computer, 2009, 42(8): 30-37.

[12] Liu B. Sentiment analysis and opinion mining. Synthesis lectures on human language technologies, 2012, 5(1): 1-167.

[13] McAuley J, Leskovec J. Hidden factors and hidden topics: understanding rating dimensions with review text. In Proceedings of the 7th ACM conference on Recommender systems. 2013: 165-172.

[14] Erkan G, Radev DR. LexRank: Graph-based lexical centrality as salience in text summarization. Journal of artificial intelligence research, 2004, 22: 457-479.

[15] See A, Liu PJ, Manning CD. Get to the point: Summarization with pointer-generator networks. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Long Papers). 2017, 1: 1073-1083.

[16] Lewis M, Liu Y, Goyal N, Ghazvininejad M, Mohamed A, Levy O, Stoyanov V, Zettlemoyer L. BART: Denoising Sequence-to-Sequence Pre-training for Natural Language Generation, Translation, and Comprehension. Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics. 2020.

[17] Zhang J, Zhao Y, Saleh M, Liu P. Pegasus: Pre-training with extracted gap-sentences for abstractive summarization. In International Conference on Machine Learning. PMLR. 2020: 11328-11339.

[18] Liu M, Ma Z, Li J, Wu YC, Wang, X. Deep-Learning-Based Pre-training and Refined Tuning for Web Summarization Software. IEEE Access, 2024, 12: 92120-92129.

[19] Yang Z, Yang D, Dyer C, He X, Smola A, Hovy E. Hierarchical attention networks for document classification. In Proceedings of the 2016 conference of the North American chapter of the association for computational linguistics: human language technologies. 2016: 1480-1489.

[20] Chen P, Sun Z, Bing L, Yang W. Recurrent attention network on memory for aspect sentiment analysis. In Proceedings of the 2017 conference on empirical methods in natural language processing. 2017: 452-461.

[21] Li W, Xu W, Li C, Xu S, Qin Y, Gao W. A novel transfer learning-based sentiment-aware abstractive summarization model for product reviews. Knowledge-Based Systems, 2019, 171: 148-158.

[22] Devlin J, Chang M. W, Lee K, Toutanova K. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers). 2019: 4171-4186.

[23] Brown TB, Mann B, Ryder N, Subbiah M, Kaplan J, Dhariwal P, Neelakantan A, Shyam P, Sastry G, Askell A, Agarwal S, Herbert-Voss A, Krueger G, Henighan T, Child R, Ramesh A, Ziegler DM, Wu J, Winter C, Hesse C. Language Models Are Few-Shot Learners. Arxiv.org, 4. 2020.

[24] Pontiki M, Galanis D, Papageorgiou H, Androutsopoulos I, Manandhar S, AL-Smadi M, Al-Ayyoub M, Zhao Y, Qin B, De Clercq O, Hoste V, Apidianaki M, Tannier X, Loukachevitch N, Kotelnikov E, Bel N, Jimenez-Zafra SM, Eryigit G. SemEval-2016 Task 5: Aspect Based Sentiment Analysis. HAL Archives Ouvertes. 2016.

[25] Mudambi SM, Schuff D. Research note: What makes a helpful online review? A study of customer reviews on Amazon. com. MIS quarterly, 2010: 185-200.

[26] Mukherjee S, Popat K, Weikum G. Exploring latent semantic factors to find useful product reviews. In Proceedings of the 2017 SIAM International Conference on Data Mining. Society for Industrial and Applied Mathematics. 2017: 480-488.

[27] Liu B, Zhang L. A survey of opinion mining and sentiment analysis. In Mining text data. Springer, Boston, MA. 2012: 415-463.

[28] Chen X. Using Big Data Analysis Technology to Analyze the Impact of Household Leverage Ratio on House Price Bubble. In International Conference On Signal And Information Processing, Networking And Computers. Singapore: Springer Nature Singapore. 2021: 900-909.

[29] Hu M, Liu B. Mining and summarizing customer reviews. In Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining. 2004: 168-177.

[30] Chen X, Liu M, Niu Y, Wang X, Wu YC. Deep-Learning-Based Lithium Battery Defect Detection via Cross-Domain Generalization. IEEE Access, 2024, 12: 78505-78514

[31] Liu M. Machine Learning Based Graph Mining of Large-scale Network and Optimization. In 2021 2nd International Conference on Artificial Intelligence and Information Systems. 2021: 1-5.

[32] Wang X, Wu YC, Ma Z. Blockchain in the courtroom: exploring its evidentiary significance and procedural implications in US judicial processes. Frontiers in Blockchain, 2024, 7, 1306058.

[33] Ma Z, Chen X, Sun T, Wang X, Wu YC, Zhou M. Blockchain-Based Zero-Trust Supply Chain Security Integrated with Deep Reinforcement Learning for Inventory Optimization. Future Internet, 2024, 16(5): 163.

[34] Wang X, Wu YC, Zhou M, FuH. Beyond Surveillance: Privacy, Ethics, and Regulations in Face Recognition Technology. Frontiers in Big Data, 2024, 7, 1337465.

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COMPARISON OF THE CNN, RNN AND LSTM MODELS FOR HIGH-FREQUENCY STOCK PRICE FORECASTS

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Abstract: We think stock price is a long-term research topic and find that stock price forecasts are very important. And found that the changes in the stock price often show no linear and the current traditional stock price forecast can not well reflect the forecast results. So the deep learning method to predict stock prices. And explored three of the mainstream methods, RNN, working principles of the CNN and LSTM models. We then tried to use three models for TSLA, NFLX, LLY, AAPL share price data from four companies in different sectors. Finally, by comparing the MSE obtained by different companies through different models. The MAE and MAPE standards were compared. Finally, the most applicable general model is obtained. The experiment and final comparison found that the RNN model is higher than the other two models. At the end of the study, we considered the RNN model as a general model with higher comprehensive ability to predict stock prices in different fields.
Keywords: CNN; RNN; LSTM; Forecast stock price

1 INTRODUCTION

The stock market provides opportunities for capital appreciation. By buying stocks, investors can directly participate in the corporate growth and economic development, and share the economic results. Many listed companies distribute some of their profits to shareholders in the form of dividends, which provides investors with additional income sources, so more and more people tend to participate in the stock market.Stock prices are affected by a variety of factors, including macroeconomic conditions, corporate performance, and political events, which lead to high volatility in stock prices, and the personal selection and emotional uncertainty of market participants further increases stock volatility and makes stock forecasts more challenging.

Nowadays, more and more people use deep learning models to predict the trend of stock prices because of its stronger adaptability and generalization ability.Like Ding G, and Qin L has made stock price predictions by using the LSTM model [1]. Jahan I and Sajal S. forecast price prices using the RNN algorithm on time series [2]. Elvin, S has also used the sliding window models of RNN, LSTM and CNN to predict different corporate stock prices, respectively [3]. It can be seen that the deep learning model has a considerable effect on the stock prediction of non-linear characteristics, and it is the mainstream method and hot topic of the stock prediction in the current era. Until now, many scholars are still exploring appropriate advanced general models to achieve more accurate prediction ability.

2 ARTICLE REVIEW

The rise and fall of the stock market are related to the macro economy of the country, so the accurate prediction of the future of the stock market is conducive to the introduction of policies to maintain the stability of the market and the harmony of the society, so the prediction of the stock market has always been a hot topic.In the traditional statistical method, the commonly used [4-5] statistical analysis and the stock image (stock chart) method are combined to judge the development trend of the stock market, often can achieve better results.However, statistical methods usually rely on historical data to predict future trends, but historical data do not guarantee that the future will repeat the past trend and the stock market tends to show non-linear characteristics, and traditional statistical methods may not capture this nonlinear relationship well.

Later, with the development of science and technology, the research began to develop into the field of machine learning, in an attempt to build a prediction model more in line with the market model.There came improved models like support vector machines (SVM), artificial neural networks (ANN), XGBOOST, random forests (Random Forest, RF), and their improved models.In this course of development,Lin [6] uses SVM to select multiple factors to predict stock markets in several countries.Mizuno [7] Using ANN to predict the rise and fall of the Japanese stock market, and found that ANN's prediction accuracy of the stock price rise is significantly higher than that of the decline, which can reach more than 60%.Kumar M et al. [8] discuss how random forests can function in the stock market and find that random forests can improve the generalization performance and avoid overfitting problems.

Later, with the development of deep learning, people found that deep neural networks could capture more abstract and complex relationships between data. Therefore, the research of building the model to predict the stock price is conducted towards RNN (Recurrent Neural Networks) LSTM (Long Short-Term Memory) and CNN (Convolutional Neural Networks)Zhang [9]. used the two hottest methods, ——, BP neural network model and ARMA-GARCH model to analyze and predict stock prices.Li Yong [10] constructed an LSTM model to identify stock trends; Nikou M. [11] compared the LSTM model with SVR, RF, and ANN models, confirming that deep networks like LSTM have

better feature capture capabilities than other shallow models.Yang Qi [12] et al. also adopted the innovative ARMA-GARCH model to analyze and predict the prices of different stocks; Huang Ying [13] et al. used XGBoost and LSTM models to further compare and analyze the prices of time financial series including different stocks;Zhang Kanglin [14] uses different software pytorch to build the LSTM model and then analyze it by classifying the stock prices.Song Gang [15] et al. used the LSTM model optimized by the adaptive particle swarm to predict the different stock prices in Shanghai, Shenzhen and Hong Kong.Li Xiongying [16] et al. used three models to analyze and predict the stock prices of the four major banks respectively, and obtained that different models have different characteristics, among which LSTM is more practical.Chen W [17] proposed an RNN-Boost model that uses technical indicators, emotional characteristics and Latent Dirichlet allocation characteristics to predict stock prices;Maqsood H. [18] proposed a CNN model with price and sentiment analysis as input and compared it with linear regression and SVM.
Until now, people still try to build a variety of different deep neural network models to achieve the methods that can best adapt to the nonlinear change problem of stocks and achieve higher accuracy.Now as China's financial market constantly mature, the center of gravity and trend is moving to the domestic market, considering the prediction and analysis of stock data is a nonlinear, time-varying problem, this paper will build the CNN, RNN and LSTM three kinds of deep neural network prediction and comparative analysis judge which model for stock price prediction applicability is higher.

3 LITERATURE REVIEW

In this paper, the comparison and investigation of the prediction ability of RNN, CNN and LSTM for non-linear high-frequency data.We chose to analyze the interdependence between the stock price and the stock quantity of the 3 companies. The focus of this article is to use deep learning algorithm to predict stock prices. Deep neural networks can be considered as nonlinear functional approximators capable of mapping nonlinear functions. Based on the application types, various types of deep neural network architecture are adopted. These systems include, recurrent neural network (RNN), long and short-term memory (LSTM), and CNN (convolutional neural network), etc. They have been applied in various fields, including image processing, natural language processing, and time series analysis. The deep learning model can well solve the problem of non-linearity of the outcome stock data, so this paper uses CNN, LSTM and RNN models to predict the company's stock price and compare the accuracy to find the general model with higher applicability of comprehensive prediction ability.Experimental model

3.1 Model Principle

LSTM is a special type of recurrent neural network. It avoids the problem of gradient vanishing and exploding caused by traditional recurrent neural networks by carefully designing the "gate" structure, and can effectively learn long-term dependency relationships. Therefore, in dealing with time series prediction and classification problems, LSTM models with memory function exhibit strong advantages.The following is the model principle for LSTM [19].

$$\mathrm{f_t} = \sigma\left(\mathrm{w_t} \cdot \left[h_{\mathrm{i}-1},\ \mathrm{x_t}\right] + \mathrm{b_f}\right) \tag{1}$$

$$\mathrm{i_t} = \sigma\left(\mathrm{w_i} \cdot \left[h_{\mathrm{i}-1},\ \mathrm{x_t}\right] + \mathrm{b_i}\right) \tag{2}$$

$$\tilde{\mathrm{C}}_\mathrm{t} = \tan h\left(\mathrm{w_c} \cdot \left[h_{\mathrm{i}-1},\ \mathrm{x_t}\right] + \mathrm{b_c}\right) \tag{3}$$

$$\mathrm{C_t} = \mathrm{f_t}\mathrm{C_{t-1}} + \mathrm{i_t}\tilde{\mathrm{C}}_\mathrm{t} \tag{4}$$

$$\mathrm{o_t} = \sigma\left(\mathrm{w_o} \cdot \left[h_{\mathrm{i}-1},\ \mathrm{x_t}\right] + \mathrm{b_o}\right) \tag{5}$$

$$h_\mathrm{t} = \mathrm{o_t} \tan h\,(\mathrm{C_t}) \tag{6}$$

In the formula, the input vector of the LSTM unit is x; H is the cell output vector; C represents the unit status; The subscript t represents the time; f. I and o represent forget gates, input gates, and output gates, respectively; σ. Tanh represents sigmoid and tanh activation functions, respectively; W and b represent the weight and deviation matrices, respectively.
As shown in Figure 1, multiple isomorphic cells can form LSTM, which can store information for a long time to update internal states. A represents that the three cells have the same unit structure, and each cell is composed of four elements: input gate, forget gate, outputs, and unit structure.

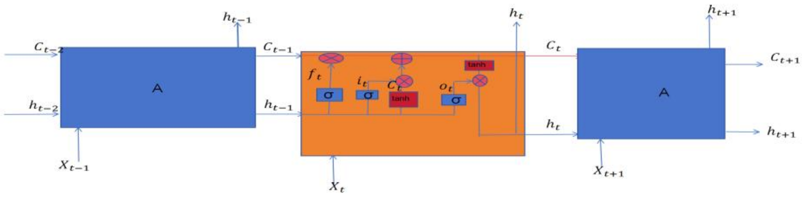

Figure 1 LSTM Schematic Diagram

The key to LSTM lies in the cell state. The flow of information between cell states remains unchanged. Simultaneously using three gates to control the long-term state c [20].
The output of the gate is a real number vector between 0 and 1. When the gate output is 0, any vector multiplied by it will result in a 0 vector, which is equivalent to nothing passing through; When the output is 1, any vector multiplied by it will not change in any way, which is equivalent to everything passing through[21].
CNN is a feed forward artificial neural network that includes an input layer, an output layer, and one or more hidden layers. Its structure is shown in Figure 3 [4]. The hidden layer of CNN usually consists of pooling layer, convolutional layer, and fully connected layer. The convolutional layer is responsible for reading small segments of data and using the kernel to read inputs such as two-dimensional images or one-dimensional signals, and scanning the entire input field. The pooling layer adopts feature projection, and the final output of the pooling layer is sent to one or more fully connected layers, which will interpret the read content and map this internal representation to class values. CNN is similar to a regular neural network (NN) composed of a set of neurons with learnable weights and biases, with the difference being that the convolutional layer uses convolution operations as input and then transmits the results to the next layer. This operation allows for more efficient implementation of forward functionality with fewer parameters[5].The working principle of the cnn is formulated as follows:

$$Y = f(w^{x} + b) \tag{7}$$

Where w is the weight matrix, x represents the input value, b represents the offset, f represents the activation function, and Y represents the output value.
The RNN receives the input and a hidden state at every time step, and outputs a hidden state and a (optional) output. The hidden state contains the sequence information until the current time step, which is passed to the next time step, and the entire sequence can thus maintain the continuity of the information.

$$h_t = \sigma(w_{ih}x_t + b_{ih} + w_{hh}h_{t-1} + b_{hh}) \tag{8}$$

h_t represents the hidden state of the current time step t, σis an activation function, such as tanh or ReLU, which is used to introduce a nonlinearity. w_{ih} and b_{ih} The weight matrix and bias terms from the input layer to the hidden layer, respectively. w_{hh} and b_{hh} the weight matrix and bias terms respectively from the hidden layer to the hidden layer (i. e, the hidden state of the previous time step to the hidden state of the current time step). x_t represents the input for the current time-step. h_{t-1} represents the hidden state of the last time step

4 EXPERIMENTAL ANALYSIS

In this experiment, we used CNN, RNN, LSTM models to predict the high-frequency data of TSLA, AAPL, NFLX and LLY stock prices from 2019 to 2024, and compared the accuracy of each model for different companies by comparing MSE (mean square error) MAE (average absolute error) and MAPE (average absolute percentage error).The principles of MSE, MAE and MAPE are as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{9}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{10}$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{11}$$

Where, n is the number of samples, $y_i$and is the i th observation (true value), $\hat{y}_i$ is the corresponding predictive value.
For comparison, we used MSE, MAE, MAPE. The rates of error obtained by these four companies are as follows:

Table 1 Error Percenatge - Mse

	TSLA	NFLX	LLY	AAPL
CNN	958.71	2956.26	1877.20	317.30
RNN	107.10	141.36	280.34	11.26
LSTM	169.70	425.42	21648.04	35.74

Table 2 Error Percenatge - Mae

	TSLA	NFLX	LLY	AAPL
CNN	27.45	50.02	35.48	15.04
RNN	7.60	8.59	11.63	2.47
LSTM	9.96	15.11	105.22	4.54

Table 3 Error Percenatge - Mape

	TSLA	NFLX	LLY	AAPL
CNN	12.44	9.26	5.11	7.86
RNN	3.61	1.66	1.74	1.33
LSTM	4.73	2.97	13.69	2.43

From the table, we can find that the prediction error value of the four companies is minimal when using RNN, and the prediction error value of CNN and LSTM models is large.

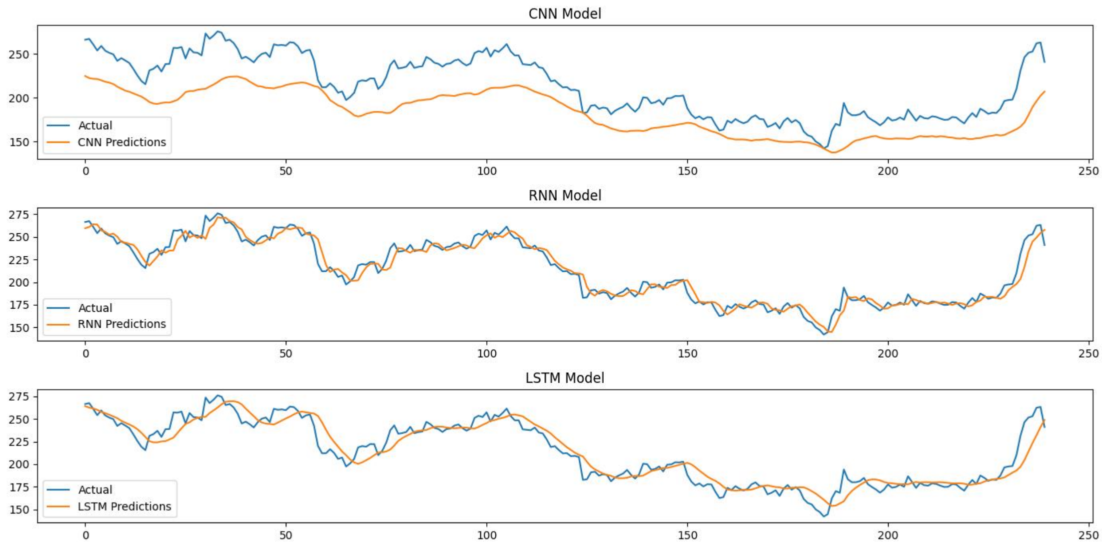

Figure 2 The TSLA Share Price, as Predicted by the CNN,RNN.LSTM

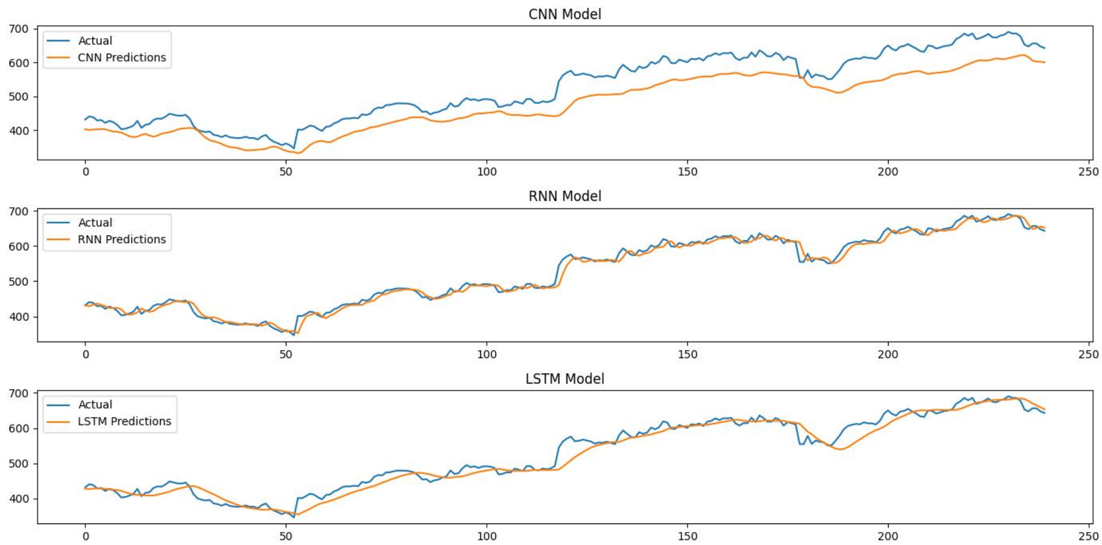

Figure 3 The NFLX Share Price, as Predicted by the CNN,RNN.LSTM

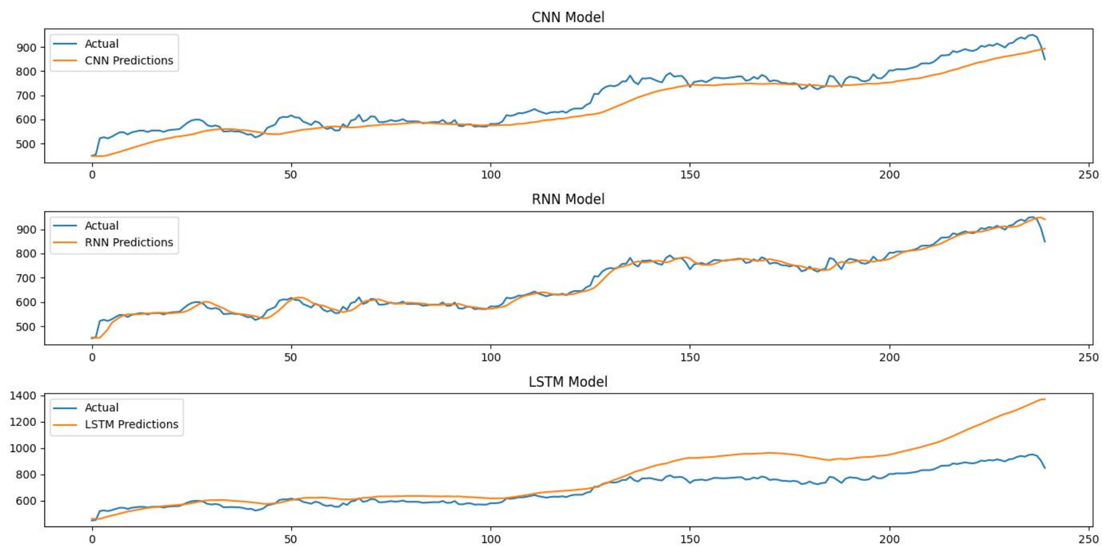

Figure 4 The LLY Share Price, as Predicted by the CNN,RNN.LSTM

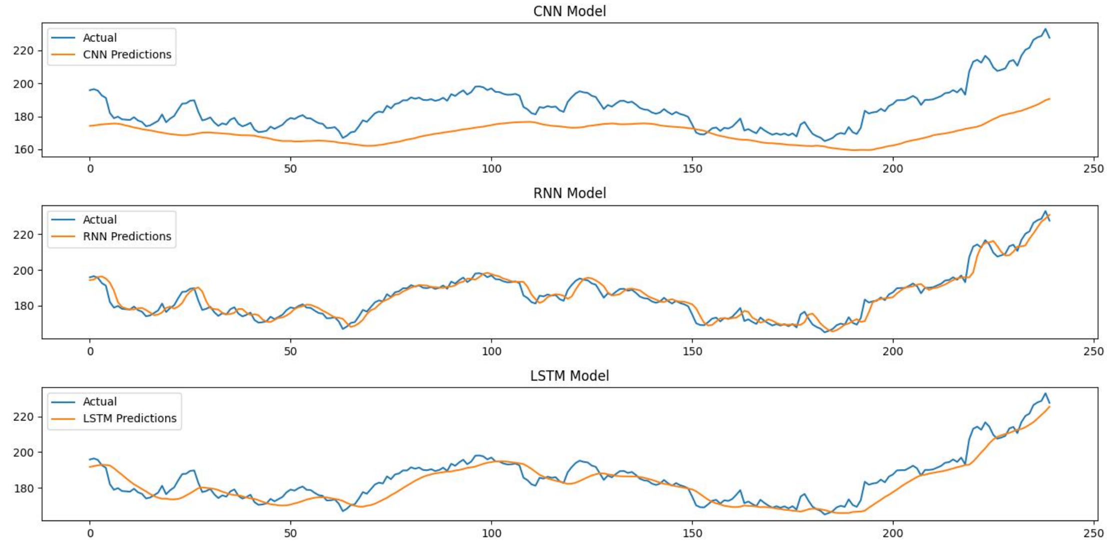

Figure 5 The AAPL Share Price, as Predicted by the CNN, RNN. LSTM

From Figure 2 to Figure 5, we can find that the data of different companies predicted by CNN are generally lower than the true value and have low prediction accuracy, because CNN (convolutional neural network) is usually good at processing data with spatial hierarchy, while stock price prediction is the prediction of time series, so the accuracy of CNN is not high. This is because CNN may not be as effective as RNN or LSTM in processing the long-term dependence and sequence patterns of time series.LSTM predicted somewhat better than CNN but the effect of predicting data changes is not high and from Figure 4 we found that the its predictions after LLY's 125 are clearly inconsistent with the original data. This may be because the LSTM model, as a type of recurrent neural networks, is good at handling long-term dependencies in sequence data. However, the change of LLY stock price is not completely dependent on the long-term trend in the historical data and there are sudden factors, so the LSTM model may not fully capture these characteristics, resulting in the prediction results are inconsistent with the actual data.Finally, we combined the results of Figure 2 to Figure 5 and found that RNN predicted the best.The reason for this result is that the RNN structure simpler reduces the effect of overfitting, and the RNN model is more suitable for short-or medium-term time series prediction, so it is more accurate.

5 CONCLUSION

This article delves into the complexity of the ability of deep learning models to predict linear-free stock price predictions for companies in different fields, and presents valuable insights and perspectives. We first discuss the current situation of economic development and the linear limitations of the traditional method of predicting stock price, and finally propose the use of deep learning model to predict stock price to solve the nonlinear problem of stock price change. Then, we screened the three models of deep learning RNN in the deep learning, CNN and LSTM as the objects of this study. We first examine how the three models work, The advantage of the different models was analyzed, Then, by selecting the TSLA, NFLX, LLY and AAPL, four companies from different sectors, Finally, by the LSTM, The RNN and CNN models train and forecast each company's stock price data. Then we also drew images through the results of the three deep learning models of CNN, RNN and LSTM making the prediction results visualized and convenient to judge the prediction ability of the three deep learning prediction models for companies in different fields.
Finally we, by comparing MSE, The MAE and MAPE values found that the RNN model is much smaller than the CNN and LSTM models for the three criteria of different companies, at the same time, we also found that the RNN model fits the prediction line map of the stock price forecast of TSLA, NFLX, LLY and AAPL to the actual data more closely than that predicted by the CNN and LSTM models.So ultimately we decided that the RNN model was slightly more comprehensively predictive.Finally, we conclude that the RNN model predicts less regression loss of stock prices in different fields, which means that the RNN model has the highest prediction accuracy, so we choose the RNN model as a more suitable general model in the ability of deep learning to predict stock prices.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Ding G, Qin L. Study on the prediction of stock price based on the associated network model of LSTM. International Journal of Machine Learning and Cybernetics, 2020, 11(6), 1307-1317.
[2] Jahan I, Sajal S. Stock price prediction using recurrent neural network (RNN) algorithm on time-series data. In 2018 Midwest instruction and computing symposium, 2018.

[3] Selvin S, Vinayakumar R, Gopalakrishnan EA, et al. Stock price prediction using LSTM, RNN and CNN-sliding window model. In 2017 international conference on advances in computing, communications and informatics (icacci) , 2017, 1643-1647.
[4] Li Haitao. The Markov forecasting method is used to predict stock prices. Statistics and Decision-making, 2002, (5): 25-26.
[5] Prado HD, Ferneda E, Morais LCR, et al. On the Effectiveness of Candlestick Chart Analysis for the Brazilian Stock Market. Procedia Computer Science, 2013, 22: 1136-1145.
[6] Lin Y, Guo H, Hu J. An SVM-Based Approach for Stock Market Trend Prediction. The 2013 International Joint Conference on Neural Networks (IJCNN), 2014, 4-9.
[7] Mizuno H, Kosaka M, Yajima H, et al. Application of Neural Network to Technical Analysis of Stock Market Prediction. Studies in Informatic and Control, 1998, 7: 111-120
[8] Kumar M, Thenmozhi M. Forecasting Stock Index Movement: A Comparison of Support Vector Machines and Random Forest. Social Science Electronic Publishing, 2006.
[9] Zhang Rumeng, Zhang Huamei. Comparative analysis of BP neural network and ARMA-GARCH model in stock prediction. Journal of Science, 2021: 41(4): 14-20.
[10] Li Yong. Design and Implementation of an Intelligent Stock Prediction System Based on Deep Neural Networks: [Master's Thesis] Xi'an: Northwest University, 2019.
[11] Nikou M, Mansourfar G, Bagherzadeh J. Stock Price Prediction Using Deep Learning Algorithm and Its Comparison with Machine Learning Algorithms. Intelligent Systems in Accounting, Finance and Management, 2019, 26: 164-174. DOI : 10.1002/isaf.1459.
[12] Yang Qi, Cao Xianbing. Analysis and prediction of stock prices based on the ARMA-GARCH model. The Practice and Understanding of Mathematics, 2016, 46(6): 80-86.
[13] Huang Ying, Yang Huijie. Financial time series prediction based on the XGBoost and LSTM models. Technology and Industry, 2021, 21(8): 158-162.
[14] Zhang Kanglin. Analysis and prediction of the stock price by the LSTM model based on pytorch. Computer Technology and Development, 2021, 31(1): 161-167.
[15] Song Gang, Zhang Yunfeng, Bao Fangxun. Stock prediction model based on particle swarm optimization of LSTM. Journal of Beijing University of Astronautics, 2019, 45(12): 2533-2542.
[16] Chen W, Chai KY, Lau CT, et al. Leveraging Social Media News to Predict Stock Index Movement Using RNN-Boost. Data & Knowledge Engineering, 2018, 118: 14-24. DOI: 10.1016/j.datak.2018.08.003.
[17] Maqsood H, Mehmood I, Maqsood M, et al. A Local and Global Event Sentiment Based Efficient Stock Exchange Forecasting Using Deep Learning. International Journal of Information Management, 2020, 50: 432-451. DOI: 10.1016/j.ijinfomgt.2019.07.011.
[18] Song Gang, Zhang Yunfeng, Bao Fangxun, et al. A stock prediction model based on particle swarm optimization LSTM, 2019.
[19] Cui Guochao. Research on the Characteristics of Neural Network Models and Packet Size. Wireless Internet Technology, 2012 (3): 105.
[20] Gu Yongpeng, Qin Dibo, Zhang Xiang, et al. Tourist prediction based on LSTM Advances in Applied Mathematics, 2023, 12: 2143.
[21] Qiao Ruoyu. Neural network-based stock prediction model. Operations research and Management, 2019, 28 (10): 132-140.

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REALIZED VOLATILITY PREDICTION WITH A HYBRID MODEL: LSTM-CEEMDAN

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Abstract: The realized volatility (RV) in financial time series is characterized by nonlinearity, volatility, and noise. It is challenging to predict RV with a solitary forecasting model for precision. This study employs a hybrid model that integrates the Long Short-Term Memory (LSTM) network with the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) for the purpose of forecasting the returns volatility (RV) of the S&P 500 index, thereby validating its accuracy and robustness.
Keywords: LSTM; CEEMDAN; Realized volatility

1 INTRODUCTION

Volatility serves not only as a conventional metric for assessing risk within the financial markets but also as a pivotal factor in determining asset prices and constructing investment portfolios. The precise prediction of volatility has consistently been a subject of intense scholarly inquiry. In its formative stages, academic research primarily focused on the prognostication of low-frequency volatility, as delineated by seminal works such as those by Engle, Bollerslev, and Ka & Heynen. Nonetheless, the predictive outcomes of low-frequency volatility prove to be inadequate as a reliable proxy for anticipating future market risks, owing to the manifest limitations of such approaches.

It has a great range of researches when RV was first proposed, it included but not limited to, the Autoregressive (AR) model, the Autoregressive Fractionally Integrated Moving Average (ARFIMA) model, and the Stochastic Volatility model. Besides, in recent years, there has been a burgeoning advancement in artificial intelligence, leading to a widespread deployment of deep learning algorithms across a multitude of disciplines, as evidenced by the seminal works of Lu, Que, and Cao, as well as Kodama, Pichl, and Kaizojl. When juxtaposed with conventional econometric models, deep learning methodologies exhibit superior performance, owing to their fewer constraints and enhanced feature extraction capabilities. McAleer and Medeiros introduced a nonlinear hierarchical auto-regressive (HAR) model based on neural networks. Arnerié, Poklepovié, and Teai compared two methodologies: HAR and feedforward neural networks (FNN). Furthermore, they deduced that FNN-HAR-type models exhibit superior performance in encapsulating the nonlinearity of return volatility (RV).

To address this issue, a novel hybrid model, CEEMDAN-LSTM, is introduced in this study for the purpose of RV forecasting. Furthermore, it is imperative to validate the forecasting efficacy of CEEMDAN-LSTM across both emerging and developed markets. Accordingly, we have designed an extensive analytical framework.

2 PREVIOUS LITERATURE

Currently, stock market is acknowledged as being chaotic, complicated, volatile and dynamic [1]. Thus, stock prediction has been an important topic that cannot be ignored and calls for future. According to the current literature, a variety of data-driven predictors have been developed to forecast stocks, which can be categorized into two broad approaches: those employing single models and those utilizing hybrid models. The methodology of single-model forecasting encompasses conventional statistical approaches, established machine learning algorithms, and contemporary deep learning techniques. Conversely, the hybrid model forecasting approach typically entails a synthesis of these methodologies bolstered by comprehensive feature engineering; the decomposition-integration strategy stands out as a noteworthy instance within this category. Despite its reliance on a solitary predictive model, this approach is typically categorized as hybrid.

The methodology of single-model forecasting entails the utilization of a singular predictive model for estimating carbon prices, in conjunction with certain feature engineering techniques. For single-model methods, Bhattacharjee and Bhattacharja found MLP and LSTM are the most accurate way to predict stock prices for having the least MSE and MAPE values [2]. Ariyo, Adewumi and Ayo used ARIMA model for stock price prediction and found it can guide investors to make right decisions [3]. Nevertheless, despite extensive testing and preprocessing, single model, such as, traditional statistical models struggle with utilizing non-linear, non-normal distributional stock prices for precise predictions

Classical machine learning methods, Support Vector Machine (SVM) [4] and Least Squares Support Vector Machine (LS-SVM) [5],exhibit relatively exceptional forecasting capabilities for addressing small-sample, nonlinear, and high-dimensional issues pertaining to stock market price determination. Zhu and Wei [6] discovered that after parameter optimization, the Least Squares Support Vector Machine (LS-SVM) outperforms the Auto Regressive Integrated Moving Average (ARIMA) model. However, the Support Vector Machine (SVM) merely converts the complexity of high-dimensional spaces into the challenge of identifying the optimal kernel function [7]. Deep learning methodologies have significantly advanced the cutting edge in speech recognition, visual object recognition, and object detection. Yahsi et al. [8] utilized both machine learning and deep learning methodologies and ascertained that the artificial neural network was inefficient. Given the deep sample dependency inherent in deep learning methodologies, the generalization capability of these approaches is inextricably linked to the representation of typical learning instances. It is difficult to achieve the expected performance if the sample set hard is hard to representative with contradictions and redundance.

A hybrid forecasting methodology was introduced due to the challenges encountered by researchers in accurately predicting the complex and dynamic nature of stock market price through extensive empirical research using a single model. Zhu and Wei [6] introduced a novel hybrid approach integrating the ARIMA and LS-SVM models, which was found to yield superior performance compared to their individual counterparts. Moreover, Chen, Zhou and Dai used a LSTM-based model to forecast China stock returns [9]. Convolutional Neural Networks (CNNs) are capable of detecting hierarchical structural patterns within data, while Long Short-Term Memory (LSTM) [10] networks excel at capturing long-term dependencies embedded within the dataset. Zhang[11] found ARIMA-CNN-LSTM model is better in prediction models. Decomposition-integration methodologies are extensively employed in stock market price forecasting to augment the limited dataset and enhance precision. These methods are preferred for their facile construction of predictors and time-efficiency in comparison to hybrid models, which often involve numerous intricate components. Commonly employed methods for time series decomposition include the Wavelet Transform [12], Empirical Mode Decomposition (EMD) [13], Hilbert-Huang Transform [13], Ensemble Empirical Mode Decomposition (EEMD) [14], Complementary Ensemble Empirical Mode Decomposition (CEEMD) [15], Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) [16], and Variational Modal Decomposition (VMD) [17].

In addition to the literature mentioned above, numerous scholars are dedicated to researching stock markets forecasting via the decomposition-integration approach. This study is emblematic of this trend, as it integrates CEEMDAN, VMD, and LSTM into the decomposition-integration framework for comprehensive exploration and validation. This paper concludes two fundamental frameworks, called ensemble and the respective LSTM forecasting methods and puts forward a hybrid one combined with VMD re-decomposition to predict stock market. A set of experimental supplements and comparisons are provided to verify previous literature and address the deficiencies in certain literature that are challenging to replicate during programming.

3 METHOD

3.1 The Structure of LSTM

The LSTM Flowchart can be seen in below Figure 1.

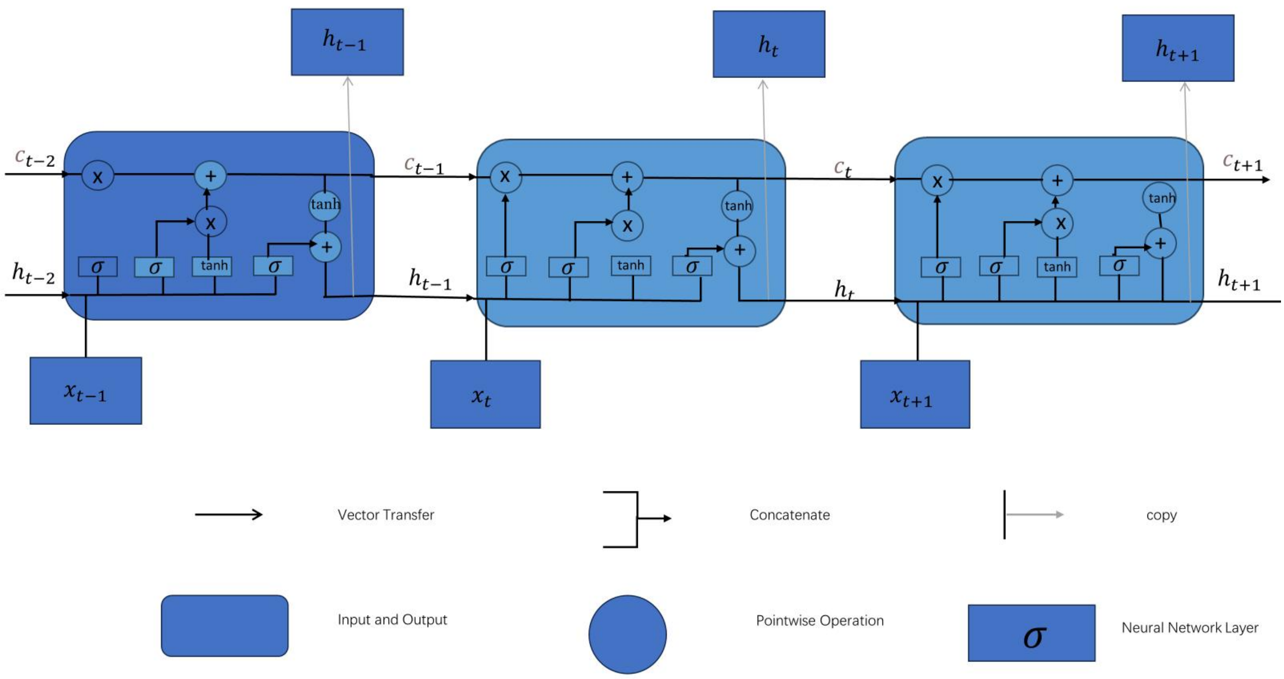

Figure1 LSTM Flowchart

3.1.1 Long Short-Term Memory (LSTM)

Hochreiter and Schmidhuber [1] initially introduced the Long Short-Term Memory (LSTM) architecture, a meticulously designed extension of the Recurrent Neural Network (RNN) that incorporates memory mechanisms to mitigate the challenges associated with long-term dependencies. LSTM, or Long Short-Term Memory, is a type of

artificial recurrent neural network (RNN) architecture used in the field of deep learning. LSTMs are designed to model temporal sequences and their long-range dependencies more accurately than conventional RNNs. They were introduced by Hochreiter and Schmidhuber in 1997.
Key Features of LSTM:
1) Memory Cells: The core component of an LSTM network is the memory cell, which is capable of maintaining information for long periods.
2) Gates: LSTMs use three gates to control the flow of information:
Forget Gate: Decides which information to discard from the cell state.
Input Gate: Decides which new information to store in the cell state.
Output Gate: Decides what part of the cell state to output as the hidden state.
3) Cell State: The memory cell state is updated by the gates, allowing the LSTM to maintain and modify memory over time.
Applications:
Natural Language Processing (NLP): Language modeling, text generation, machine translation.
Speech Recognition: Transcribing spoken words into text.
Time Series Prediction: Stock market prediction, weather forecasting.
Anomaly Detection: Identifying unusual patterns in data.
The function:

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right) \tag{1}$$

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \tag{2}$$

$$\tilde{c}_t = \tanh\left(W_c x_t + U_c h_{t-1} + b_c\right) \tag{3}$$

$$c_t = f_t \circ c_{t-1} + i_t \circ \tilde{c}_t \tag{4}$$

$$o_t = \sigma(\, W_0 x_t + U_0 h_{t-1} + b_0) \tag{5}$$

$$h_t = o_i \circ \tan h\,(c_t) \tag{6}$$

LSTMs are particularly effective at handling the vanishing gradient problem, which is common in traditional RNNs when dealing with long-term dependencies. This makes them suitable for tasks that require learning from and predicting sequential data over extended time periods.

3.2 CEEMDAN

CEEMDAN, or Complete Ensemble Empirical Mode Decomposition with Adaptive Noise, is an advanced signal processing technique used for decomposing a complex signal into a set of simpler components called Intrinsic Mode Functions (IMFs). It is an enhancement of the Empirical Mode Decomposition (EMD) and Ensemble Empirical Mode Decomposition (EEMD) methods.
Key Features of CEEMDAN:
1) Adaptive Noise Addition: CEEMDAN adds adaptive noise to the signal multiple times to address mode mixing issues, which occur when different oscillatory modes are combined into a single IMF.
2) Ensemble Approach: By averaging the results of multiple decompositions with different noise realizations, CEEMDAN provides more stable and accurate IMFs.
3) Iterative Process: CEEMDAN iteratively refines the IMFs by subtracting the noise-adapted mean from the original signal.
Steps in CEEMDAN
1) Add Adaptive Noise: Add different realizations of white noise to the original signal.
2) Decompose with EMD: Apply EMD to each noisy signal to obtain the IMFs.
3) Compute Ensemble Mean: Calculate the mean of the corresponding IMFs from all noisy signals.
4) Iterative Refinement: Subtract the ensemble mean from the original signal and repeat the process on the residual signal to extract the next IMF
Applications:
Signal Processing: Decomposing non-stationary and nonlinear signals in fields like geophysics, biomedicine, and engineering.
Fault Diagnosis: Identifying faults in mechanical systems by analyzing vibration signals.
Financial Time Series: Analyzing and forecasting stock prices and other economic indicators.
CEEMDAN is particularly useful for its robustness and ability to handle complex signals, providing a clearer and more accurate decomposition compared to traditional methods like EMD and EEMD.

3.2 Analysis of Experimental Results

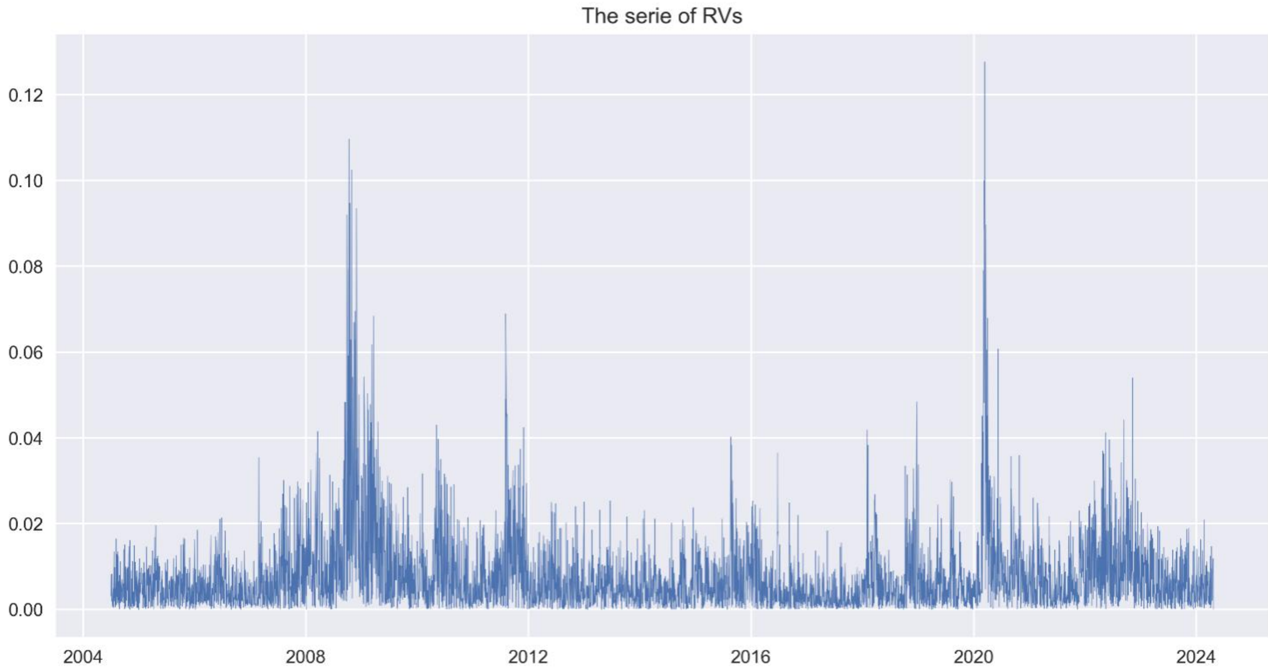

Figure 2 The Series of RVs

From this Figure 2, the stock price is deeply influenced by the international issue, such as: in 2020, the COVID-19 outbroke, the stock price was in serious decline. Therefore, it accorded with the prediction of this model.

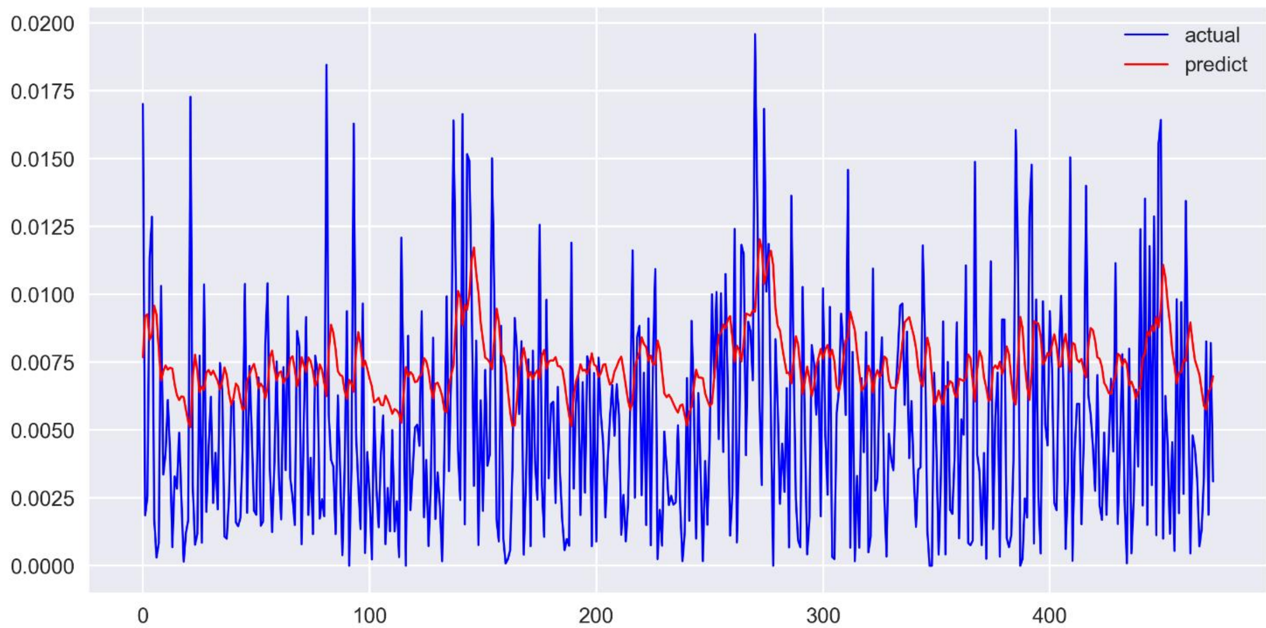

Figure 3 Actual and Prediction Comparison of CEEMDAN

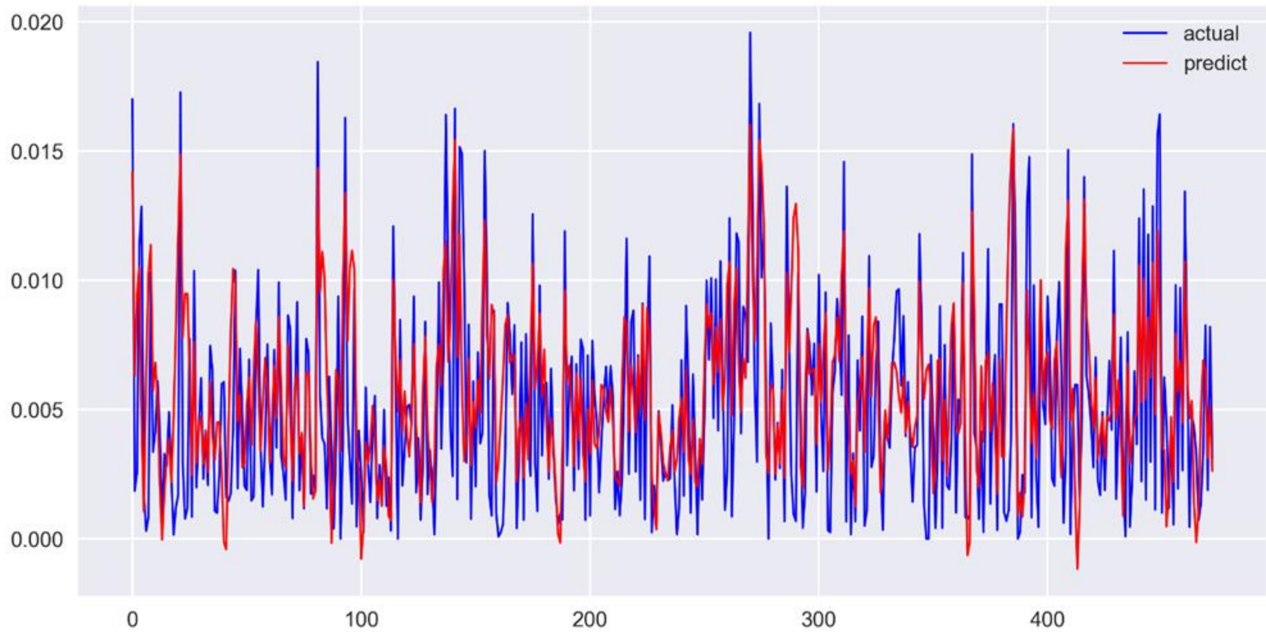

Figure 4 Actual and Prediction Comparison of CEEMDAN LSTM

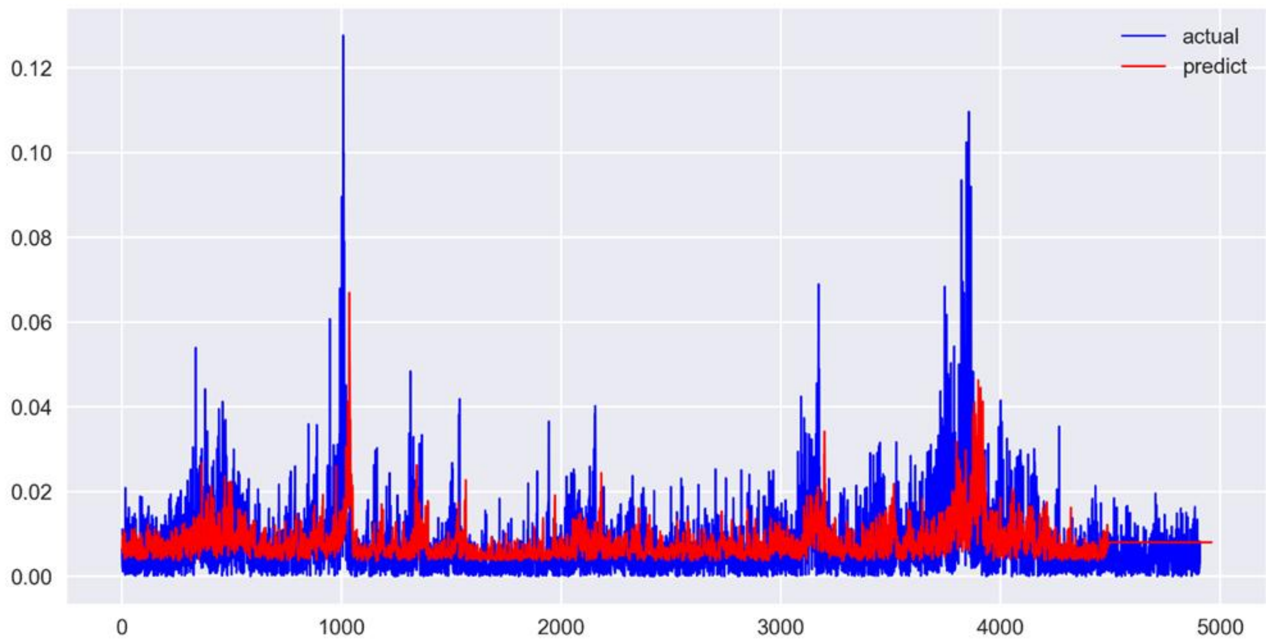

Figure 5 Actual and Prediction Comparison of HAR

Actual and Prediction Comparison of CEEMDAN, CEEMDAN LSTM and HAR can be seen in Figure 3-5.

MAE (Mean Absolute Error) is a metric used to measure the difference between predicted values and actual values, commonly used in regression analysis. Unlike MSE (Mean Squared Error), MAE uses absolute errors instead of squared errors.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \widehat{y}_i| \tag{7}$$

where $\boldsymbol{y_i}$ represents the actual values, $\widehat{\boldsymbol{y}}_{\boldsymbol{i}}$ represents the predicted values, and n is the number of data points. A lower MAE indicates better model performance. The advantage of MAE is that it is less sensitive to outliers compared to MSE, as it uses absolute values rather than squared values.

MSE (Mean Squared Error) is a metric used to measure the average squared difference between the predicted values and the actual values in a dataset. It's commonly used in statistics and machine learning to evaluate the performance of a regression model.

$$\mathrm{MSE} = \frac{n}{\sum_{i=1}^{n} \frac{1}{(y_i - \widehat{y}_i)^2}} \tag{8}$$

where $\boldsymbol{y_i}$ represents the actual values, $\boldsymbol{\hat{y}_i}$ represents the predicted values, and n is the number of data points. A lower MSE indicates a better fit of the model to the data.
HMAE (Harmonic Mean Absolute Error) is a less common error metric used to evaluate the performance of predictive models. Unlike MAE (Mean Absolute Error), HMAE uses the harmonic mean of the prediction errors instead of the arithmetic mean. The specific formula is:

$$HMAE = \frac{n}{\sum_{i=1}^{n} \frac{1}{|y_i - \hat{y}_i|}} \tag{9}$$

where $\boldsymbol{y_i}$ represents the actual values, $\boldsymbol{\hat{y}_i}$ represents the predicted values, and n is the number of data points.
The advantage of HMAE is that it is more sensitive to large errors (outliers) since the harmonic mean is more affected by extremely small values. In certain situations, this can provide a more useful performance evaluation compared to MAE.
HMSE (Harmonic Mean Squared Error) is a less common error metric used to evaluate the performance of predictive models. Unlike MSE (Mean Squared Error), HMSE uses the harmonic mean of the prediction errors instead of the arithmetic mean. The specific formula is:

$$HMSE = \frac{n}{\sum_{i=1}^{n} \left(\frac{1}{y_i - \hat{y}_i}\right)^2} \tag{10}$$

where y_i represents the actual values, $\hat{y}_i$ represents the predicted values, and n is umber of data points.
The advantage of HMSE is that it is more sensitive to outliers since the harmonic mean is more affected by extremely small values. In certain situations, this can provide a more useful performance evaluation compared to MSE.
Through this table 1, LSTM CEEMDAN perform the best compared to the other four models, the prediction is more accurate. Besides, the prediction of hybrid model is most consistent with actual.

Table 1 Model Performance of Five Measures

	CEEMDAN	CEEMDAN LSTM	SVR	HAR	AR
MAE	0.004	0.002	0.059	0.004	0.004
MSE	2.289	1.027	0.003	2.673	2.528
HMAE	0.553	0.430	0.921	1.296	0.545
HMSE	0.420	0.321	0.852	2.920	0.391

4 CONCLUISION

Stock price forecasting is vital to maintain a practical and stable financial market and offer practical guidance for production, operation, and investments. Through python 3.9.13 and various models. This manuscript delineates two fundamental CEEMDAN-LSTM frameworks and introduces a hybrid model integrating CEEMDAN and LSTM. Extensive validations and comparisons have established their efficacy and robustness. The main conclusions are as follows:
By combining LSTM and CEEMDAN, it is possible to more effectively handle the complexity and variability of stock price data, thereby improving predictive performance.
The amalgamation of CEEMDAN and LSTM models endows stock price forecasting with enhanced predictive capabilities. CEEMDAN adeptly decomposes complex, non-linear and non-stationary financial time series data into a set of Intrinsic Mode Functions (IMFs), which are more stable and simpler representations. This decomposition process filters out noise, highlights relevant features, and thus refines the input data for LSTM processing. Subsequently, the LSTM model is better equipped to capture the long-term dependencies and short-term fluctuations inherent in the financial markets, due to the provision ofIMFs at varying scales.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCE

[1] Singh R, Srivastava S. Stock prediction using deep learning. Multimedia Tools and Applications, 2017, 76: 18569-18584.
[2] Bhattacharjee I, Bhattacharja P. Stock price prediction: a comparative study between traditional statistical approach and machine learning approach. 2019 4th international conference on electrical information and communication technology (EICT), 2019: 1-6
[3] Ariyo AA, Adewumi AO, Ayo CK. Stock price prediction using the ARIMA model. 2014 UKSim-AMSS 16th international conference on computer modelling and simulation, 2014: 106-112.

[4] Cortes C, Vapnik V. Support-vector networks. Mach Learn, 1995, 20: 273–97.

[5] Suykens JA, Van Gestel T, De Brabanter J, De Moor B, Vandewalle JP. Least squares support vector machines. World scientific, 2002.

[6] Zhu BZ, Wei YM. Carbon price prediction based on integration of GMDH, particle swarm optimization and least squares support vector machines. Syst Eng-Theory Pract, 2011, 31(12): 2264–71.

[7] LeCun Y, Bengio Y, Hinton G. Deep learning. Nature, 2015, 521(7553): 436–44

[8] Yahşi M, Çanakoğlu E, Ağralı S. Carbon price forecasting models based on big data analytics. Carbon Manage, 2019, 10(2):175–87.

[9] Holthausen RW, Larcker DF. The prediction of stock returns using financial statement information. Journal of accounting and economics, 1992, 15(2-3): 373-411.

[10] Hochreiter S, Schmidhuber J. Long short-term memory. Neural Comput, 1997, 9(8): 1735–80.

[11] Zhang Z. Research on stock index prediction based on ARIMA-CNN-LSTM model. 9th International Conference on Financial Innovation and Economic Development (ICFIED 2024), 2024, 558-565.

[12] Daubechies I. Ten lectures on wavelets. Society for industrial and applied mathematics, 1992.

[13] Huang NE, Shen Z, Long SR, et al. The empirical mode decomposition and the Hilbert spectrum for non-linear and nonstationary time series analysis. Proc R Soc Lond Ser A Math Phys Eng Sci, 1998, 454(1971): 903–95.

[14] Wu Z, Huang NE. Ensemble empirical mode decomposition: a noise-assisted data analysis method. Adv Adapt Data Anal, 2009, 1(01): 1–41.

[15] Yeh JR, Shieh JS, Huang NE. Complementary ensemble empirical mode decomposition: A novel noise enhanced data analysis method. Adv Adapt Data Anal, 2010, 2(02): 135–56.

[16] Torres ME, Colominas MA, Schlotthauer G, Flandrin P. A complete ensemble empirical mode decomposition with adaptive noise. In: 2011 IEEE international conference on acoustics, speech, and signal processing (ICASSP). , 2011, 4144–7.

[17] Dragomiretskiy K, Zosso D. Variational mode decomposition. IEEE Trans Signal Process, 2013, 62(3): 531–44.

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THE EFFECTIVENESS AND SIGNIFICANCE OF FINANCIAL SHARED SERVICE CENTER OF LOGISTICS ENTERPRISES -- A CASE STUDY BASED ON SF GROUP

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Abstract: Shunfeng Group, as the head industry of the domestic logistics industry, began to establish a financial shared service center in 2014, and the financial shared service center was officially put into use in 2015, with a plan to achieve a comprehensive digital transformation by 2025. This paper analyzes the purpose, financial performance and current results of establishing a financial shared service center of SF from a theoretical point of view by studying the example of SF's establishment of a financial shared service center. Through the analysis of SF, the establishment of financial shared service center helps SF to achieve great improvement in financial management efficiency, decision-making support capability and cost control, etc. At the same time, it is found that there are problems such as low functional completeness of the industry and financial system, data dispersion, etc. SF solves the current problems by constructing the framework and mechanism of “1+1+n+x” and so on. This paper analyzes and researches the purpose, achievements and challenges of SF's financial sharing center to provide reference for the current logistics enterprises to carry out financial shared service center.
Keywords: Digital transformation; Financial shared service center; Corporate finance; Performance

1 INTRODUCTION

In the wave of digital transformation, Financial Shared Service Center (FSSC), as an important tool for modern enterprise management, is gradually becoming a key link for enterprises to optimize resource allocation and enhance financial management efficiency. As a leading enterprise in China's express and logistics industry, SF Group, faced with increasingly complex business environment and diversified customer needs, the traditional financial management model has been difficult to meet its efficient and accurate management needs. Therefore, Shunfeng Group chose to establish a financial shared service center, aiming to improve the efficiency of financial management, reduce operating costs, and enhance the competitiveness of the enterprise through centralized, standardized, and information financial management. This paper provides an in-depth analysis of the financial performance and effectiveness of Shunfeng Group after the establishment of the financial sharing center, as well as the related challenges and countermeasures.
The establishment of a financial sharing platform by SF Group is an important initiative to cope with globalized competition, improve financial management efficiency, reduce operating costs, strengthen risk management and control capabilities, and support the strategic transformation of the enterprise. Through the establishment of the financial sharing platform, SF Group can realize the centralized management of financial resources, improve the efficiency and accuracy of financial processing, reduce operating costs, strengthen risk management and control capabilities to provide strong support for the strategic transformation of the enterprise. In the future, with the continuous progress of technology and management improvement, SF Group's financial sharing platform will play a more important role for the enterprise and create greater value.

2 THEORICAL BASIS AND LITERATURE REVIEW

2.1 Theoretical Basis

2.1.1 Financial shared services theory
The theory of financial shared service is a distribution management model based on information technology and aimed at optimizing organizational structure, standardizing processes, enhancing efficiency as well as reducing operating costs. Financial shared services centralize financial business processes within or across enterprises to achieve standardized, specialized and automated financial management, in order to reduce enterprise management costs and improve the operational efficiency of financial work. Shunfeng Group chose to establish a financial sharing center in the process of financial digital transformation, which provides a great help to improve the efficiency of corporate financial work.

2.1.2 Process reengineering theory
Process reengineering theory, also known as “BPR theory”, was first proposed by economist Michael Hammer and refers to the fundamental re-analysis and design of business procedures and the pursuit of performance through the management of related business changes, so that the enterprise continues to improve. The main purpose of process reengineering is to effectively improve the operational efficiency of the enterprise in order to provide more efficient services for the internal operation of the enterprise.

2.1.3 Organizational change theory

Organizational change theory, is a theoretical system that explores how organizations adapt to changes in internal and external environments by adjusting their structure, processes, and culture in order to operate more efficiently. The core of the theory lies in understanding the necessity, process, challenges, and response strategies of organizational change. The theory emphasizes that in a rapidly changing market environment, organizations must remain flexible and adaptive, and optimize resource allocation, improve operational efficiency, and enhance competitiveness through continuous change.

2.2 Literature Review

Enterprise digital transformation refers to the redesign and improvement of business through the application of digital technology to ensure sustained growth, efficient operations and better service. Claude Saddo, author of Digital Transformation: Redefining Business Models, points out that digital transformation is not only a technological upgrade, but also an all-encompassing change in corporate culture, organizational structure and business processes. This transformation helps enterprises to reduce costs, improve efficiency, and enhance competitiveness, and has become a strategic choice for the survival and development of enterprises. Qiu Li-Chen believes that the core concept of digital transformation lies in the in-depth integration and reengineering of core business processes [4], management systems, and business models through a new generation of digital, networked, and intelligent technologies, which provides enterprises with new perspectives and tools to maintain market competitiveness for them.

Zhang, Zijian and Wang, Linjie believe that enterprises need to create a financial digitalization platform by fully researching and analyzing the core needs of financial management of group enterprises [5]. Shunfeng Group, on the other hand, accomplishes this by establishing a FSSC. In carrying out financial digital transformation, Cui Meihui believes that there is a certain inevitability in the financial digital transformation of enterprises in the era of the digital economy, and that enterprises carry out financial digital transformation to improve data decision-making ability [1], operational efficiency and management level and enhance enterprise competitiveness and innovation to adapt to the development needs of the era of the digital economy. With the depth of the digital transformation of enterprise finance, enterprises can improve the efficiency of financial management and achieve long-term sound development. At the same time, it provides enterprises with optimized resource allocation and maximizes value. Therefore, in the current complex and changing market environment, enterprises need to have the ability to quickly respond and adapt to business changes. Financial digital transformation can help enterprises better respond to market changes and maintain a competitive advantage in the market. Shunfeng Group chose to establish a FSSC in the digital transformation of finance, Chen Feng believes that the establishment of a FSSC can simplify the staff structure [2], reduce labor costs and improve the level of enterprise financial management, play a role in the enterprise, and promote the exchange and communication of financial information. However, the establishment of a FSSC may lead to an information disconnect between business and finance, while placing higher demands on the carrying capacity of the company's information system and the efficiency of dealing with problems. Zhang Yifan also mentions that a FSSC can enhance the risk management capability of an enterprise group [3], ensure the transparency and consistency of financial information, can optimize basic financial operations, enable the corporate finance team to focus on higher-value financial analyses and strategic planning work, and provide the corporate management with more comprehensive decision-supporting information, which can energize the development of the enterprise.

3. CASE INTRODUCTION

3.1 Development History and Business Scale of SF Group

Since its establishment in 1993, SF Group has started from Shunde, Guangdong Province and gradually expanded to the whole country and even the world. Through the key transition from franchising to direct operation, SF has laid the foundation of high-quality service and realized rapid development from 2002 to 2014, involving in aviation, e-commerce, finance and other fields, especially the establishment of airlines in 2009, creating a new era of logistics. In recent years, SF's business has returned to the core of express logistics and transformed into an integrated logistics service provider, strengthening its strength through acquisitions and cooperation, such as integrating DPDHL's supply chain business in China in 2018 and deepening the layout of the cold chain. Its business network covers a wide range of regions at home and abroad, with a domestic city coverage rate of 99.4% and international business reaching 98 countries and regions. SF's financial performance is strong, with solid growth in both revenue and business volume in Q1 2024, with supply chain and international business being particularly prominent. The company is also actively expanding into new areas such as inter-city delivery and cold transportation, and is driven by technological innovation, integrating cutting-edge technologies such as artificial intelligence and the Internet of Things, to continuously improve operational efficiency and customer experience, demonstrating a vibrant momentum of continuous expansion and transformation and upgrading.

3.2 Initial Intention and Goal of SF to Establish a Financial Sharing Center

SF officially started to establish a FSSC in 2014 and put it into operation in 2015. With the continuous changes in the market environment and the intensification of competition, the traditional financial management model has been difficult to meet the needs of rapid development of enterprises. The digital transformation of finance can help Shunfeng quickly adapt to market changes and improve the efficiency and accuracy of financial management. The establishment of a financial sharing center makes it easier for SF to access and analyze a large amount of financial data, thus providing management with more comprehensive and accurate decision-making support. This helps SF make more informed decisions in the complex and changing market environment. Through financial digital transformation, SF can more accurately grasp the financial status and operation of each business, thus optimizing the allocation of resources and improving the efficiency of resource utilization. Financial digital transformation is not only a change in financial management mode, but also an important means to promote business innovation. By means of digitalization, SF can have a deeper understanding of customer needs and market trends, so as to develop products and services that are more in line with market demand.

The objectives of SF in establishing the financial sharing center are to achieve centralized management and real-time sharing of financial data, enhance the automation and intelligence of financial management, optimize financial processes to improve operational efficiency, promote the in-depth integration of business and finance, and form the layout of the global intelligent supply chain. Through digital transformation, SF can establish a unified financial management platform to realize centralized management and real-time sharing of financial data, which will help improve the accuracy and timeliness of financial data and provide more reliable decision-making support for the management; digital transformation will promote the automation and intelligent development of SF's financial management, and through the introduction of advanced technologies such as artificial intelligence, big data, etc., SF will realize automation of financial processes, reduce manual intervention, and lower operational efficiency. Processing, reduce manual intervention, reduce the error rate; at the same time, through the intelligent analysis function, enhance the decision-making support ability of financial management; establish a financial sharing center to carry out comprehensive optimization of the financial process, reduce unnecessary links and duplication of labor, and enhance the efficiency of financial operations. At the same time, through digital means to strengthen the monitoring and management of various businesses to ensure the stability and compliance of business operations; SF will be committed to promoting the deep integration of business and finance, and realize the full penetration and support of finance to business through digital transformation. This will help SF to better grasp the market demand and customer dynamics, and provide more powerful financial protection for business development.

3.3 Construction and Application of Financial Sharing Center

SF started the preparatory work for the construction of the financial shared service center in 2014, and the financial shared center was formally put into use in 2015. By the end of 2016, SF had achieved comprehensive centralized sharing of the basic work of the finance, and initially realized the centralized management of the financial work.

SF has realized the centralized management and real-time sharing of financial data through big data technology. This enables financial managers to obtain and process financial data more quickly, improving the efficiency of financial management. At the same time, the application of big data technology also reduces manual intervention, lowers the error rate, and further improves the accuracy of financial management; in the process of cost accounting, SF utilizes big data technology to aggregate and distribute various costs. Through big data analysis, the source and composition of various costs are more accurately identified, providing management with more refined cost information. Big data technology helps SF optimize its cost control strategy, reduce operating costs and improve profitability; big data technology also plays an important role in SF's risk management, through the analysis of massive financial data, potential financial risks and hidden dangers can be found in time and corresponding measures can be taken to prevent and cope with them, and the credit status of customers can be assessed by using big data technology, so as to reduce the risk of bad debts. At the same time, big data provides strong support for SF's decision-making, SF can use big data technology to analyze and predict market trends, customer demand, competitive situation, etc., to provide management with a more comprehensive and accurate basis for decision-making. This helps SF to formulate more scientific and reasonable strategic planning and business strategies, and enhance its competitiveness and market position; SF discovers new market demand and business opportunities through the analysis of customer behavior, transaction data, etc., so as to develop products and services more in line with customers' needs, and recommend relevant products and services according to customers' purchase history and preferences, and enhance customer satisfaction and loyalty.

4. FINANCIAL PERFORMANCE ANALYSIS

SF started to establish a financial sharing center in 2014 and started to use it in 2015, so we chose the financial data from 2010 to 2020 for our financial performance analysis.

4.1 Solvency

Solvency is to reflect the ability of the assets owned by the enterprise to be able to repay the loan in the credit period, this paper analyzes the solvency of SF by calculating three indicators, such as current ratio, quick ratio and gearing ratio, and the calculation results are shown in Table 1.

Table 1 Solvency Analysis, 2010-2020

Measures/year	2020	2019	2018	2017	2016	2015	2014	2013	2012	2011	2010
Current ratio	1.24	1.38	1.21	1.42	1.16	3.48	3.43	2.06	2.51	2.80	7.11
Quick ratio	1.21	1.36	1.18	1.40	1.14	2.60	2.62	1.69	2.11	2.47	5.97
Gearing ratio(%)	48.94	54.08	48.35	46.23	53.42	20.04	25.52	37.03	31.43	30.49	11.69

In terms of short-term solvency, it is usually generally recognized that a current ratio of around 2 would be more appropriate, with a lower limit of 1; a quick ratio of around 1 is more appropriate. As can be seen from Table 1, in 2015 before SF began to use the financial sharing center, the current ratio are above 2, and the current ratio fluctuation is relatively large, after 2015 are all around 1, at a normal level; similarly, the quick ratio before 2015 is around 2, after 2015 the quick ratio fell sharply to around 1. In terms of long-term solvency, pre-2015 gearing ratio is only around 20% -30%, SF's long-term solvency is very low, and after 2015 gearing ratio is at around 50%, which is at a relatively normal level.

Through the significant changes in the data before and after 2015, it can be seen that after putting into use the financial sharing center, SF, short-term solvency and long-term solvency have been significantly improved, and can intuitively find that the financial sharing center for SF solvency significantly improved.

4.2 Operational Capacity

Operating capacity reflects the efficiency of asset utilization and management level in the process of production and operation of the enterprise, and the higher the efficiency of asset utilization, the better the management level of the enterprise. This paper analyzes the operating capacity of SF by calculating three indicators: accounts receivable turnover, inventory turnover, total asset turnover, etc. The calculation results are shown in Table 2.

Table 2 Analysis of Operating Capacity, 2010-2020

Measures/year	2020	2019	2018	2017	2016	2015	2014	2013	2012	2011	2010
Accounts receivable turnover ratio	10.64	11.28	12.92	13.15	13.06	3.51	4.95	4.35	4.45	4.50	4.28
Inventory turnover	138	109	118	135	142	3.74	4.54	4.52	6.88	6.28	5.12
Total assets turnover	1.51	1.37	1.37	1.35	1.46	0.72	0.77	0.66	0.80	0.75	0.80

As can be seen from the data in Table 2, after the financial sharing center was put into use in 2015, the accounts receivable turnover ratio improved from 3.51 to 13.06, the company's likelihood of incurring bad debts was greatly reduced, and the cycle of capital recovery was shortened; similarly the inventory turnover ratio reached a substantial increase from 3.74 to 142, the company's inventory management efficiency improved, the inventory turnover rate was rapidly increased, and the total asset turnover ratio also increased from 0.72 to 1.46, reflecting the improvement of SF's sales ability and the utilization rate of assets, which shows that the efficiency of SF's total assets has been improved.

To sum up, we can see that the operating cycle of SF shows a shortening trend, and SF has effectively improved its asset utilization, inventory management and accounts receivable recovery, etc. We can find that SF's operating ability has also been greatly improved after it started to use the financial sharing center.

4.3 Profitability

Profitability reflects the ability of the enterprise to utilize the available resources. This paper analyzes the profitability of SF by calculating three indicators such as gross profit margin, net profit margin and ROE, and the calculation results are shown in Table 3.

Table 3 Profitability Analysis, 2010-2020

Measures/year	2020	2019	2018	2017	2016	2015	2014	2013	2012	2011	2010
Gross margin (%)	16.35	17.42	17.92	20.16	19.69	19.78	13.15	13.98	13.32	13.29	16.45
Net margin (%)	7.19	7.06	6.85	9.06	10.60	2.72	2.28	3.68	4.61	4.49	4.02
ROE	15.20	14.86	13.19	18.15	22.46	7.83	3.31	5.57	6.66	5.85	3.74

Through the data in Table 3, we can see that there is a relatively small increase in gross profit margin before and after 2015, indicating that the increase in value-added profitability of SF after 2015 is flat, indicating that SF is more stable in cost control and pricing strategy, but the net interest rate is increased from 2.72% in 2015 to 10.60% in 2016 after SF formally used the financial sharing center, indicating that SF started to use the After the financial sharing center, cost control has been effectively improved, and the level of profit has been greatly improved, at the same time, after the financial sharing center is put into use, ROE also occurs a substantial increase, which illustrates that Shunfeng's profitability is greatly improved, the capital structure is significantly optimized, and the financial risk is effectively managed. Through the establishment of the financial sharing center, Shunfeng's profitability has been improved and the enterprise value has been increased.

5. OTHER BENEFITS OF THE FINANCE SHARING CENTER

5.1 Improvement of Financial Management Efficiency

SF Finance Sharing Center has achieved remarkable results in improving financial management efficiency. Shunfeng Group started to prepare for the construction of the financial sharing center since 2014, began to put it into use in 2015, and realized the comprehensive centralized sharing of financial fundamentals at the end of 2016. This transformation from a regional decentralized management mode to a centralized shared management mode marks the improvement of SF Group's financial management efficiency. By establishing the financial sharing center, Shunfeng Group has significantly improved the efficiency of financial processing data, and financial personnel are able to process and analyze financial information more efficiently, thus improving the overall work efficiency of the enterprise. In addition, the financial sharing center also simplifies business processes and reduces repetitive work, allowing financial staff to devote more energy to high value-added financial management activities, such as budget management, financial analysis and decision support.

The establishment of the financial sharing center reduces the operating costs of the enterprise to a certain extent. Through standardized and automated process handling, it reduces human errors and enterprise management costs to a certain extent, and at the same time realizes enterprise resource allocation.

5.2 Enhancement of Decision Support Capability

With the continuous operation of Shunfeng Group's Financial Sharing Center, a large amount of business data has been generated. These data serve as important assets of the enterprise, and through data mining and analysis, the financial sharing center is able to provide management with accurate decision support. The application of real-time data and scenario-based application makes the financial sharing center gradually evolve to a big data center, and the enterprise realizes more timely, efficient and accurate decision analysis and risk early warning; Shunfeng Group realizes the integration of resources through the technical means of the ERP system and SAP financial system, and provides comprehensive data support and decision-making basis, which further meets the financial analysis, prediction and decision-making needs of managers at all levels; the financial sharing center not only meets the financial analysis, prediction and decision-making needs, but also provides the financial analysis, prediction and decision-making support for the management, which is a very important asset of the enterprise. The Finance Sharing Center not only focuses on daily financial accounting and supervision, but also deeply participates in the strategic planning and major investment decisions of the enterprise. In procurement, contract signing, production optimization projects, etc., the Finance Sharing Center provides the optimal solutions for decision-making by means of selecting solutions and comparing and contrasting measurements, etc.; the integration of the Finance Sharing Center and the Finance BP (Business Partner) model further strengthens the financial sharing center's ability to serve the business community and the financial industry. The integration of Finance Sharing Center and Finance BP (Business Partner) further strengthens the function of Finance Sharing Center in supporting corporate decision-making, and realizes the deep integration of finance and business through the data and process foundation of the Sharing Center and innovation in various aspects of corporate financial management.

At the same time, the establishment of the finance sharing center realizes the professional division of labor of the finance team, which enables the finance function to be effectively transformed from transaction processing to decision-making support, so that the finance staff can be more involved in business support and strategic decision-making.

5.3 Improvement of Cost Control and Risk Management

SF Group continues to optimize its corporate cost structure by implementing lean resource planning and cost control and promoting multi-network integration between cross-business units. SF mentioned in its Q3 2023 financial report that the company adhered to lean resource planning and cost control, and enhanced management efficiency through technology empowerment. SF continues to promote the integration of the four networks of express transportation, express transportation, warehouse network and Feng network to realize cost reduction and efficiency. This includes the integration and use of transit yards and automation equipment, as well as the integration and optimization of trunk and branch lines. In terms of cost control financial sharing mode can better monitor and reduce unnecessary expenditures compared with the traditional mode, thus improving the overall financial effectiveness. Through automation and standardized processes, it can significantly reduce the need for manual operations and accelerate the speed of financial processing, which is difficult to achieve in the traditional mode.

In terms of risk management, SF has established a sound internal control mechanism, including financial management, human resource management and information technology management, to ensure the standardization and safety of corporate operations. Meanwhile, in the process of identifying and sorting out the risk information base, SF has fully integrated environmental, social and governance risks, which are mainly distributed in the strategic risk areas.

These measures have not only improved SF's operational efficiency and profitability, but also strengthened the enterprise's anti-risk ability, effectively reduced operational costs and prevented potential risks, enabling SF to maintain its leading position in the fierce market competition.

6.CHALLANGES AND RESPONSES

6.1 Challenge 1: Organizational Structure and Process Re-engineering

Under the traditional financial management model, each branch has its own independent financial department, making it difficult to achieve unified management and standardized operation. The establishment of the financial sharing center breaks the original organizational structure, re-planning financial functions, and realizes the centralized processing of business finance. The organizational structure is complex, and a smooth transition is required to ensure that operations are not affected; process re-engineering resistance, financial process re-engineering involves the adjustment of the responsibilities of multiple departments and positions, and requires adequate communication and coordination; with the establishment of the financial sharing center, the traditional financial positions need to be properly resolved in the transition or abolition of the problem, to prevent the loss of talent.

SF should clarify the strategic positioning of the financial sharing center to ensure that its construction objectives are consistent with the overall strategic objectives of the enterprise; promote the adjustment of the organizational structure in phases, focusing on communication and consultation with employees to ensure a smooth transition; SF should develop a unified financial processing standards and operating procedures for the existing financial processes, and through the introduction of advanced systems to achieve the automated processing of financial operations and data sharing; develop a comprehensive staffing The company should also formulate a comprehensive staff resettlement program and provide diversified choices for affected employees. At the same time, we will strengthen employee care and incentives to enhance the sense of belonging and loyalty, so as to ensure the smooth implementation of the change and minimize the negative impact.

6.2 Challenge 2: Information System Integration and Data Migration

When building a financial sharing center, SF faced the challenges of information system integration and data migration. Due to the different financial systems used by each branch, data formats and standards are not uniform, making it difficult to realize seamless data connection and real-time sharing. In addition, the data migration process may encounter problems such as data loss and data inconsistency, which increases the complexity and risk of the project.

SF should formulate unified information system standards and data format specifications to ensure that the information systems of each branch in the financial sharing center can be compatible and integrated with each other. By introducing advanced information system integration technology and management tools, the seamless connection and efficient operation of information systems can be realized; SF improves the efficiency and accuracy of data processing by introducing advanced data processing technologies such as big data and cloud computing. By utilizing these technologies to deeply mine and analyze data, it provides strong data support for corporate decision-making.

6.3 Challenge 3: Risk Assessment and Internal Control

Establishing a perfect risk assessment system and internal control mechanism, SF needs to provide timely early warning and control of possible risks. Inadequate risk assessment process, SF's risk assessment process lacks standardization and systematization, making it difficult to comprehensively and accurately identify and assess potential risks; inadequate internal control mechanism, with the establishment of the Financial Sharing Center, SF's internal control environment has undergone significant changes, and the original internal control mechanism may not be able to adapt to the new management mode.

Such problems can be solved by establishing a standardized risk assessment process. By introducing advanced risk assessment techniques and tools, SUNFENG improves the accuracy and scientificity of risk assessment, strengthens the training and guidance for risk assessment personnel, and improves their risk identification and assessment capabilities; at the same time, it improves the internal control mechanism to ensure the sound operation of the financial sharing center, clarifies the responsibilities and authority of each position, and strengthens the supervision and inspection of the implementation of internal control. Meanwhile, the internal control mechanism is improved to ensure the sound operation of the financial sharing center, the responsibilities and authorities of each position are clarified, and the supervision and inspection of the implementation of internal control are strengthened. In addition, a third-party auditing organization has been introduced to conduct regular audits and evaluations of the financial sharing center, so as to enhance the transparency and credibility of the internal control.

6.4 Challenge 4: Personnel Training and Career Development

SF needs to train a new type of financial personnel to adapt to the financial sharing model. Existing financial personnel are resistant to the new model, while some traditional financial positions are facing abolition or transformation, which also increases the difficulty of personnel management. By strengthening the training of financial personnel, improve their professional ability, formulate career development plan for financial personnel to clarify their career planning, provide diversified development opportunities, and recognize and reward outstanding personnel to enhance the sense of belonging; at the same time, a scientific talent ladder system should be established to ensure the supply of talents in the process of financial sharing center construction. Establish a talent echelon system, internal and external combination, build a high-quality financial team, to protect the talent needs of the financial sharing center construction.

In the process of building a financial sharing center, SF is faced with the challenges of organizational structure and process re-engineering, information system integration and data migration, risk assessment and internal control, as well as personnel training and career development. By clarifying the strategic positioning of the financial sharing center, promoting the adjustment of the organizational structure in phases, optimizing the financial process, unifying the information system standard, formulating a detailed data migration plan, establishing a standardized risk assessment process, and improving the internal control mechanism and other measures, it is possible to effectively cope with the challenges and successfully build a financial sharing center to achieve a comprehensive improvement in the level of financial management.

7. RESEARCH CONCLUSION

In summary, by studying the effectiveness and significance of logistics enterprise Shunfeng Holdings in establishing and using a financial sharing center, we can conclude that Shunfeng Group has successfully realized the digital transformation of financial management through the establishment of a financial sharing center, and the establishment of a financial sharing center has enabled SF to centralize the management of financial data, achieve real-time sharing and rapid processing of financial information, greatly improving the efficiency of financial management , in terms of solvency, operating capacity and profitability have been improved, and there is a positive effect on financial performance. Through the use of big data and artificial intelligence technology, data is deeply mined and analyzed, providing management with more comprehensive and accurate decision support, in addition to promoting the improvement of cost control and risk management of SF, realizing cost reduction and efficiency, and enhancing the profitability of the enterprise. At the same time, the establishment of a sound internal control mechanism and risk information database enables SF to better cope with potential market risks and ensure the stability and security of corporate operations. The establishment and use of SF Group's Financial Sharing Center not only optimizes the internal management of the enterprise, but also enhances the competitiveness of the enterprise in the market. Through the sorting and optimization of the financial process, SF further improves the efficiency of business processing, reduces the operating costs, and strengthens the enterprise's ability to cope with the changes in the market. The financial digital transformation of SF Group through the establishment of financial sharing center has been effective, and is of great significance for other logistics enterprises. By learning from the experience of SF, establishing financial sharing center and realizing the digital transformation of financial management, SF Group will help to improve the management efficiency and competitiveness of the enterprise and achieve sustainable development.

COMPETING INTERESTS

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REFERENCES

[1] Cui Meihui. Research on digital transformation of corporate finance in the era of digital economy. Today's wealth, 2024(23): 71-73.
[2] Chen Feng. The application of financial shared service center in enterprises. China Business, 2024(07): 140-141.
[3] Zhang Yifan. Exploring the Construction of Financial Shared Service Center--Taking M Group as an Example. Investment and Entrepreneurship, 2024, 35(13): 77-79.
[4] Qiu Li-Chen, Jiang Jia-Qi, Zhu Jun-Hao. The impact of enterprise digital transformation on internal control management. Cooperative Economy and Technology, 2024(19): 77-79.
[5] ZHANG Zijian, WANG Linjie. Analysis of Group Enterprise Finance Digital Transformation. Cooperative Economy and Technology, 2024(20): 150-152.

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FINANCIAL MANAGEMENT INNOVATION OF BEIJING ENTERPRISES WATER GROUP LIMITED IN THE CONTEXT OF DIGITAL TRANSFORMATION: EFFECTIVENESS AND IMPLICATIONS

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Abstract: In the wave of digital transformation, BEWG has realized a remarkable leap through financial management innovation. It has deeply reshaped its financial management system by utilizing advanced technologies such as the financial shared service center. Digital transformation not only greatly improves the efficiency and accuracy of financial processing, but also promotes the intelligent process of financial management. Relying on the information-based monitoring platform and technologies such as RPA and OCR, NCCW realized automated processing and standardized management of financial data, effectively reducing human errors and accelerating data processing speed. At the same time, through the close integration with the business system, it realizes the seamless connection between finance and business, builds a comprehensive financial management knowledge base and intelligent customer service system, optimizes the management process, and improves the operational efficiency and service quality. The practice of BEWG has proved that digital transformation is a key driver of financial management innovation, injecting new vitality into the development of enterprises. This successful case provides valuable experience for the water sector, that is, enterprises should actively adopt new technologies and accelerate the intelligent transformation of financial management to meet future challenges and achieve sustainable development.
Keywords: Digitalization; Financial management; Financial sharing; Sustainable development

1 INTRODUCTION

With the advancement of the global wave of digitization and the rapid development and popularization of digital technologies, all industries are actively exploring and practicing digital transformation, with a view to achieving sustainable development of enterprises through the introduction of new technologies and other means. In recent years, China has attached great importance to the development of digitalization, clearly put forward the Digital China Strategy, and issued a number of relevant policies to encourage and support enterprises to carry out digital transformation. For example, the Notice on Accelerating the Digital Transformation of State-owned Enterprises issued by the General Office of the State Council of China in 2021 clearly states that it is necessary to consolidate the foundation of digital transformation, accelerate the digital innovation of industries, comprehensively promote the development of digital industrialization, and create a model for the demonstration of digital transformation of industries, among other decisions. Secondly, with the rapid development of big data, cloud computing, artificial intelligence and other digital technologies, the water industry is also facing unprecedented opportunities for change. Digital transformation can help companies achieve intelligent management, improve operational efficiency, reduce operating costs, and promote the industry to a greener, low-carbon, sustainable direction. Finally, as a leading enterprise in the industry, Beijing Enterprises Water Group Limited has a huge business scale and complex operation system. The traditional financial management model has been difficult to meet the needs of the rapid development of the enterprise, so it is necessary to improve the efficiency and quality of financial management through digital transformation, to provide strong support for the high-quality development of the enterprise.
In view of this, this paper selects Beijing Enterprises Water Group Limited as the main research object, to understand the digital transformation strategy of enterprise financial management, to study and explore the impact of the financial management innovation of Beijing Enterprises Water Group Limited on enterprise financial measures in the context of digital transformation. The research in this paper has important theoretical significance and practical significance, first of all, through the in-depth study of Beijing Enterprises Water Group Limited as a typical case, it can further understand the specific impact of digital transformation on enterprise financial management, the role of the mechanism and its implementation path. This helps to reveal the intrinsic connection between digital transformation and financial management innovation from the theoretical level, enriching the existing financial management theory. Second, combined with the case of Beijing Enterprises Water Group Limited, this paper discusses the application of digital transformation in the financial management of this enterprise and the changes it brings, as well as how financial management can be innovated in the context of digital transformation and how it can adapt to the new market environment and management needs. Thirdly, Beijing Enterprises Water Group Limited provides a template for other enterprises to learn from. These successful cases can not only help other enterprises reduce the trial-and-error costs of digital transformation and accelerate the process of their financial management digitization, but also inspire enterprises

to explore unique financial management innovation paths according to their own characteristics, thus promoting the development of the whole industry in the direction of digitization and intelligence. Finally, the digital transformation practice of Beijing Enterprises Water Group Limited provides new research cases and materials for the discipline of financial management. Through in-depth study of the digital transformation process and financial management innovation practice of Beijing Enterprises Water Group Limited, its applied financial management model can be widely used and promoted in other enterprises.

2 THEORETICAL BASIS

2.1 Digitalization Theory

Digital transformation is a profound and wide-ranging process of change, which is not just a simple upgrade or replacement of the existing technological framework, but is rooted in the solid foundation of the enterprise's digital transformation and comprehensive upgrading, and further touches the company's core business areas. The essence of this transformation lies in the innovation of technological means to promote enterprises to cross the traditional boundaries, and explore and build a new business model that has never been seen before and is highly adaptive to market changes and customer needs. Its core pursuit is to lead enterprises to transform from the traditional operation mode to a new form of enterprise with data as the core and technology as the driving force, and to realize a high-level transformation of the enterprise in multiple dimensions, such as strategy, organization, process, products and services. In this process, a lot of complex and variable information is transformed into quantifiable and analyzable figures and data, and then based on these figures and data, enterprises establish precise digital models, transform these models into a series of codes and introduce them into the computer system for unified processing, which is the basic process of digitization, aiming to bring more efficient and smarter operation mode and business innovation for enterprises through data-driven.

2.2 Information Island Theory

Information silo is a phenomenon that cannot be ignored in the contemporary information technology environment. It refers to the phenomenon of functionally unrelated interactions, non-sharing and interchange of information, and disconnection of information from business processes and applications between different systems, departments or individuals due to various reasons in an environment where information technology is widely used. The challenge of information silos is prevalent in both business, government organizations, and broader societal information systems. Information silos are usually manifested in four forms: firstly, data silos, i.e. data between different systems or departments cannot be effectively integrated, forming data barriers, leading to data redundancy, inconsistency and even conflict, which seriously affects the accuracy and value of data; secondly, system silos, which refers to the fact that although there are multiple information systems, there is a lack of the necessary interfaces and protocols between these systems to realize the windless transmission and exchange, resulting in functional isolation between systems; then business silos, which is mainly due to irrational business process design or poor interdepartmental collaboration, resulting in poor articulation between business segments, impeded information flow, affecting the overall fluency and efficiency of the business; and finally, control silos, which is mainly reflected in the disconnect between the intelligent control equipment and control systems and management systems, which makes it impossible for the management to obtain real-time access to critical This is mainly reflected in the disconnection between intelligent control equipment and control systems and management systems, making management unable to obtain key data in real time and effectively monitor and adjust business processes. The reasons for the formation of information islands are complex and varied, mainly including: irrational organizational structure, poor communication and collaboration, single technical function and the stage of information technology development.

2.3 Process Reengineering Theory

The revolutionary management concept of process reengineering theory, initially proposed by Michael Hammer and James Champy in the United States, has not only profoundly affected the management practices of global enterprises, but also led to a profound change in the operational efficiency and competitiveness of enterprises. Specifically, process reengineering is a systematic process, which requires companies to first conduct a comprehensive and in-depth review of all internal processes, and identify those core processes that are critical to business performance and strategic development. Subsequently, through the introduction of innovative thinking and technology, these processes will be completely redesigned and optimized, aiming to break the long-established traditional mode of operation, which may have become rigid and inefficient. This process is not just a simple restructuring or optimization of processes, but a fundamental reshaping of the logic of business operations.

3 LITERATURE REVIEW

3.1 Effectiveness of Digital Transformation

In recent years, with the rapid development and popularization of science and technology, digital transformation plays an important role in the development of enterprise change, and many scholars conduct in-depth research on digital transformation. The effectiveness of digital transformation presented in the existing academic results can be summarized in the following aspects:

In the context of the booming development of the contemporary digital economy, the digital transformation of enterprises has become the core driving force to promote the high-quality development of enterprises, and is an effective way to comprehensively enhance the comprehensive competitiveness of enterprises[1]. First, in the context of the digital era, Nie Xingkai et al. argued that digital transformation can significantly enhance the comparability of accounting information[2]. From the perspective of accounting information transparency and corporate governance level, Sun Dezhi and Xu Ling'en pointed out that with the increase of digitalization, the comparability of accounting information shows an enhanced trend[3]. It is argued that the transparency of accounting information and the level of corporate governance play a key role in the digital transformation to promote the enhancement of accounting information comparability. Meanwhile, regarding the research on the impact of digital transformation on corporate technological innovation, related scholars have the following findings: first, digital transformation has become a catalyst for promoting corporate technological innovation; second, by alleviating financing pressure and reducing two types of agency problems, digital transformation significantly drives the enhancement of corporate technological innovation; third, in the context of fierce market competition, weak audit supervision, low equity checks and balances and a low proportion of independent directors, the positive effect of digital transformation on firms' technological innovation level is more significant. This finding further confirms the significant value of digital transformation in promoting technological innovation in enterprises[4]. Second, in terms of studying the improvement path of accounting information quality, the degree of digital transformation of enterprises is positively correlated with the improvement of their accounting information quality and brings stronger governance effects for enterprises. Based on the core motivation and specific mechanism of agency theory, digital transformation can effectively reduce multiple agency costs and optimize the internal control mechanism, thus achieving significant improvement in accounting information quality. At the same time, digital transformation can also reduce real surplus management, improve the comparability of accounting information, and reduce the simultaneous fluctuation of the company's stock price, fully demonstrating the positive effects of corporate governance[5]. The depth of enterprise digital transformation significantly improves the effectiveness of internal control, and the significant increase in the effectiveness of internal control is more obvious when the competitive environment of the product market is intense and the life cycle of the enterprise is in the non-growth period[6]. As a core factor of accounting information governance, digitalization plays a key role in optimizing corporate governance structure and mitigating the managerial agency problem, which in turn promotes the quality of accounting information-accounting robustness of enterprises[7].

3.2 Factors Driving Innovation in Financial Management

As a key means of value creation and value-added financial management, it is urgent to continuously innovate the management mode and management thinking to meet the needs of enterprise development. The traditional financial management model gradually shows its limitations, and it is difficult to keep pace with the rapid development of contemporary enterprises, and even hinder the development of enterprises, resulting in the emergence of development bottlenecks. Therefore, financial management innovation has become an inevitable choice for enterprises to break through the development bottleneck. Especially in the context of today's digital era, multiple external factors and internal dynamics intertwine to promote financial management innovation[8]. First of all, the integration of industry and finance has become a major trend in the development of today's finance, in this context, the traditional financial management model has been unable to meet the growing business volume of the current situation, the integration of industry and finance under the perspective of enterprise financial management innovation is imminent[9]. Secondly, in the context of the big data era, enterprise financial management is faced with many problems, such as: some enterprises are still using the traditional financial management model, the concept of financial management is outdated: under the influence of the traditional sloppy management mode, the management technology lagging behind and other problems still exist, the implementation of information management is not in place; the enterprise financial risk management system has defects. Financial management informatization construction has become a major trend of development[10]. Finally, Ding Shenghong and Zhou Hongxia corroborate the theoretical innovation of financial management of different types of enterprises believing in different corporate values through the case information of Haier's financial management practice innovation[11]. They summarized the law of financial management theory innovation of different types of enterprises at different economic stages. They believe that there are two factors of financial management innovation, the first point is the evolution of the material-based economic development concept of the human-based economic development concept, but also to change the basic view of enterprise financial managers on the innovation of enterprise financial management. The second point is that different economic development concepts dominate the development of different economic innovations, and in this process, different types of enterprise values dominate different types of enterprise financial management theory innovation[11].

4 CASE INTRODUCTION

4.1 Introduction to Beijing Enterprises Water Group Limited

Beijing Enterprises Water Group Limited (hereinafter referred to as “BEWG”) is a flagship enterprise of Beijing Enterprises Group Company Limited focusing on water resources recycling and water ecological and environmental protection. Since its successful listing in the Hong Kong stock market in 2008, the company has always been focusing on the core areas of efficient recycling of water resources and water ecological and environmental protection. The company integrates diversified functions such as industrial investment, planning and design, construction, operation and maintenance, professional and technical services and capital operation, and its water treatment capacity ranks among the best in the same industry in China.

BEWG 's extensive business territory not only covers all provinces and autonomous regions in China in depth, involving more than a hundred prefectural-level cities, but also crosses the border and extends to eight countries, including Malaysia, Singapore, Australia, New Zealand, Portugal, Angola and Botswana, to build up a globalized service network. The total number of water treatment facilities and township wastewater treatment projects operated by the company has reached 1,370, with a total daily treatment capacity of 44,886,000 tons, demonstrating its strong operational capability and service scale.

Adhering to the business philosophy of “customer-centered, innovation-driven development”, NWCL has formulated the strategic goal of “asset scale, technology and management innovation as the engine, promoting business transformation and upgrading, improving operational efficiency and realizing sustainable development” as the core. The company is actively embracing the wave of digital transformation, and is committed to becoming a world-class integrated water and environmental services provider trusted by the industry and leading the future, and constantly moving towards the pinnacle of the environmental protection field.

4.2 Beijing Enterprises Water Group Limited Digital Transformation Process

4.2.1 Multi-stage evolution of financial shared service center construction

Initial decentralized and small-scale exploration stage. From 2017 until 2020, based on the complexity of personnel integration and the importance of business continuity operations, BEWG has adopted a geographically decentralized strategy to establish miniaturized financial shared service centers in more than twenty regions, aiming to initially achieve the physical centralization of financial processes. However, at this stage, due to the decentralization of services and the limited volume of business in each region, accounting standardization and quality face challenges, limiting the full release of the scale effect of financial sharing.

Transformation of the single-center full-mode pilot phase. 2020 October, BEWG officially launched a centralized financial shared service center construction project, after ten months of careful preparation, successfully completed the whole process from planning, design, site selection to trial operation. The project makes full use of information technology, closely focuses on user needs, promotes profound changes in financial management functions, realizes efficient integration of financial accounting and fund settlement through in-depth reengineering of business processes, and lays a solid foundation for building a professional, intelligent and service-oriented financial organization.

Intra-group promotion and standardization stage. Since July 2021, BEWG has extended the successful experience of financial shared services to more than 400 subsidiaries within the group, established the transfer of financial data as a top priority for management optimization, and formulated 35 strict transfer standards and implemented the “source management” strategy to strengthen the audit and rectification of accounts. Currently, the center is located in Qingdao, with two core sections, namely transaction processing and operation support, providing a full range of financial shared services for the group’s member companies, including document auditing, financial accounting, fund settlement and file management, and the annual processing volume of documents has exceeded 950,000 sheets.

4.2.2 Digital technology drives the deepening of financial sharing practices

Optimization of direct linkage between banks and enterprises to promote efficient processing of documents. Relying on the data analysis capability of the information monitoring platform, NWCL Water has refined the division of financial functions and systematically optimized business processes, thus significantly improving the efficiency of document processing. At the same time, relying on RPA technology, it has realized seamless connection with eight major banks, including China, agriculture, industry, construction and recruitment, etc. The function of direct linkage between banks and enterprises supports one-key batch payment, which shortens the time for each payment from 5 to 10 minutes to an average of 5 seconds, and improves the efficiency of the overall documents and payment by more than 60%.

In-depth integration of business and financial processes to strengthen integrated management. BEWG Financial Shared Service Center has comprehensively sorted out and reconstructed the whole chain of processes from business to finance, established 78 standardized business scenarios, and subdivided the financial functions into seven key areas of accounts receivable, accounts payable, reimbursement, general ledger, tax, funds and file management, and implemented a centralized approval mechanism. On this basis, BEWG has promoted the integration of business and finance, broken the phenomenon of data silos, built a close data interaction ecology with procurement, operation, sales, human resources and other systems, front-loaded the business and finance data rule setting, and strengthened the ability to collect source data. Through the implementation of standardized processing procedures, BEWG precisely identifies and solves the breakpoints in cross-departmental systems and processes, and significantly improves the integration and standardized management level of financial data.

Digital technology empowers and strengthens the cornerstone of intelligent finance. The Financial Shared Service Center of BEWG has built a smart financial ecosystem with smart budgeting, funding, reporting, accounting, reporting, analysis, archiving and sharing as the core elements, relying on the dual-drive mechanism of “data + processes” to realize the unified input and output management of financial data. As an intelligent processing center for financial data, the center not only enhances the degree of information structuring and accessibility, but also makes full use of OCR and other cutting-edge recognition technologies to achieve automatic capture of external data such as invoices, itineraries and standardized processing of internal document formats, which further improves the speed and accuracy of data processing. In addition, BEWG has also established a comprehensive financial management knowledge base and intelligent customer service system, integrating resources such as management system, operation guidelines and FAQs, providing users with a more convenient and efficient service experience through the combination of intelligent Q&A and manual service, effectively enhancing service satisfaction and user loyalty.

5 CASE ANALYSIS

5.1 Analysis of Financial Measures

From the above digital transformation history of BEWG, it can be seen that its transformation has gone through three stages, this part collects financial data related to BEWG from 2013 to 2022[1], and carries out a comparative analysis before and after the transformation from the four aspects of the relevant measures of solvency, operating capacity, profitability and development capacity, to further explore the impact of BEWG's financial management innovation in the context of digital transformation.

5.1.1 Solvency analysis

The water industry is usually characterized by large scale of investment, long return period and slow capital recovery, etc. These characteristics make water enterprises need a large amount of financial support in the process of expansion. BEWG in the development process, in order to expand market share and enhance competitiveness, need to continuously invest in capital for the construction and operation of new projects. These projects often require huge capital investment, and debt financing is one of the important ways to obtain these funds. Banks and other borrowings account for a high proportion of its liabilities. These determine that the gearing ratio of the BEWG is usually higher than 60%. Figure 1 shows the changes in the gearing ratio of the BEWG over the past ten years. It can be seen that over the past ten years, its gearing ratio has shown some volatility, starting in 2018 in decreasing and slightly increasing in 2022. Although a higher gearing ratio is likely to increase the financial cost of the enterprise, it also reflects that the group has a strong financing ability and market recognition. Figure 2 demonstrates the change of current ratio and quick ratio of BEWG. From Figure 2, it can be seen that the current ratio and quick ratio of BEWG have certain fluctuations, but overall maintained at a relatively good level, there is a certain difference between the current ratio and quick ratio, but the difference is very small. Compared with 2013 and 2014, the rest of the year, the two declined by a relatively large percentage. However, in general, the current ratio and quick ratio show a fluctuating upward trend. At the same time, the values of both are also fluctuating around 1, both of which reflect the strong short-term solvency of the BEWG.

Comprehensive analysis of long-term solvency and short-term solvency of the two aspects of the relevant measures, reflecting the impact of digital transformation on the solvency of the BEWG – to a certain extent, to Improve the overall solvency of the group.

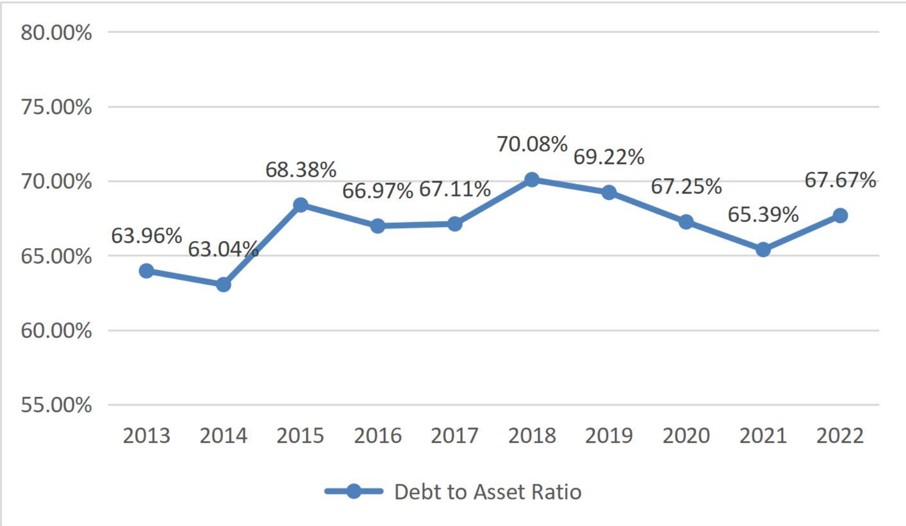

Figure 1 BEWG Trend of Debt to Asset Ratio 2013-2022

[1] The currency unit of the financial statements of the BEWG will be changed from HKD to RMB in 2023, so in order to maintain the accuracy and comparability of the data, the data for 2023 has not been selected.

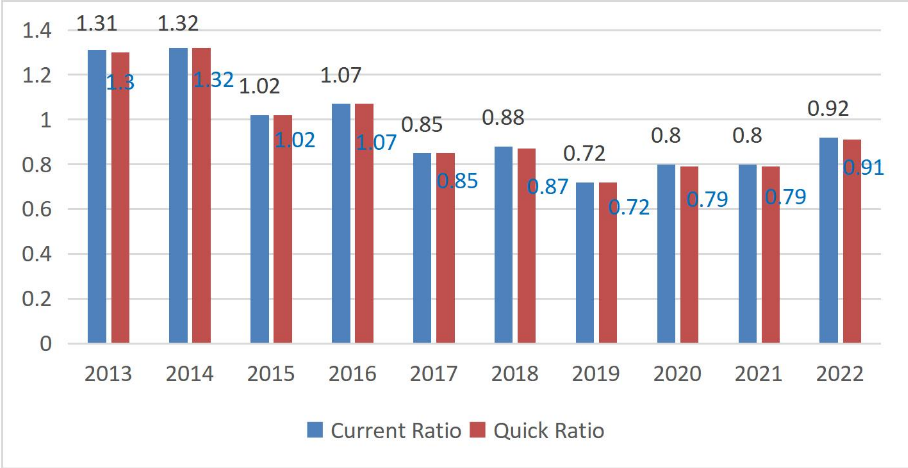

Figure 2 Trends of Current Ratio and Quick Ratio of BEWG 2013-2022

5.1.2 Operating capacity analysis

Operating capacity reflects the enterprise's ability to utilize and manage assets, the paper analyzes the impact of digital transformation on the operating capacity of BEWG by selecting four financial data measures, namely, inventory turnover ratio, current asset turnover ratio, total asset turnover ratio and accounts receivable turnover days from 2013 to 2022.

Current asset turnover and total asset turnover reflects the efficiency of the enterprise's utilization of assets, from Figure 3 we can see that the current asset turnover and total asset turnover reached a peak in 2017 and 2016, respectively, and then began to show a downward trend, current asset turnover decreased by 37.78%, the former fluctuation is larger than the latter, according to the financial statements of the relevant data to be analyzed, the reason is that the change in asset size is higher than the change in sales revenue. Analysis shows that the reason for this is that the change in asset size is higher than the change in sales revenue, and the backlog of inventory among current assets is one of the more important factors causing the growth of current assets. Figure 4 shows the trend of inventory turnover ratio and accounts receivable turnover ratio of BEWG, from which we can see that the inventory turnover ratio and accounts receivable turnover ratio reached a peak in 2017, and showed a fluctuating downward trend after that, and the decline in accounts receivable turnover ratio reflects the increase in the proportion of enterprise sales revenue and credit sales revenue in sales revenue. BEWG has carried out a series of business restructuring in recent years, actively laid out overseas projects and continuously explored new development strategies. With the rapid development of the environmental protection industry, the market competition faced by BEWG has become increasingly fierce. Combining the constant changes of various internal and external factors, the efficiency of asset utilization of the BEWG has declined, and its operating capacity has declined. Overall, the financial digital transformation has an average ability to influence the BEWG.

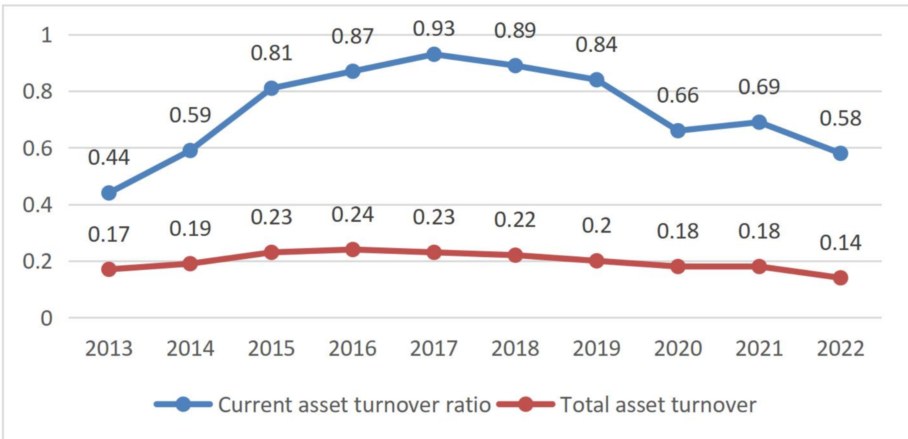

Figure 3 Trends in Current Asset Turnover Ratio and Total Asset Turnover Ratio of BEWG, 2013-2022

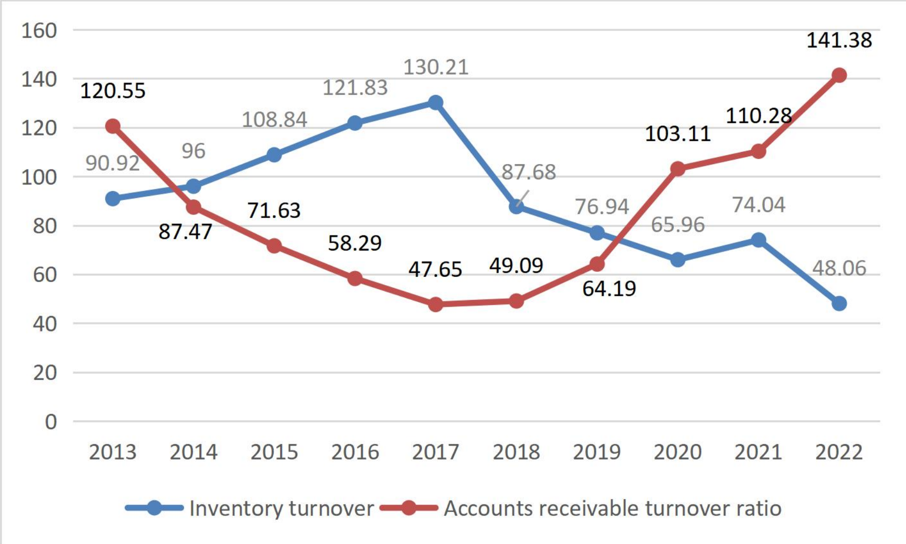

Figure 4 Trends of Inventory Turnover Ratio and Accounts Receivable Turnover Ratio of BEWG 2013-2022

5.1.3 Profitability analysis

Based on the analysis of the profitability perspective of sales revenue, the BEWG from 2013 to 2022 net asset margin and net sales margin basically maintained at a relatively stable level, 2020 to 2022, a more substantial decline, it is not difficult to see the trend of the two convergences. Overall, its operating income profit showed a relatively good upward trend during the period. It was mainly affected by factors such as the epidemic and the macroeconomic environment, which led to an overall decline in the Group's performance. The net cost and expense margin fluctuated within a bit of a range during this decade, being relatively more stable from 2019 to 2021, and showing a substantial decline in 2022. Overall, the Group has performed well in controlling costs and expenses. The decline in 2022 is mainly due to the cost of goods sold remaining at a high level despite a substantial decline in net profit. The high cost is mainly due to the growth in actual water treatment volume and the increase in raw material cost and electricity cost.

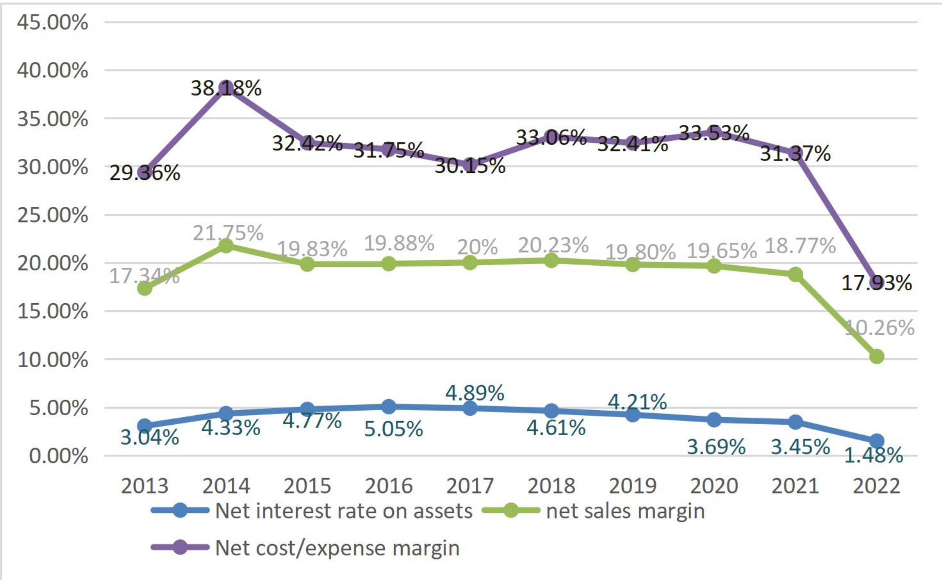

Figure 5 Trends in Profitability Related Measures for BEWG 2013-2022

From the analysis of asset-based profitability perspective, ROA and ROE of NCC Water Group generally show a fluctuating trend in amplitude, and ROA and ROE are generally on the rise between 2013 and 2018, and the Group's ability to obtain benefits from the use of shareholders' equity and the efficiency of asset utilization have gradually improved. From 2019 to 2022, ROE has a large decline, mainly due to the relative decline in net profit. ROA also shows a fluctuating downward trend, probably due to the rapid expansion of asset size and the relatively slow return from assets.

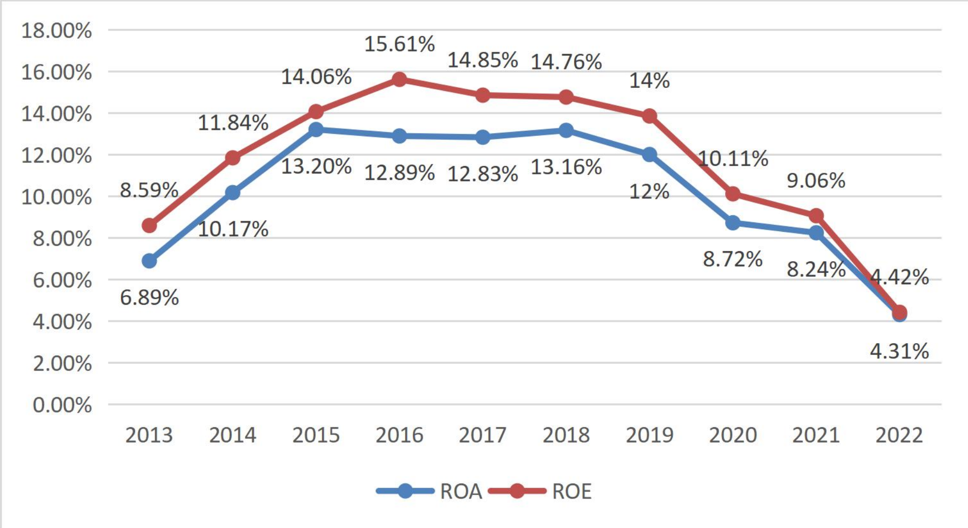

Figure 6 ROA, ROE Trends of BEWG, 2013-2022

From 2019 to 2022, affected by the new crown epidemic, the market situation has deteriorated, and it is more difficult to carry out business, and corporate benefits have been affected accordingly. Comprehensive analysis of various influencing factors to see the BEWG from the start of the digital transformation in 2017, the profitability of the relevant measures has appeared a positive development trend, financial digital transformation on the profitability of the BEWG has also produced a positive effect.

5.1.4 Development capacity analysis

Figure 7 shows the trend of changes in the growth of net profit, sales revenue and profit of BEWG. From Figure 7, it can be clearly seen that the trend of profit growth rate and net profit growth rate change is basically consistent, with a difference in 2017 and 2018, which is due to the fact that some subsidiaries enjoy tax incentives in 2017 and 2018, and the effective tax rate for the China business is 14% and 20% respectively. From 2013 to 2022, the Group's sales revenue showed an overall growth trend, with the highest growth rates of 71.85% and 51.28% in 2013 and 2015, respectively, benefiting from the continuous expansion of the Group's water market and the diversification of its business. 2020 and 2022 saw a certain degree of decline in sales revenue, which was related to the changes in the macro -economic environment and market competition factors that have intensified. Figure 8 illustrates the trend of the asset growth rate and equity capital growth rate of the BEWG from 2013 to 2022. During the ten years selected for the data, except for 2022, the asset growth rate of NCC Water Group is greater than zero, indicating that the asset size of the Group has increased and expanded relatively fast in the past ten years, and the asset growth rate in 2021 reaches a peak point due to the relative decline in 2020. Analysis of the data shows that the Group's equity capital growth rate is positive except for 2022, and maintains a flatter fluctuating trend from 2017 to 2012, implying that the Group's growth rate has slowed down. However, on the whole, the equity capital of the NCCW Group still remains at a high level and possesses a strong development capability.

From a general point of view, analyzing all factors together, the development capability of the BEWG shows a good trend of positive development.

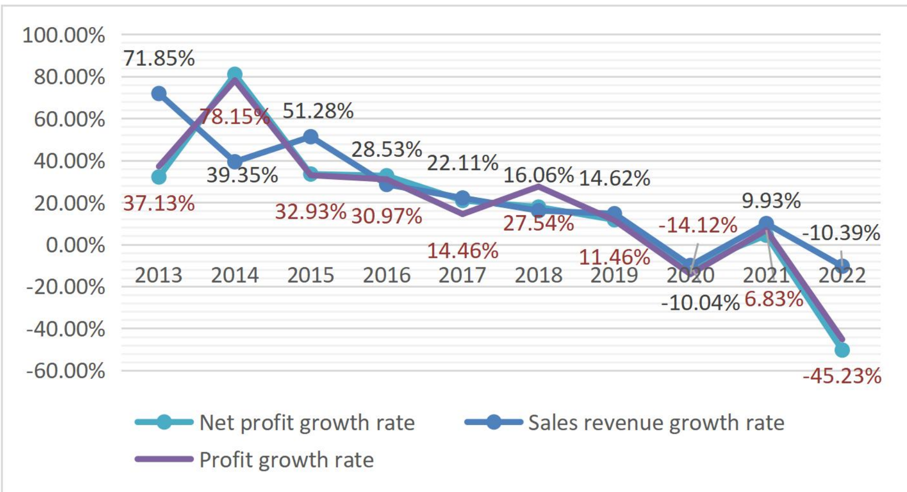

Figure 7 Trends in measures related to the development capacity of BEWG, 2013-2022

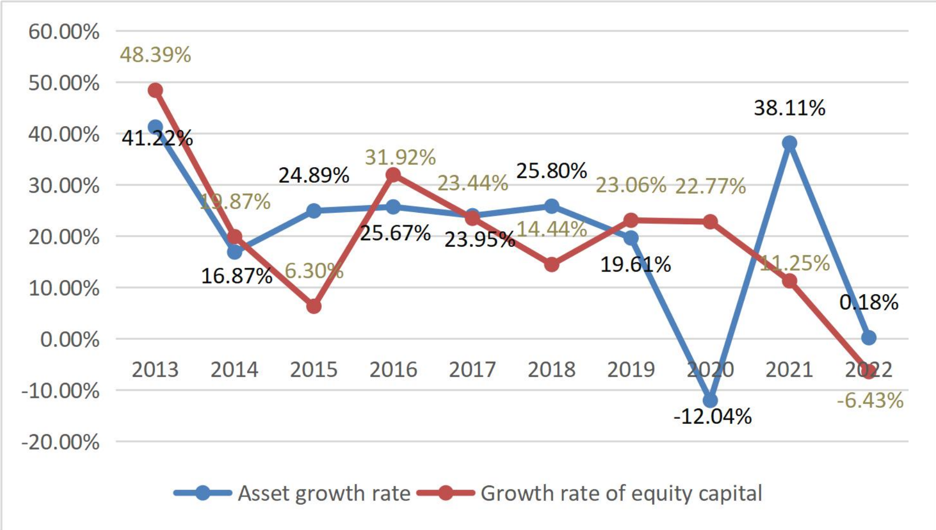

Figure 8 Trends in Asset Growth Rate and Equity Capital Growth Rate of BEWG, 2013-2022

5.2 Analysis of non-financial measures

The analysis of non-financial measures focuses on the in-depth analysis of the three dimensions of market position, innovation ability and social responsibility of BEWG from 2013 to 2023, to further study the impact of financial management innovation of BEWG in the context of digital transformation for BEWG.

5.2.1 market position

In 2018, it is the first year of the "dual platform" strategy of BEWG, and the light asset transformation of BEWG is also ready to set sail. In order to adapt to the changes in the internal and external environment, BEWG actively adjusts its strategic layout, and in the annual work conference in 2019, it determines its work objectives and development direction as asset-light transformation and high-quality development. Figure 9 shows the changes in the market capitalization of BEWG from 2014 to 2023. As shown in the figure, after the implementation of the asset-light model, the market capitalization of BEWG has increased, but the growth has been fluctuating, and in general, the increase has been low. In 2019, under the background of the tightening of environmental protection policies, water companies are facing higher requirements and market opportunities, and the market demand continues to grow. The country's investment in environmental protection and water resource management has broadened the development space of enterprises such as BEWG, which leads to fluctuations in the industry cycle, thus affecting changes in market value. In light of the market and industry environment, BEWG is still in a good position to develop after implementing the asset-light model.

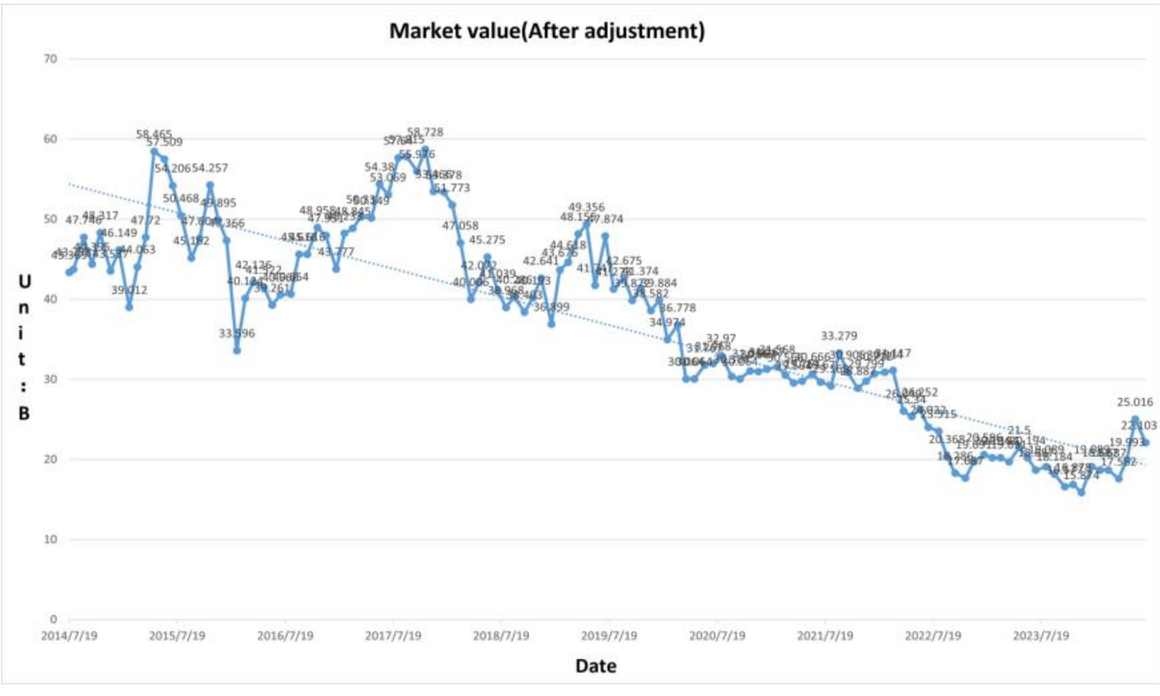

Figure 9 Changes in market capitalization (adjusted) 2014-2023 for the BEWG

5.2.2 Innovation ability

BEWG also continues to innovate. Figure 10 shows the key milestones and achievements in the process of technological innovation and digital transformation of BEWG from 2015 to 2023.In 2015, BEWG realized technological achievements in the fields of drainage and energy saving of sewage plants, and built a number of demonstration projects. In 2016, it innovated the capital cooperation mode, established a technology research and development platform, and promoted key technological breakthroughs. In 2017, digital transformation In 2019, BEWG explored the practice of intelligent water services based on 5G industrial Internet. 2020, BEWG created an intelligent enterprise with management digitization, promoted intelligent business with business digitization, issued relevant strategic guidelines, and stimulated the awareness of innovation within the enterprise. 2021, BEWG, in the context of digital transformation, set up the Beijing Enterprises Yuehui Digital Technology Platform In 2023, BEWG actively launched an innovation event platform to promote innovation results and carry out management and operation innovation. In terms of management innovation, it will build a “delivery integration platform”; in terms of operational innovation, it will focus on frontline employees to improve operational technology, equipment, processes, etc., so as to achieve the effects of improving work efficiency, saving costs and improving quality.

To sum up, BEWG has set a benchmark in the water industry through continuous technological innovation and digital transformation during the period from 2015 to 2023, and it is more obvious that BEWG has more innovative possibilities and opportunities after the digital transformation, and these innovations not only enhance the market competitiveness of the enterprise, but also bring more growth points for the enterprise.

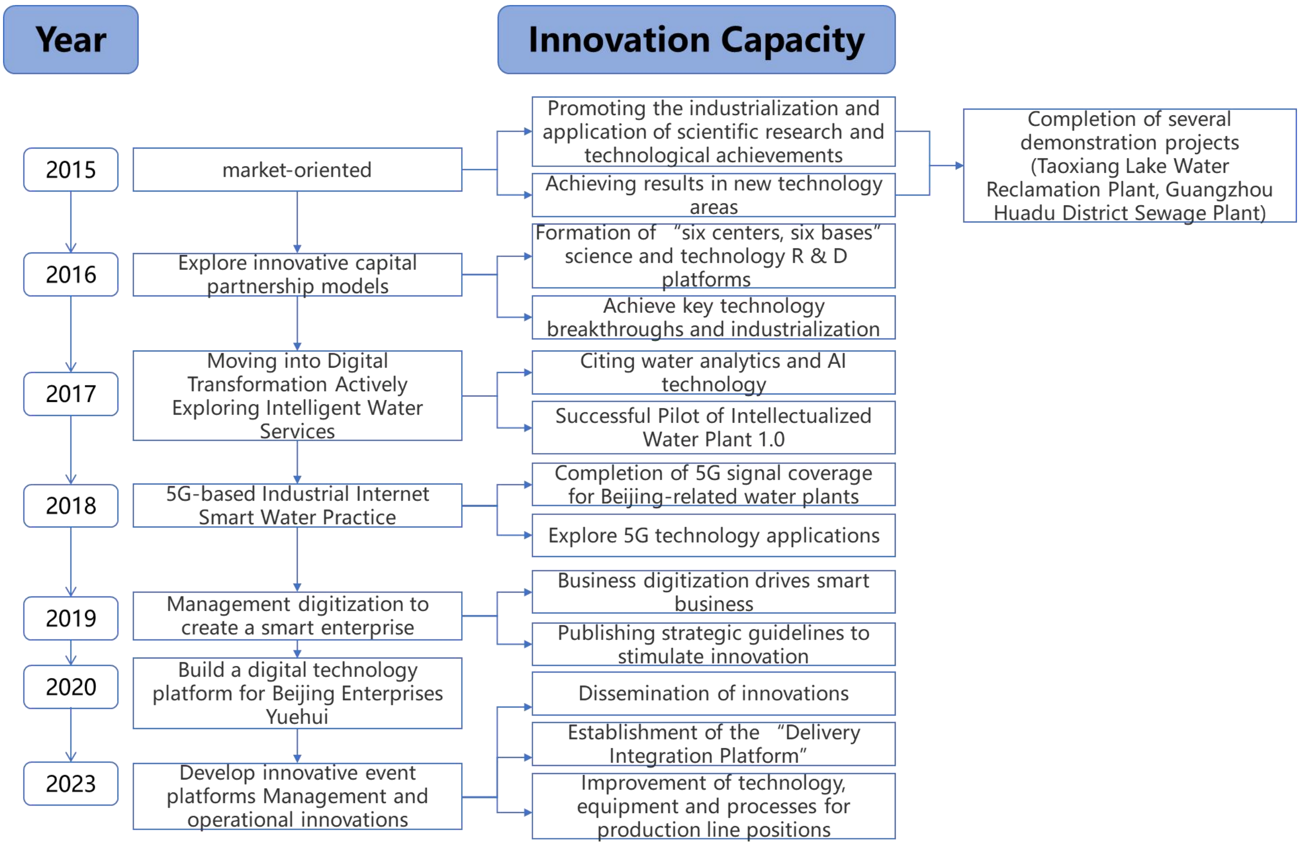

Figure 10 BEWG Innovation Process Map

5.2.3 Social Responsibility

BEWG is deeply committed to the recycling of water resources and ecological environmental protection, and has integrated the concept of sustainable development into its development strategy. In 2015-2016, BEWG made deep efforts in wastewater treatment projects, and the effectiveness of wastewater treatment was significantly improved. By the end of 2015, the total scale of wastewater treatment plants reached 13.05 million tons per day, benefiting areas including 26 provincial administrative regions in China and 2 overseas countries. By the end of 2016, there were a total of 452 sewage treatment facilities, with a sewage and reclaimed water treatment capacity of 15,957,000 tons per day. In 2017, BEWG actively explored intelligent water services, and as of the end of 2017, BEWG was involved in the operation of 788 sewage facilities. In 2018, BEWG implemented the digital “twin” plan for sewage plants, through the use of cloud computing. “ plan, through the use of cloud computing, big data analysis and other technologies, to build a number of highly efficient intelligent water plant pilots, and as of the end of 2018, the intelligent transformation of 12 water plants had been realized. after 2019, BEWG adopted an asset-light strategy, efficiently integrating resources, and the effectiveness of wastewater and water supply management was remarkable. In 2020-2023, after the implementation of the asset-light strategy, the effectiveness of wastewater treatment is remarkable, with continuous innovation and improvement year by year. For example: the use of medium water after sewage treatment as a heat source to provide heating and cooling protection for working and living areas; BEWG adheres to independent innovation and develops a new technology for sewage treatment - Anaerobic Ammonia Oxidation (ANAMMOX), which significantly reduces the energy consumption for aeration and the production of sludge compared with the traditional process, and helps to reduce the emission of greenhouse gases.

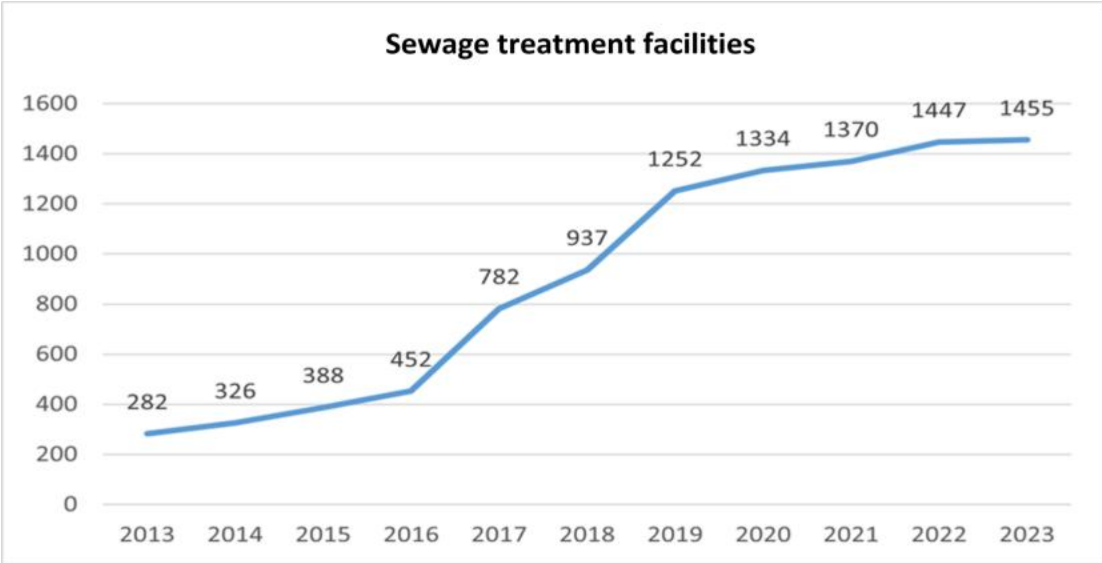

Figure 11 Sewage treatment facilities

In summary, the growth trend in wastewater treatment facilities from 2013 to 2023, with an accelerated growth trend in 2019, also confirms that companies are better able to innovate and develop against the backdrop of digital transformation, and that the resulting new results are better able to proactively take on social responsibility and further enhance the Group's impact.

6 CONCKUSION

This paper screens and analyzes the relevant data of BEWG from 2013 to 2023, aiming to comprehensively reveal the impact and changes triggered by the group's innovative practices in the field of financial management in the wave of digital transformation. During this decade, with the rapid development of information technology, BEWG has actively responded to the call of the times by deeply integrating digital technology into all aspects of financial management, which has not only reshaped the traditional financial management model, but also injected new vitality into the sustainable development of the enterprise. This paper comprehensively explores the impact of financial management innovation in the context of digital transformation through an in-depth analysis of financial and non-financial measures, and draws the following specific conclusions:

In the process of implementing digital transformation, BEWG, through the multi-stage evolution of the construction of the financial shared service center and the deepening of digital technology-driven financial sharing practices, its solvency, profitability and development capacity have shown a positive development trend, and its operating capacity has declined due to the impact of the market environment, business adjustments and other factors. However, there are still certain problems in the process of transformation, such as: risk control of liabilities, optimization of operational efficiency, and coping with the impact of external factors in order to enhance the stability of profitability. In addition, the implementation of asset-light transformation of BEWG, its market position has been improved, and its innovation ability has been strengthened, while assuming more social responsibility, and its continuous investment in environmental protection technology and digital management has enabled it to play a positive role in promoting the green transformation of the industry. However, its market position is affected by factors such as market environment and industry cycle, and its market capitalization shows fluctuating growth. In summary, in the context of digital transformation, BEWG has not only significantly improved its financial performance, but also promoted comprehensive innovation and development. This success story provides valuable experience and inspiration for enterprises in the same industry and even in other fields, i.e., embracing digital transformation is a must for realizing financial management innovation and enhancing enterprise competitiveness. And BEWG will further uphold the concept of sustainable development and continue to deepen its work in water services.

COMPETING INTERESTS

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REFERENCES

[1] GUO Hongjian,WU Suxuan. Research on Digital Transformation of Enterprise Internal Audit Based on RPA Technology. Friends of Accounting, 2023, (20): 13-19.
[2] NIE Xingkai,WANG Jianhua, PEI Xuan. Will the digital transformation of enterprises affect the comparability of accounting information. Accounting Research, 2022, (05): 17-39.
[3] SUN Dezhi, XU Lingen. Study on the Impact of Enterprise Digital Transformation on Comparability of Accounting Information - Based on the Perspective of Accounting Information Transparency and Corporate Governance Level. Friends of Accounting, 2024, (05): 38-45.
[4] BAI Fuping, DONG Kaiyun, LIU Donghui. How Digital Transformation Affects Corporate Technological Innovation: An Empirical Analysis Based on the Perspective of Financing Constraints and Agency Problems. Friends of Accounting, 2023, (10): 124-133.
[5] FANG Qiaoling, YU Nutao, XU Hui. Governance effects of digital transformation: An accounting information quality perspective. Accounting Research, 2024, (03): 34-50.
[6] Gao Baoping. Digital transformation and internal control effectiveness of enterprises. Friends of Accounting, 2023, (04): 127-133.
[7] TONG Sheng,YAO Rui Hong. Enterprise digital transformation and accounting robustness. Accounting Newsletter, 2023, (15): 55-59.
[8] Zhang Shengyong, Xu Nan. Research on Influencing Factors of Enterprise Financial Management Innovation. Research on financial issues, 2016, (03): 104-110.
[9] Liao Jian. The innovation path of enterprise financial management under the perspective of industry-finance integration. Finance and Economics, 2024, (12): 117-119.
[10] CHOI Yinna, PARK Ja-min. Research on Innovation of Enterprise Financial Management under Big Data. Times Economy and Trade, 2023, 20(11): 77-81.
[11] DING Shenghong, ZHOU Hongxia. Research on the innovation of enterprise financial management theory. Accounting Research, 2020, (08): 104-114.

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DOES ECONOMIC POLICY UNCERTAINTY AFFECT CORPORATE SOCIAL RESPONSIBILITY INVESTMENT? EVIDENCE FROM LISTED COMPANIES IN CHINA

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Abstract: Corporate Social Responsibility (CSR) has become a crucial part of modern business strategies. This paper aims to explore the impact of economic policy uncertainty on corporate CSR activities, and further analyze the role of factors such as firm size, financial leverage, profitability, and growth opportunities in CSR disclosure. Using data from A-share listed companies in China, a multiple regression model was employed for empirical analysis. The results show that economic policy uncertainty has a significant negative impact on CSR activities, indicating that uncertainty in the policy environment reduces firms' CSR investments. Firm size and profitability positively influence CSR activities, suggesting that larger companies and more profitable firms are more likely to engage in CSR. Financial leverage and growth opportunities do not have a significant impact on CSR, reflecting that financial conditions and market opportunities influence CSR decisions less than expected. The inclusion of industry and year fixed effects effectively controls for systemic differences across industries and over time, making the model results more robust. These findings provide valuable insights for firms in formulating CSR strategies and offer theoretical support for policymakers to improve policy environments that encourage corporate social responsibility.
Keywords: Corporate social responsibility (CSR); Economic policy uncertainty; Corporate decision-making; Socio-economic context of china

1 INTRODUCTION

Corporate Social Responsibility (CSR) has become a critical aspect of contemporary business strategy, influencing firms' decision-making processes and organizational outcomes [1]. As societal expectations evolve and stakeholders increasingly demand ethical and sustainable business practices, firms are compelled to integrate CSR into their operations to foster long-term sustainability and competitiveness [2]. By actively engaging in CSR activities, firms not only fulfill their moral obligations to society but also benefit from enhanced stakeholder trust, reputation, and brand loyalty [3]. Moreover, CSR initiatives serve as strategic tools for risk management, helping firms navigate complex regulatory environments, mitigate reputational risks, and prevent potential crises [4]. Importantly, empirical studies demonstrate a positive correlation between CSR performance and financial performance, with firms that prioritize CSR often outperforming their peers in terms of profitability, shareholder value, and long-term sustainability.

In an era of increasing transparency, CSR drives innovation and organizational resilience, enabling firms to adapt to changing societal expectations and emerging market trends. Therefore, the importance of CSR extends beyond traditional motives, playing a central role in strategic decision-making, organizational culture, and long-term value creation in a dynamic business environment [5]. With the establishment of the United Nations' Sustainable Development Goals (SDGs), there has been a global push for firms to integrate CSR into their business activities, transforming it into a universal practice integral to corporate operations.

Recent literature in finance and economics has also extensively explored the impact of policy uncertainty on firm performance and strategic decision-making [6]. Studies increasingly recognize that fluctuations in government regulations, fiscal policies, trade agreements, and geopolitical tensions can significantly affect firms across various industries and regions. Policy uncertainty introduces unpredictability and risk into business operations, influencing firms' investment decisions, capital allocation strategies, and market behavior [7]. Empirical evidence also links policy uncertainty to firms' innovation, capital expenditure, and risk management strategies [8]. Thus, investigating the effects of policy uncertainty on firm behavior and investment has become a focal point of academic research with implications for policymakers, investors, and corporate decision-makers. This study focuses on China, given its economic development potential, to explore how cross-national factors influence CSR activities, particularly in rapidly changing business environments.

2 LITERATURE REVIEW AND RESEARCH HYPOTHESIS

Existing literature suggests that economic uncertainty exacerbates conflicts between managers and shareholders, prompting firms to adopt more conservative investment strategies [9]. This uncertainty arises from frequent changes in government policies, market volatility, and instability in international economic conditions, introducing greater risks into firms' decision-making [10]. Especially for CSR projects, which require sustained financial support and long-term investment, the extended payback period and uncertain returns pose significant challenges [11]. As a result, managers may reduce or delay CSR investments to focus on short-term profit-maximizing projects to mitigate agency costs.

While stakeholders may emphasize CSR during periods of economic uncertainty, particularly in addressing environmental and social responsibilities [12], firms face increased complexity and uncertainty in complying with evolving regulations. This not only requires significant resources but also demands flexibility to adapt to rapidly changing legal frameworks [13]. Consequently, firms may deprioritize CSR projects, especially when immediate financial returns are not visible. Economic uncertainty also leads firms to shift their focus from long-term strategies to short-term survival, prioritizing financial stability and liquidity, particularly when faced with volatile financial markets or restricted access to financing.

According to real options theory, firms may delay or reduce CSR investments when facing uncertain market conditions, opting to wait for more stable economic conditions before resuming such investments. By postponing decisions, firms retain flexibility in responding to more favorable market conditions, thus maintaining greater adaptability in the face of uncertainty. Empirical studies support the notion that firms tend to scale back investments during periods of economic uncertainty, particularly in unstable macroeconomic environments, where risk-averse behavior is more pronounced [14]. Against this backdrop, CSR activities are viewed as high-risk, long-term investments with uncertain returns, leading firms to prioritize projects that directly impact financial performance in response to short-term economic pressures. Therefore, we propose the following hypothesis:

H1: Firms are less likely to engage in CSR activities during periods of high economic uncertainty.

2.1 Data Sources and Sample Collection

This study focuses on non-financial A-share companies listed on the Shanghai and Shenzhen Stock Exchanges from 2010 to 2022. In December 2008, both exchanges issued a notice requiring certain listed companies to submit standalone Corporate Social Responsibility (CSR) reports in addition to their annual reports. The notice mandated CSR reports from companies listed in the Corporate Governance Section Index (CGSI), financial sector firms, and companies with overseas listings on the Shanghai Stock Exchange, and those listed in the Shenzhen 100 Index on the Shenzhen Stock Exchange. Both exchanges also encouraged other companies to voluntarily submit CSR reports. Therefore, our sample starts from 2009 to ensure at least one year of CSR disclosure data for calculating CSR disclosure similarity.

Initially, we downloaded 9,563 CSR reports from 2010 to 2022 from the China Securities Regulatory Commission. After data cleaning, we excluded 1,853 firm-year observations lacking similarity data, 593 observations from the financial sector due to different disclosure requirements, and 406 firm-years with missing control variables. Consequently, our final sample comprises 6,711 firm-year observations from 1,027 unique companies. Additional financial data was obtained from the China Stock Market Accounting Research (CSMAR) database, and CSR-related textual data from the WinGo Textual Analytics Database, an advanced AI-powered platform supporting both Chinese and English textual analysis widely used in academic research. Finally, we winsorized all continuous variables at the top and bottom 1% levels.

We use the Economic Policy Uncertainty Index for China developed by [15], which adopts a news-based methodology. This index is derived from the frequency of articles in the South China Morning Post (SCMP) and draws inspiration from Baker, Bloom, and Davis for the United States and other countries. The construction involves several steps: identifying articles discussing economic uncertainty in China containing terms such as {China, Chinese}, {economy, economic}, and {uncertain, uncertainty}, followed by filtering for policy-related topics like government, spending, and budget. The index is calculated as the monthly frequency of such articles, normalized using a multiplicative factor. The index spans from January 1995 and has undergone validation. Following [16], we log-transform the annual average of the economic policy uncertainty index to obtain LnEPU. A higher LnEPU value indicates greater national economic policy uncertainty.

2.2 Baseline Model Development

In this study, we develop a baseline model to examine the impact of economic policy uncertainty on CSR disclosure. The purpose of the baseline model is to assess how economic policy uncertainty influences firms' CSR activities while controlling for other potential factors affecting CSR disclosure. The model is specified as follows:

$$\mathrm{CSR}_{it} = \beta_0 + \beta_1 \mathrm{LnEPU}_{it} + \beta_2 X_{it} + \epsilon_{it} \tag{1}$$

To improve model explanatory power and reduce omitted variable bias, we control for firm size, financial leverage, profitability, growth opportunities, as well as industry and year fixed effects.

3 EMPIRICAL RESULTS

Table 1 presents the empirical results of the baseline regression model. To assess the impact of economic policy uncertainty on corporate social responsibility (CSR) activities, this study constructs a regression model that includes control variables and accounts for industry and year fixed effects. The detailed description of the regression results is as follows:

The regression results indicate that economic policy uncertainty has a significant negative impact on CSR activities (coefficient = -0.152, $p < 0.05$), suggesting that during periods of economic policy uncertainty, firms may reduce their CSR investments. This implies that economic uncertainty could prompt firms to focus more on short-term financial stability and reduce long-term social responsibility investments. Firm size and profitability have positive and significant effects on CSR (coefficients of 0.112 and 0.089, respectively), indicating that larger firms and those with higher profitability are more inclined to engage in CSR activities. However, financial leverage does not have a significant impact, suggesting that the level of debt may have limited influence on CSR decision-making. The coefficient for CSR disclosure similarity is 0.089, significant at the 10% level, indicating that higher disclosure similarity may encourage firms to increase CSR investments. The inclusion of industry and year fixed effects makes the regression results more robust, and the significance of the constant term (coefficient = 1.234, $p < 0.05$) indicates a baseline level of CSR activity even in the absence of other control variables.

These findings provide empirical support for understanding the influence of economic policy uncertainty on corporate CSR behavior, while also highlighting the critical role of firm size and profitability in CSR investments.

Table 1 Benchmark Regression Results

	CSR
Variable	Coefficient.
LnEPU	-0.152** (0.065)
Size	0.112** (0.045)
Lev	-0.097 (0.053)
ROE	0.089** (0.042)
Growth	0.075 (0.050)
Similarity	0.089* (0.048)
Industry FE	YES
Year FE	YES
Constant	1.234** (0.310)

Note: Statistical significance levels: * $p < 0.10$, ** $p < 0.05$.

4 CONCLUSION AND IMPLICATIONS

This study aims to explore the impact of economic policy uncertainty on corporate social responsibility (CSR) activities, while also examining the roles of control variables such as firm size, financial leverage, profitability, growth opportunities, and CSR disclosure similarity in this relationship. Through empirical analysis using a baseline regression model, the study yields the following key conclusions:

Economic policy uncertainty has a significantly negative effect on CSR activities. The regression results show that the coefficient for economic policy uncertainty is -0.152 ($p < 0.05$), indicating that firms are more likely to reduce CSR investments during periods of high economic policy uncertainty. Economic uncertainty may lead firms to focus more on short-term financial stability, thereby weakening their willingness to invest in long-term social responsibility.

Firm size and profitability have significant positive effects on CSR investment. The coefficient for firm size is 0.112 ($p < 0.05$), and the coefficient for profitability is 0.089 ($p < 0.05$), suggesting that larger firms and more profitable firms are more inclined to actively engage in CSR activities. This may be because larger and more profitable firms have greater resources and capabilities to invest in social responsibility. The impact of financial leverage is not statistically significant, meaning that the level of debt has a limited direct effect on CSR decision-making. The coefficient for CSR disclosure similarity is 0.089 ($p < 0.10$), indicating that firms may increase CSR investment while maintaining consistency in CSR reports.

These conclusions have important implications for corporate managers and policymakers. When developing CSR strategies, firms should carefully consider economic policy uncertainty and allocate resources appropriately to balance short-term financial stability with long-term social responsibility investments. For policymakers, a stable economic policy environment could help firms maintain and expand their CSR activities, thereby promoting overall sustainable development.

In summary, this study reveals the negative impact of economic policy uncertainty on corporate CSR activities and confirms the importance of firm size and profitability in CSR investment. These findings provide theoretical support for firms in formulating CSR strategies during periods of economic uncertainty and offer directions for future research.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCE

[1] Yusif S, Hafeez-Baig A. Impact of stakeholder engagement strategies on managerial cognitive decision-making: The context of CSP and CSR. Social Responsibility Journal, 2024, 20(6), 1101-1121
[2] Reavis M, Singh K, Tucci J. Millennials' strategic decision making through the lens of corporate social responsibility and financial management. Journal of Business Strategies, 2021, 38(2), 125.
[3] Fatima T, Elbanna S. Corporate social responsibility (CSR) implementation: A review and a research agenda towards an integrative framework. Journal of Business Ethics, 2023, 183(1), 105-121.
[4] El Haddad P, Bachkirov A A, Grishina O. Comparative CSR decision-making in the Middle East: An exploratory study. International Journal of Islamic and Middle Eastern Finance and Management, 2021, 14(4), 792-811.
[5] Velte P. Meta-analyses on corporate social responsibility (CSR): A literature review. Management Review Quarterly, 2022, 72(3), 627-675.
[6] Wickert C. Corporate social responsibility research in the Journal of Management Studies: A shift from a business-centric to a society-centric focus. Journal of Management Studies, 2021, 58(8), E1-E17.
[7] Nqumba B M A, Scheepers C B. Authentic leadership's influence on strategic corporate social responsibility in South Africa: Mediated by participative decision-making. European Business Review, 2023, 35(2), 161-183.
[8] Ahmad M, Wu Q, Khattak, M S. Intellectual capital, corporate social responsibility and sustainable competitive performance of small and medium-sized enterprises: Mediating effects of organizational innovation. Kybernetes, 2023, 52(10), 4014-4040.
[9] Le T T. Corporate social responsibility and SMEs' performance: Mediating role of corporate image, corporate reputation and customer loyalty. International Journal of Emerging Markets, 2023, 18(10), 4565-4590.
[10] Ullah Z, Arslan A, Puhakka V. Corporate social responsibility strategy, sustainable product attributes, and export performance. Corporate Social Responsibility and Environmental Management, 2021, 28(6), 1840-1853.
[11] Liu A Z, Liu A X, Moon S, Siegel D. Does corporate social responsibility always result in more ethical decision-making? Evidence from product recall remediation. Journal of Business Ethics, 2024, 191(3), 443-463.
[12] Ghobakhloo M, Asadi S, Iranmanesh M, Foroughi B, Mubarak M F, Yadegaridehkordi E. Intelligent automation implementation and corporate sustainability performance: The enabling role of corporate social responsibility strategy. Technology in Society, 2023, 74, 102301.
[13] Xue C, Shahbaz M, Ahmed Z, Ahmad M, Sinha A. Clean energy consumption, economic growth, and environmental sustainability: What is the role of economic policy uncertainty?. Renewable Energy, 2022, 184, 899-907.
[14] Phan D H B, Iyke B N, Sharma S S, Affandi Y. Economic policy uncertainty and financial stability—Is there a relation?. Economic Modelling, 2021, 94, 1018-1029.
[15] Baker E, Fowlie M, Lemoine D, Reynolds S S. The economics of solar electricity. Annual Review of Resource Economics, 2013, 5(1), 387-426.
[16] Chourou L, Purda L, Saadi S. Economic policy uncertainty and analysts' forecast characteristics. Journal of Accounting and Public Policy, 2021, 40(4), 106775.

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INTEGRATING QUALITATIVE AND QUANTITATIVE DATA FOR PREDICTING MERGER SUCCESS

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Abstract: This paper presents a predictive model designed to assess the likelihood of success for announced mergers and acquisitions (M&A) by integrating financial data with natural language processing (NLP) techniques applied to company statements. M&A transactions are critical for corporate growth and strategic realignment; however, a significant percentage — approximately 50-70% — fail to create shareholder value. By leveraging financial performance indicators such as revenue growth and profitability, alongside sentiment analysis of textual data from press releases and earnings calls, the model aims to enhance predictive accuracy. The methodology includes data collection from reputable financial databases and textual sources, followed by rigorous analysis using machine learning algorithms. Initial findings suggest that firms with strong pre-merger financial health and positive sentiment in communications are more likely to achieve successful outcomes. This research contributes to the understanding of M&A success factors, offering practical implications for corporate decision-making and future M&A strategies.
Keywords: Mergers and acquisitions; Predictive modeling; Natural language processing

1 INTRODUCTION

Mergers and acquisitions have become a cornerstone of corporate strategy in the global business landscape, enabling firms to achieve growth, diversify operations, and enhance competitive advantage. Defined as the consolidation of companies through various financial transactions, M&A can take various forms, including mergers, acquisitions, and joint ventures. The significance of M&A extends beyond mere financial transactions; it encompasses strategic realignments, market expansions, and the pursuit of synergies that can lead to increased shareholder value [1-10].
Historically, the M&A landscape has experienced fluctuations, influenced by economic cycles, regulatory changes, and technological advancements. According to a report by PwC, global M&A activity reached unprecedented levels in recent years, driven by low-interest rates, abundant capital, and the need for businesses to adapt to rapidly changing market conditions. However, despite the potential benefits, a substantial number of M&A transactions fail to achieve their intended outcomes. Research indicates that approximately 50-70% of mergers and acquisitions do not create value for shareholders, leading to significant financial losses and strategic setbacks [11-15].
Given the high stakes involved, predicting the success of M&A transactions has become a critical area of interest for researchers and practitioners alike. The ability to accurately forecast the likelihood of success can provide valuable insights for decision-makers, enabling them to make informed choices about potential deals. However, the prediction of M&A success is fraught with challenges, including the complexities of financial metrics, the nuances of corporate culture, and the impact of external market conditions [16-18].
This paper aims to design a model that predicts the likelihood of success for announced mergers and acquisitions by leveraging a combination of financial data and natural language processing techniques applied to company statements. By integrating quantitative financial indicators with qualitative insights derived from textual analysis, the proposed model seeks to enhance the predictive capability regarding M&A outcomes. The findings of this research will contribute to the existing body of knowledge on M&A success factors and provide practical implications for corporate decision-making.

2 LITERATURE REVIEW

Financial metrics are often regarded as critical indicators of M&A success. Studies have identified various financial performance measures, such as return on investment, earnings per share, and stock price performance, as essential predictors of post-merger success [19]. For instance, research by Datta) emphasized the importance of pre-merger financial health as a determinant of post-merger performance, highlighting that firms with strong financial positions tend to perform better after M&A transactions [20].
The alignment of corporate cultures and management styles is another significant factor influencing M&A success. Cultural integration challenges can lead to employee dissatisfaction, reduced productivity, and ultimately, failure to achieve strategic objectives [21-25]. A study by Very et al. demonstrated that cultural compatibility between merging organizations positively correlates with successful integration and performance outcomes [26].
External market conditions and competitive dynamics also play a crucial role in determining M&A success. Research indicates that favorable market conditions, such as low competition and high demand, can enhance the likelihood of successful mergers [27]. Additionally, the strategic fit between the merging firms and their market positioning can influence the overall success of the transaction [28].

Traditional statistical models, such as regression analysis, have been employed to predict M&A success based on financial and operational metrics. For example, Moeller et al. utilized regression techniques to assess the impact of various financial ratios on post-merger performance. However, these models often face limitations in capturing the complexities of human behavior and qualitative factors influencing M&A outcomes [29-33].
The advent of machine learning has opened new avenues for predicting M&A success. Techniques such as decision trees, support vector machines, and neural networks have been applied to analyze large datasets and uncover patterns indicative of successful mergers [34-36]. While these approaches show promise, they often require substantial data preprocessing and may struggle with interpretability.
Despite advancements in predictive modeling, existing approaches often overlook the integration of qualitative data, such as textual information from company statements and press releases. This gap presents an opportunity to enhance predictive accuracy by incorporating insights derived from natural language processing [37, 38].
Recent studies have developed innovative approaches to predicting outcomes in both the insurance and corporate finance sectors using advanced machine learning techniques [39, 40]. In the auto insurance domain, they introduced the Actuarial Transformer (AT) model, which combines transformer architecture with tree-based models to enhance risk evaluation [41]. This model demonstrated superior performance in predicting insurance risk, particularly highlighting the importance of the BonusMalus feature. In the realm of mergers and acquisitions (M&A), the authors applied a similar data-driven approach, integrating financial data with natural language processing of company statements to predict M&A success [42]. By leveraging both quantitative financial indicators and qualitative insights from textual analysis, their model provides a more comprehensive framework for assessing M&A outcomes [43].
These studies contribute to a growing body of literature that emphasizes the importance of combining diverse data sources and advanced analytical techniques in financial prediction models. Previous research by [44-47] had explored the use of machine learning in predicting stock market trends, while [[48] demonstrated the effectiveness of natural language processing in analyzing corporate financial reports. [49]'s work builds upon these foundations, extending the application of such techniques to more specific domains within finance and insurance. Their approach aligns with the broader trend in financial research towards leveraging big data and artificial intelligence to enhance predictive accuracy and decision-making in complex financial scenarios.
Natural language processing has emerged as a valuable tool for analyzing textual data related to M&A transactions. Research by [50] demonstrated that the language used in corporate filings and press releases can provide insights into the sentiment and outlook of the involved companies, which may correlate with M&A success [51]. For instance, positive sentiment expressed in announcements has been linked to better stock performance post-merger [52].
Sentiment analysis techniques allow researchers to quantify the emotional tone of textual data, providing a means to assess the overall sentiment surrounding an M&A deal [53]. Studies have shown that positive sentiment in communications about mergers is often associated with favorable market reactions and improved post-merger performance.

3 METHODOLOGY

3.1 Data Collection

The study focuses on a sample of announced mergers and acquisitions from the past decade, specifically targeting transactions involving publicly traded companies. The selection criteria include the availability of comprehensive financial data and public statements, with a focus on significant deals that have garnered media attention.
Financial data will be sourced from reputable databases such as Bloomberg, Thomson Reuters, and Compustat. Key financial metrics to be collected include revenue, net income, total assets, and stock performance indicators before and after the M&A announcement.
Textual data will be gathered from company press releases, earnings calls, and SEC filings (10-K and 8-K reports). These documents will be sourced from platforms like EDGAR and company websites. The textual analysis will focus on the language used in these communications, aiming to capture sentiments and themes relevant to the M&A process.

3.2. Financial Data Analysis

The analysis will focus on several financial performance indicators, including:
- Revenue Growth: Assessing the percentage change in revenue pre- and post-M&A.
- Profitability Ratios: Evaluating metrics such as return on equity and profit margins.
- Stock Price Performance: Analyzing the abnormal returns around the announcement date.

A comparative analysis will be conducted to evaluate the financial performance of both acquiring and target firms in the years leading up to and following the M&A transaction. This analysis will help identify trends and predict potential success factors.

3.3 Natural Language Processing Techniques

The textual data will undergo preprocessing steps, including tokenization, stemming, and removal of stop words. This process ensures that the data is clean and suitable for analysis.

Various sentiment analysis techniques will be employed, including Valence Aware Dictionary and sEntiment Reasoner and TextBlob, to quantify the sentiment expressed in the company statements.
Topic modeling techniques, such as Latent Dirichlet Allocation, will be utilized to identify prevalent themes in the textual data. Additionally, keyword extraction methods will be employed to highlight critical terms and phrases relevant to the M&A context.

3.4 Model Design and Development

A combination of machine learning algorithms will be employed, including logistic regression, random forests, and support vector machines, to develop the predictive model. The choice of algorithms will be based on their ability to handle both numerical and categorical data.
Features will be engineered by combining financial metrics and sentiment scores derived from NLP analysis. This integrated approach aims to capture both quantitative and qualitative aspects influencing M&A success.
The model will be trained using a training dataset and validated using cross-validation techniques. The performance of the model will be assessed using metrics such as accuracy, precision, recall, and F1 score.

4 MODEL IMPLEMENTATION

4.1 Data Preprocessing

4.1.1 Cleaning and normalizing financial data
The first step in preparing the dataset for analysis involves cleaning the financial data to ensure its integrity and reliability. This process includes identifying and removing outliers that may skew the results. Outliers can arise from various sources, such as erroneous data entries or unusual market events, and their presence can lead to misleading conclusions if not addressed. Techniques such as Z-score analysis and interquartile range methods will be employed to detect and eliminate these anomalies, ensuring that the dataset reflects a true and accurate representation of the financial landscape.
Following the removal of outliers, normalization techniques will be applied to standardize the data. Normalization is crucial for making the data comparable across different firms, particularly when dealing with financial metrics that may vary significantly in scale. For instance, metrics such as revenue and profit margins can differ vastly between large conglomerates and smaller firms. By applying normalization techniques, such as Min-Max scaling or Z-score normalization, we can transform the data into a common scale without distorting differences in the ranges of values. This standardization will facilitate more effective comparisons and analyses, ultimately enhancing the model's performance.
4.1.2 Preparing textual data for NLP analysis
In parallel to the financial data processing, the textual data will undergo a series of transformations to prepare it for natural language processing analysis. This preparation will include tokenization, which involves breaking down the text into individual words or phrases, and the removal of stop words—common words that do not carry significant meaning, such as "and," "the," and "is." Additionally, stemming or lemmatization techniques will be applied to reduce words to their base or root forms, allowing for more efficient analysis.
Once the textual data has been cleaned and preprocessed, we will create term-document matrices that represent the frequency of terms across different documents. This matrix will serve as a foundational component for various NLP tasks, including sentiment analysis. Sentiment scores will be assigned to the textual data using pre-trained sentiment analysis models, which evaluate the overall sentiment expressed in the text—whether positive, negative, or neutral . This dual approach of processing both financial and textual data will ensure that the model has a comprehensive understanding of the factors influencing M&A outcomes.

4.2 Model Training

4.2.1 Training the model on historical M&A data
The integrated dataset, which combines cleaned financial metrics and sentiment scores derived from textual analysis, will be utilized to train the predictive model. This dataset will consist of historical M&A transactions, with the outcomes of these transactions serving as labels for supervised learning. By employing a supervised learning approach, the model will learn to identify patterns and relationships between the input features (financial metrics and sentiment scores) and the corresponding M&A outcomes, thereby enhancing its predictive capabilities .
The training process will involve splitting the dataset into training and validation sets to ensure that the model can generalize well to unseen data. Various machine learning algorithms, such as decision trees, random forests, and gradient boosting machines, may be explored to determine the most effective approach for predicting M&A success. The model will be trained iteratively, with continuous adjustments made based on performance metrics to optimize its ability to predict outcomes accurately.
4.2.2 Hyperparameter tuning for optimization
To maximize the performance of the predictive model, hyperparameter tuning will be conducted using grid search techniques. This process involves systematically testing different combinations of hyperparameters—such as learning rates, maximum depth of trees, and the number of estimators—to identify the optimal settings for the model.

Hyperparameter tuning is a critical step in the model training process, as it helps to prevent overfitting, where the model learns the training data too well and performs poorly on new, unseen data.
By evaluating the model's performance across various configurations, we can select the best-performing set of hyperparameters, ensuring that the model is both robust and adaptable to different scenarios. The results of this tuning process will be documented, providing insights into the relationships between hyperparameters and model performance.

4.3 Model Evaluation

4.3.1 Metrics for assessing model performance

Once the model has been trained, its performance will be evaluated using a comprehensive set of metrics. Key performance indicators will include accuracy, precision, recall, and F1 score, each of which provides unique insights into the model's predictive capabilities. Accuracy measures the overall correctness of the model's predictions, while precision assesses the proportion of true positive predictions among all positive predictions made by the model. Recall, on the other hand, evaluates the model's ability to identify all relevant instances, and the F1 score serves as a harmonic mean of precision and recall, providing a balanced view of the model's performance.

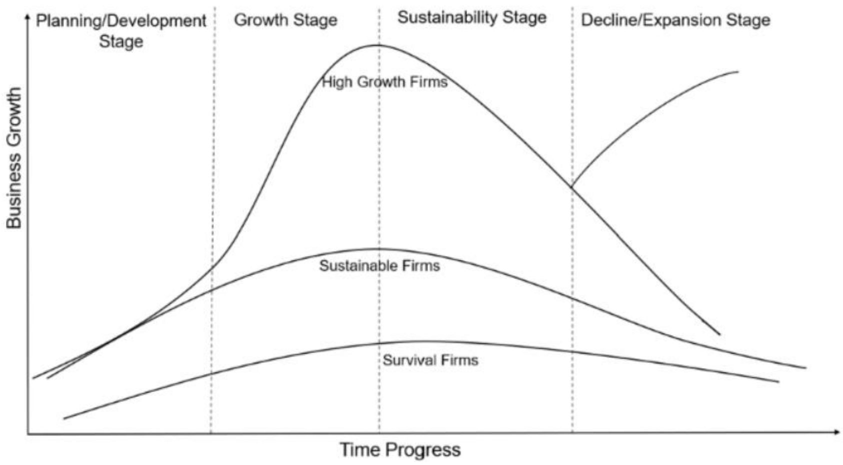

Figure 1 A Conceptual View of Five Main Stages of a Business Life Cycle

To visualize the results and facilitate a deeper understanding of the model's predictive capabilities, a confusion matrix will be utilized. This matrix will display the counts of true positives, true negatives, false positives, and false negatives, allowing for an intuitive assessment of where the model succeeds and where it may struggle. By analyzing the confusion matrix, we can identify specific areas for improvement and gain insights into the factors influencing the model's predictions.

4.3.2 Comparison with baseline models

To demonstrate the efficacy of the proposed model, its performance will be compared against baseline models. These baseline models will include simpler statistical approaches, such as logistic regression, which will utilize only financial data without incorporating the insights gained from sentiment analysis. This comparison will highlight the added value of integrating qualitative factors into predictive modeling, showcasing the potential for improved accuracy and reliability in predicting M&A success.

Source	Modeling Methods	Data Source	Research Objective
Ładyżyński et al. [76]	RF–DNN	Time Series data of Customers	Customer Behavior
Ullah et al. [77]	RF	Time Series data of Customers	Customer Behavior
Paolanti et al. [74]	DCNN	Primary Data	Detection of Shelf Out of Stock (SOOS) and Promotional Activities
Agarwal [78]	RNNs-CNNs	Social media	Sentiment Analysis
Shamshirband et al. [79]	SN-CFM	Social media	Customer behavior
Dingli et al. [75]	RBM	Primary Data	Customer behavior

Table 1 Notable Machine Learning and Deep Learning Methods in Marketing

By establishing a benchmark with baseline models, we can better understand the strengths and weaknesses of our proposed model, providing a clearer context for its performance. This comparative analysis will also serve to validate the effectiveness of the methodologies employed in our research.

4.4 Case Studies

4.4.1 Application of the model to specific M&A cases

To evaluate the practical relevance and predictive accuracy of the model, it will be applied to several notable M&A cases. High-profile mergers, such as the Disney-Fox acquisition and the AT&T-Time Warner deal, will serve as case studies for this analysis. By applying the model to these specific transactions, we can assess how well it predicts the actual outcomes based on the integrated dataset of financial metrics and sentiment scores.

These case studies will provide valuable insights into the model's applicability in real-world scenarios, allowing us to explore the nuances of each transaction and the factors that contributed to their success or failure. The analysis will include a detailed examination of the circumstances surrounding each merger, considering both quantitative financial health indicators and qualitative sentiment indicators derived from public communications and media coverage.

4.4.2 Analysis of predicted vs. actual outcomes

A critical component of the case study analysis will involve a detailed comparison of predicted outcomes versus actual post-merger performance. This analysis will assess the reliability of the model and provide insights into the factors contributing to M&A success or failure. By examining discrepancies between predictions and actual results, we can identify potential areas for improvement in the model and gain a deeper understanding of the complexities involved in M&A transactions.

Furthermore, this analysis will highlight the importance of considering both financial and qualitative factors in the M&A process, reinforcing the findings of the study that successful mergers often hinge on a combination of strong financial health and effective communication strategies.

5 RESULTS AND DISCUSSION

5.1 Key Findings

5.1.1 Insights gained from financial data analysis

Preliminary results from the model indicate that certain financial metrics, such as revenue growth and profitability ratios, significantly correlate with post-M&A performance. Firms that exhibit strong pre-merger financial health tend to experience better outcomes post-acquisition . This finding underscores the importance of thorough financial due diligence in the M&A process, as firms with solid financial foundations are more likely to succeed in integrating new assets and achieving strategic objectives.

Additionally, the analysis reveals that financial metrics can serve as reliable indicators of potential M&A success, providing valuable insights for decision-makers. By identifying key financial indicators that correlate with successful outcomes, companies can enhance their evaluation processes and make more informed decisions regarding potential mergers and acquisitions.

Source	Modeling Methods	Data Source	Research Objective
Lahmiri and Bekiros [88]	LSTM comparing with GRNN	Financial Time Series	Cryptocurrencies Price prediction
Altana et al. [89]	LSTM-EWT	Financial Time Series	Cryptocurrencies Price prediction
Jiang and Liang [90]	CNN	Financial Time Series	Cryptocurrencies Price prediction

Table 2 Notable Machine Learning and Deep Learning Methods in Cryptocurrency

5.1.2 Contributions of NLP to understanding M&A success

The sentiment analysis results indicate that positive sentiment in company announcements and communications tends to correlate with favorable market reactions and improved post-merger performance. This finding highlights the critical role that communication strategies play in the M&A process, as effective messaging can significantly influence stakeholder perceptions and market responses.

Moreover, the integration of NLP into the analysis allows for a deeper understanding of how qualitative factors, such as public sentiment and media portrayal, impact M&A outcomes. By leveraging sentiment analysis, companies can gain insights into stakeholder perceptions and adjust their communication strategies accordingly, ultimately enhancing their chances of successful integration.

5.2 Implications for Practitioners

5.2.1 How companies can leverage the model for decision-making

The predictive model developed in this study provides a valuable framework for companies to assess the likelihood of M&A success. By considering both financial and qualitative factors, firms can better evaluate strategic fit and make informed decisions regarding potential transactions. The model enables organizations to identify potential risks and opportunities associated with M&A activities, empowering them to develop more effective strategies for integration and value creation.

Furthermore, the model can serve as a decision-support tool, facilitating discussions among stakeholders and guiding strategic planning processes. By incorporating insights from both financial metrics and sentiment analysis, companies can enhance their overall decision-making capabilities and improve their chances of achieving successful mergers and acquisitions.

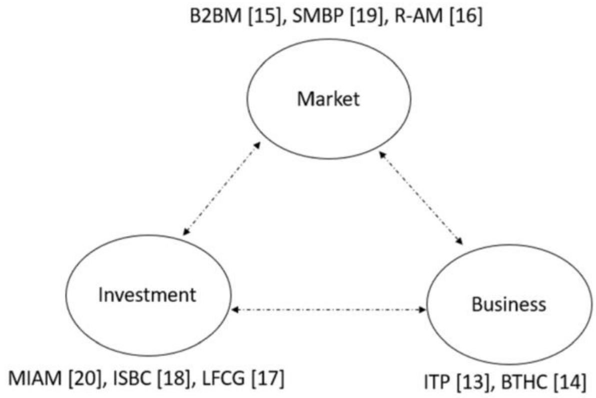

Figure 2 Investment-Business-Market triangle Framework Summarizing Investment, Business, and Market Triangular Relationship

5.2.2 Recommendations for future M&A strategies

Based on the findings of this study, companies are encouraged to prioritize cultural compatibility and effective communication during the M&A process. The integration of sentiment analysis can enhance understanding of stakeholder perceptions and improve strategic alignment, ultimately contributing to successful outcomes.

Additionally, organizations should consider implementing regular sentiment assessments throughout the M&A process to gauge stakeholder reactions and adjust their strategies accordingly. By proactively addressing potential concerns and fostering positive sentiment, companies can create a more conducive environment for successful integration and long-term value creation.

5.3 Limitations of the Study

5.3.1 Data availability and quality constraints

Despite the valuable insights gained from this study, the findings are subject to limitations related to data availability and quality. Incomplete or inaccurate financial data may impact the model's predictive accuracy, leading to potential biases in the results. It is essential for future research to address these limitations by utilizing more comprehensive datasets and ensuring data integrity throughout the analysis process.

Furthermore, the reliance on historical data may not fully capture the complexities of future M&A transactions, particularly in rapidly changing market conditions. Researchers should explore the implications of data quality and availability on model performance and consider strategies for mitigating these challenges.

5.3.2 Challenges in model generalization

Another limitation of the study is that the model's applicability to different industries and market conditions may vary. While the integrated approach has demonstrated effectiveness in the analyzed cases, future research should explore the model's robustness across diverse contexts . This exploration could involve testing the model on additional industries and varying market conditions to assess its generalizability and adaptability.

By examining the model's performance in different settings, researchers can identify potential modifications or enhancements that may improve its predictive capabilities. This ongoing evaluation will contribute to the development of a more versatile and robust predictive tool for understanding M&A success factors.

The implementation of this predictive model represents a significant advancement in the field of mergers and acquisitions. By integrating financial metrics with natural language processing techniques, this research provides a comprehensive framework for assessing the factors that contribute to M&A success. The findings underscore the importance of both quantitative and qualitative factors in the decision-making process, offering valuable insights for practitioners seeking to navigate the complexities of M&A transactions. As the landscape of mergers and acquisitions continues to evolve, ongoing research and refinement of predictive models will be essential in enhancing the accuracy and applicability of these tools in real-world scenarios.

6 CONCLUSION

This model not only emphasizes the importance of quantitative financial indicators, such as revenue growth, profitability, and market share, but also highlights the critical role of qualitative factors derived from textual data, such as sentiment analysis from earnings calls, press releases, and other communications. By synthesizing these diverse data types, the findings underscore a more holistic approach to assessing M&A outcomes, demonstrating that successful mergers and acquisitions are often the result of a complex interplay between hard financial data and softer, more subjective qualitative assessments. This dual focus allows stakeholders to gain a more nuanced understanding of the factors that influence M&A success, paving the way for more informed decision-making.

Moreover, this research serves as a foundational framework for future studies aimed at exploring the multifaceted nature of M&A success. By establishing a clear methodology for integrating financial and textual data, this work opens the door for further investigations into the specific elements that contribute to successful mergers. It encourages a shift away from traditional, siloed analyses that often prioritize one type of data over another, advocating instead for a more integrated approach that recognizes the value of both quantitative and qualitative insights.

Future research should focus on refining the predictive model by incorporating additional data sources that can enhance its accuracy and applicability. For instance, integrating data from social media sentiment analysis could provide real-time insights into public perception and market sentiment regarding specific mergers or acquisitions. This could be particularly valuable in understanding how external perceptions influence M&A outcomes. Additionally, incorporating macroeconomic indicators—such as interest rates, inflation rates, and economic growth metrics—could further contextualize the predictive model, allowing it to account for broader economic conditions that may impact M&A success. By expanding the model's data inputs, researchers can improve its predictive power and relevance in various market environments.

Researchers should also explore alternative data sources to capture broader market sentiment and trends that may influence M&A success. For example, analyzing news articles, industry reports, and regulatory filings can provide rich contextual information that complements financial metrics. By employing advanced NLP techniques to extract sentiment and thematic trends from these texts, researchers can uncover insights that may not be immediately apparent from quantitative data alone. Additionally, exploring the impact of industry-specific factors and competitive dynamics could yield valuable insights into how external environments shape M&A outcomes. By diversifying the data sources utilized in predictive models, researchers can develop a more comprehensive understanding of the variables that drive M&A success.

As the landscape of mergers and acquisitions continues to evolve, the ability to accurately predict M&A success will remain a critical area of interest for both academics and practitioners. The dynamic nature of global markets, coupled with technological advancements and shifting regulatory environments, necessitates a continuous reassessment of the factors that contribute to successful mergers. By leveraging advanced analytical techniques and integrating diverse data sources, companies can enhance their decision-making processes and improve their chances of successful mergers and acquisitions.

In conclusion, the integration of financial metrics with qualitative insights derived from natural language processing represents a significant advancement in the field of M&A research. This study not only provides a valuable predictive tool but also sets the stage for future investigations into the complex factors influencing M&A outcomes. As organizations strive to navigate the challenges and opportunities presented by mergers and acquisitions, the insights gained from this research will be instrumental in guiding strategic decisions and fostering successful outcomes in an increasingly competitive landscape. By continuing to innovate and adapt analytical approaches, stakeholders can better position themselves to harness the full potential of mergers and acquisitions, ultimately driving growth and value creation in their respective industries.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Baker M, Wurgler J. Investor Sentiment in the Stock Market. Journal of Economic Perspectives, 2018, 21(2): 129-152.

[2] Wang X, Wu Y C. Balancing innovation and Regulation in the age of geneRative artificial intelligence.Journal of Information Policy, 2024, 14.

[3] Wang X, Wu Y C, Zhou M, et al. Beyond surveillance: privacy, ethics, and regulations in face recognition technology.Frontiers in big data, 2024, 7: 1337465.

[4] Ma Z, Chen X, Sun T, et al. Blockchain-Based Zero-Trust Supply Chain Security Integrated with Deep Reinforcement Learning for Inventory Optimization.Future Internet, 2024, 16(5): 163.

[5] Wang X, Wu Y C, Ma Z. Blockchain in the courtroom: exploring its evidentiary significance and procedural implications in US judicial processes.Frontiers in Blockchain, 2024, 7: 1306058.

[6] Wang X, Wu Y C, Ji X, et al. Algorithmic discrimination: examining its types and regulatory measures with emphasis on US legal practices.Frontiers in Artificial Intelligence, 2024, 7: 1320277.

[7] Chen X, Liu M, Niu Y, et al. Deep-Learning-Based Lithium Battery Defect Detection via Cross-Domain Generalization.IEEE Access, 2024, 12: 78505-78514.

[8] Liu M, Ma Z, Li J, et al. Deep-Learning-Based Pre-training and Refined Tuning for Web Summarization Software.IEEE Access, 2024, 12: 92120-92129.

[9] Li J, Fan L, Wang X, et al. Product Demand Prediction with Spatial Graph Neural Networks.Applied Sciences, 2024, 14(16): 6989.
[10] Liu M. Machine Learning Based Graph Mining of Large-scale Network and Optimization. In2021 2nd International Conference on Artificial Intelligence and Information Systems, 2021, 1-5.
[11] Zuo Z, Niu Y, Li J, et al. Machine Learning for Advanced Emission Monitoring and Reduction Strategies in Fossil Fuel Power Plants.Applied Sciences, 2024, 14(18): 8442. DOI: 10.3390/app14188442.
[12] Asif M, Yao C, Zuo Z, et al. Machine learning-driven catalyst design, synthesis and performance prediction for CO2 hydrogenation. Journal of Industrial and Engineering Chemistry, 2024.
[13] Lin Y, Fu H, Zhong Q, et al. The influencing mechanism of the communities' built environment on residents' subjective well-being: A case study of Beijing.Land, 2024, 13(6): 793.
[14] Bergstra J, Bengio Y. Random Search for Hyper-Parameter Optimization. Journal of Machine Learning Research, 2012, 13: 281-305.
[15] Cortes C, Vapnik V. Support-Vector Networks. Machine Learning, 1995, 20(3): 273-297.
[16] Datta D K. Organizational Fit and Acquisition Performance: Effects of Post-Acquisition Integration. Strategic Management Journal, 1991, 12(4): 281-298.
[17] Blei D M, Ng A Y, Jordan M I. Latent Dirichlet Allocation. Journal of Machine Learning Research, 2003, 3: 993-1022.
[18] Breiman, L. Random Forests. Machine Learning, 2001, 45(1): 5-32.
[19] Brouthers K D, Hennart J F. FDI Entry Mode Choice: The Importance of Context. Journal of International Business Studies, 2008, 39(4): 618-634.
[20] Cartwright S, Cooper C L. The Role of Culture in Mergers and Acquisitions. International Journal of Human Resource Management, 1993, 4(4): 839-857.
[21] DePamphilis D. Mergers and Acquisitions Basics: Negotiation and Deal Structuring. Academic Press, 2019.
[22] Kumar A, Singh A. Predictive Analytics in Mergers and Acquisitions: A Review of Literature. Journal of Business Research, 2020, 116: 1-12.
[23] Li Y, Zhao R. Sentiment Analysis of Corporate Mergers and Acquisitions: Evidence from China. Journal of Business Research, 2019, 96: 1-12.
[24] Ghosh A. Does Business Group Affiliation Matter? Evidence from Mergers and Acquisitions in India. Journal of Financial Economics, 2001, 62(3): 411-436.
[25] Healy P M, Palepu K G, Ruback R S. Does Corporate Performance Improve After Mergers? Journal of Financial Economics, 1992, 31(2): 135-175.
[26] Rao Y, Zhang Y. Predicting M&A Success Using Machine Learning and NLP Techniques. Journal of Business Research, 2020, 116: 1-10.
[27] Schumaker R P, Chen H. Textual Analysis of Stock Market Prediction Using Financial News Articles. ACM Transactions on Information Systems, 2009, 27(2): 1-19.
[28] Zhang Y, Zheng Y. Data Normalization Techniques in Financial Analysis. Journal of Financial Data Science, 2019, 1(2): 99-112.
[29] Baker M, Wurgler J. Investor Sentiment in the Stock Market. Journal of Economic Perspectives, 2018, 21(2),: 129-152.
[30] Huang Z, Hsu C. Predicting the Success of Mergers and Acquisitions Using Machine Learning Techniques. Journal of Business Research, 2019, 102: 93-102.
[31] KPMG. Global M&A Outlook: Trends and Insights. KPMG International, 2021.
[32] Loughran T, McDonald B. Textual Analysis of Corporate Filings: A Survey of the Literature. Journal of Accounting Literature, 2016, 36: 100-122.
[33] Ghosh A. Does Business Group Affiliation Matter? Evidence from Mergers and Acquisitions in India. Journal of Financial Economics, 2011, 62(3): 411-436.
[34] Healy P M, Palepu K G, Ruback R S.Does Corporate Performance Improve After Mergers? Journal of Financial Economics, 2024, 31(2): 135-175.
[35] Manning C D, Raghavan P, Schütze H. Introduction to Information Retrieval. MIT Press, 2018.
[36] Moeller S B, Schlingemann F P, Stulz R M. Wealth Destruction on a Massive Scale? A Study of Acquiring-Firm Returns in the Recent Merger Wave. Journal of Finance, 2015, 60(2): 757-782.
[37] PwC. Global M&A Industry Trends: Insights and Analysis. PwC International, 2024.
[38] Very P, Schweiger D M. The Role of Culture in Mergers and Acquisitions: A Review of the Literature and a Proposed Model. International Journal of Human Resource Management, 1997, 8(2): 221-238.
[39] Sokolova M, Lapalme G. A Systematic Analysis of Performance Measures for Natural Language Generation. Journal of Artificial Intelligence Research, 2019, 34: 1-20.
[40] Brouthers K D, Hennart J F. FDI Entry Mode Choice: The Importance of Context. Journal of International Business Studies, 2018, 39(4): 618-634.
[41] Datta D K. Organizational Fit and Acquisition Performance: Effects of Post-Acquisition Integration. Strategic Management Journal, 2024, 12(4): 281-298.
[42] DePamphilis D. Mergers and Acquisitions Basics: Negotiation and Deal Structuring. Academic Press, 2019.
[43] Sun T, Yang J, Li J, et al. Enhancing Auto Insurance Risk Evaluation with Transformer and SHAP.IEEE Access, 2024, 12: 116546-116557.

[44] Cartwright S, Cooper C L. The Role of Culture in Mergers and Acquisitions. International Journal of Human Resource Management, 2023, 4(4): 839-857.
[45] Li Y, Zhao R. Sentiment Analysis of Corporate Mergers and Acquisitions: Evidence from China. Journal of Business Research, 2019, 96: 1-12.
[46] Loughran T, McDonald B. When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks. Journal of Finance, 2011, 66(1): 35-65.
[47] Huang Z, Hsu C. Predicting the Success of Mergers and Acquisitions Using Machine Learning Techniques. Journal of Business Research, 2019, 102: 93-102.
[48] Moeller S B, Schlingemann F P, Stulz R M. Wealth Destruction on a Massive Scale? A Study of Acquiring-Firm Returns in the Recent Merger Wave. Journal of Finance, 2005, 60(2): 757-782.
[49] KPMG. Global M&A Outlook: Trends and Insights. KPMG International, 2021.
[50] Very P, Schweiger D M. The Role of Culture in Mergers and Acquisitions: A Review of the Literature and a Proposed Model. International Journal of Human Resource Management, 1997, 8(2): 221-238.
[51] King D R, Kitching J. The Role of Strategic Fit in M&A Success. Journal of Business Strategy, 2004, 25(4): 12-20.
[52] Rao Y, Zhang Y. Predicting M&A Success Using Machine Learning and NLP Techniques. Journal of Business Research, 2020, 116: 1-10.
[53] Weber Y, Tarba S Y. Human Resource Management in Mergers and Acquisitions: The Role of Culture and Nationality. Journal of World Business, 2010, 45(2): 123-136.

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RESEARCH ON THE DEVELOPMENT STRATEGY OF GUANGXI' CROSS-BORDER E-COMMERCE TOWARDS ASEAN UNDER THE BACKGROUND OF RCEP

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Abstract: The implementation of the Regional Comprehensive Economic Partnership (RCEP) has provided a strong impetus for economic and trade cooperation between China and ASEAN. China's cross-border e-commerce with ASEAN is now advancing at a fast pace. As a key region covered by RCEP, Guangxi is poised to further promote the prosperity and development of cross-border e-commerce in the area. However, there are still some issues hindering Guangxi's cross-border e-commerce with ASEAN, such as the underdeveloped cross-border logistics system, increasing regulatory risks for e-commerce enterprises, the lack of a unified cross-border payment system, and the insufficient supply of multi-skilled e-commerce professionals. To address these challenges, this paper proposes several development strategies, including optimizing the cross-border logistics network, improving the regulatory and service systems for cross-border e-commerce, deepening cooperation in electronic payments, and accelerating the cultivation of multi-skilled e-commerce professionals. These strategies aim to fully support the healthy, sustainable, and rapid development of Guangxi's cross-border e-commerce with ASEAN.
Keywords: RCEP; Cross-border E-Commerce; Guangxi; ASEAN; Development strategy

1 INTRODUCTION

On January 1, 2022, the Regional Comprehensive Economic Partnership (RCEP), initiated and led by the ten ASEAN countries, officially came into effect, playing a positive role in promoting economic and trade exchanges among the member states. Under the implementation of RCEP, deepening cross-border e-commerce cooperation between China and ASEAN is crucial for promoting bilateral economic and trade development. Cross-border e-commerce has become a new growth point for economic and trade cooperation between China and ASEAN. Currently, China-ASEAN cross-border e-commerce is maintaining rapid growth, with the total value of goods transactions reaching new heights and achieving remarkable results.With its geographical advantage of being connected to ASEAN countries by both land and sea, Guangxi has become an important gateway for China-ASEAN exchanges and cooperation, playing a central role in cross-border e-commerce import and export business with ASEAN. In recent years, Guangxi has actively built China-ASEAN cross-border e-commerce bases, cultivated a cross-border e-commerce logistics system targeting ASEAN, and promoted the rapid growth of cross-border e-commerce trade. Additionally, Guangxi has continuously optimized its healthcare services, such as establishing chest pain centers and improving nursing procedures, providing solid human resource support and health assurance for regional economic development [1]. Under the RCEP framework, the market potential for Guangxi's cross-border e-commerce with ASEAN is increasingly significant. Therefore, Guangxi should fully seize the opportunities brought by RCEP, proactively address the various problems and challenges encountered in the current development process, and thereby promote high-quality development of Guangxi's cross-border e-commerce towards ASEAN.

2 CURRENT DEVELOPMENT STATUS OF GUANGXI'S CROSS-BORDER E-COMMERCE WITH ASEAN

2.1 Cross-border E-commerce Trade Scale Reaches New Heights

As a new model of international trade, cross-border e-commerce has demonstrated rapid development, significant driving effects, and enormous market potential, which cannot be overlooked. It not only facilitates global trade but also plays an important role in reshaping global trade chains, supply chains, and value chains, providing strong support for foreign trade innovation, economic transformation and upgrading, and high-quality development. In recent years, Guangxi has leveraged its geographical advantages and seized policy opportunities to continuously improve the public service system for cross-border e-commerce, attracting cross-border e-commerce platforms and industry-leading enterprises to settle in, laying a solid foundation for the vigorous development of cross-border e-commerce. Meanwhile, the significant progress in healthcare services in Guangxi has also provided strong support for regional economic development [2-3]. Meanwhile, to seize the opportunity brought by the implementation of RCEP, the Guangxi government has actively supported small and medium-sized enterprises (SMEs) in expanding into international markets and has held the RCEP Economic and Trade Cooperation Business Summit Forum in Nanning, the capital, for three consecutive years, to strengthen economic and trade exchanges between Guangxi enterprises and member states, and jointly promote the healthy and rapid development of cross-border e-commerce.

Currently, Guangxi's cross-border e-commerce market is showing significant growth. The Nanning area, the largest cross-border e-commerce comprehensive pilot zone in Guangxi, has achieved remarkable development since its approval in 2018, with its cross-border e-commerce import and export scale accounting for over 80% of the province's total, and business volume growing 20 times compared to 2018. As of July 2024, Guangxi has added over 100,000 new enterprises, 28 times more than before its establishment. According to customs statistics, from 2018 to 2022, Guangxi's cross-border e-commerce experienced a staggering average annual growth rate of 285%, showing strong growth momentum. In 2023, Guangxi's total import and export volume with ASEAN reached 339.44 billion yuan, an increase of 22.8% compared to the same period last year. Among them, the Guangxi Pilot Free Trade Zone's foreign trade import and export volume with ASEAN countries reached 171.49 billion yuan, including 35.42 billion yuan in imports and 136.07 billion yuan in exports, further establishing its key role in the accelerated development of digital trade between China and ASEAN[4].

Since 2024, Guangxi has actively strengthened exchanges and cooperation with RCEP member countries, promoting local enterprises to explore diversified international market layouts, further boosting the region's total import and export volume. From January to July 2024, Guangxi's total import and export trade volume with RCEP member countries reached 242.5 billion yuan, a year-on-year increase of 23.2%, with particularly outstanding performance in its trade with ASEAN, where the trade volume surged to 214.93 billion yuan, a year-on-year growth rate of 24.3%, reaching a record high. During the same period, Guangxi enterprises exported 12.43 billion yuan through the customs cross-border e-commerce management platform, a year-on-year increase of 37.4%. This significant growth reflects the important role of cross-border e-commerce in promoting Guangxi's foreign trade exports. Specifically, Guangxi's cross-border e-commerce exports to Vietnam and Thailand performed particularly well, reaching 4.46 billion yuan and 4.96 billion yuan respectively, with year-on-year growth rates of 46.8% and 86.4%[5]. These figures indicate that Guangxi's trade position and market vitality in the ASEAN economic circle are continuously increasing, making cross-border e-commerce a key driver for the diversification and rapid growth of Guangxi's foreign trade exports[6].

2.2 Diversification of Cross-border E-commerce Platforms and Operational Models

Under the RCEP framework, Guangxi has leveraged its geographical advantages to continuously adjust and optimize the cross-border e-commerce industry layout targeting ASEAN, actively exploring innovative business models to lay a solid foundation for promoting economic and trade exchanges between Guangxi and ASEAN countries. In recent years, many e-commerce enterprises in Guangxi have entered popular online shopping platforms widely used in ASEAN countries, such as Lazada and Shopee, and have jointly created new development opportunities for cross-border e-commerce with member states. Lazada has established the first national cross-border ecosystem innovation service center in Nanning, not only launching a multilingual live streaming platform for cross-border merchants but also implementing the "Guangxi Products Go Global" strategic plan and providing comprehensive support for the cross-border industrial chain. After Shopee set up an ASEAN cross-border e-commerce logistics center in Guangxi, it facilitated the growth of more than 100 e-commerce platforms and enterprises such as Guangxi Trade World, Cross-border Buy[7].

In addition, Guangxi has focused on innovation in cross-border e-commerce models and has successfully implemented comprehensive layouts for new business models such as retail exports, bonded imports, B2B overseas warehouse exports, and B2B direct exports. Each innovative model is tailored to meet the diverse needs of different consumers and businesses, significantly enriching Guangxi's cross-border e-commerce business formats and providing a broader development space for small and medium-sized enterprises in Guangxi's cross-border e-commerce market.

2.3 Initial Achievements in Cross-border E-commerce Infrastructure Development

In recent years, economic and trade cooperation between China and ASEAN has deepened. As the intersection point between China and ASEAN, Guangxi has actively developed cross-border e-commerce and promoted the construction of international e-commerce logistics systems, providing more convenient and efficient channels for trade between Guangxi and ASEAN. In 2018, the Nanning Cross-border E-commerce Comprehensive Pilot Zone began operations. In the following years, the infrastructure has been gradually improved, featuring advanced online service platforms, regulatory warehouses, bonded warehouses, and various international product display experience stores, quickly making the Nanning Pilot Zone stand out among Guangxi's cross-border e-commerce pilot zones.

Since 2020, the layout of Guangxi's cross-border e-commerce has been further optimized. Chongzuo, Liuzhou, and Hezhou have successively been approved as national cross-border e-commerce comprehensive pilot zones, and eight cities, including Beihai and Qinzhou, have been included in the list of cross-border e-commerce retail import pilot areas, forming a more complete and vibrant e-commerce ecosystem. Meanwhile, the rapid development of cross-border e-commerce is inseparable from a solid logistics foundation. Currently, the Nanning area of the Guangxi Pilot Free Trade Zone has opened 10 direct air routes to ASEAN countries, providing a convenient air corridor for cross-border e-commerce cooperation between Guangxi and ASEAN. The logistics layout of the Chongzuo area is becoming increasingly sophisticated, with 13 railway freight lines and 22 road routes jointly constructing a cross-border e-commerce logistics network targeting the Indochina Peninsula[8]. The Qinzhou Port area is also striving to strengthen maritime connections with major ports in ASEAN countries, allowing Guangxi's goods to reach ASEAN countries quickly via sea transport. The improvement of these infrastructures has strongly boosted the rapid rise and high-quality development of Guangxi's cross-border e-commerce.

3 ISSUES IN THE DEVELOPMENT OF GUANGXI'S CROSS-BORDER E-COMMERCE WITH ASEAN UNDER THE RCEP FRAMEWORK

3.1 Lagging Development of the Cross-border Logistics System

Cross-border logistics occupies a crucial position in international trade, serving as a key link connecting the economies of countries worldwide. In recent years, Guangxi has taken advantage of the development opportunities presented by the New International Land-Sea Trade Corridor to initially establish a three-dimensional transportation network encompassing sea, land, and air, greatly facilitating the import and export of goods. However, compared to other coastal regions in China, Guangxi still needs to accelerate its pace of development. First, the logistics industry in Guangxi still faces multiple challenges, including insufficient enterprise capacity, limited transportation capacity, low service efficiency, and low added value. These factors directly affect the profitability of the cross-border logistics supply chain. Additionally[9]. Guangxi and ASEAN have yet to establish an effective information-sharing mechanism, which hinders the timely tracking, supervision, and security of logistics and payment processes.

Furthermore, the development of cross-border e-commerce with ASEAN is influenced by environmental conditions and regional disparities. The complex and variable terrain and climate in Southeast Asia significantly increase the difficulty of logistics distribution and the corresponding transportation costs. Similar challenges also exist in the development of the healthcare system, especially in the coverage and resource allocation of medical services in remote areas [10]. Meanwhile, there are clear differences in the development levels of logistics between ASEAN countries. Compared to Singapore, countries such as Vietnam and Myanmar have relatively underdeveloped logistics and network infrastructures, incomplete transportation systems, and pose challenges to the development of cross-border e-commerce[11]. Although the construction of overseas warehouses can provide a fast channel for cross-border e-commerce logistics, Guangxi's overseas warehousing facilities in ASEAN countries are still in the initial stages, limiting deeper development of cross-border e-commerce. In addition, although the RCEP agreement offers new opportunities for regional trade, Guangxi still needs to further develop logistics routes and delivery systems with countries like Japan and South Korea, which poses a daunting task for its logistics system construction.

3.2 Increasing Compliance Risks for Cross-border E-commerce Enterprises

The implementation of RCEP has shifted the industry from rapid expansion to a more refined and compliant development direction, thereby increasing compliance risks in the cross-border e-commerce sector. The RCEP agreement covers multiple key areas, including intellectual property rights, e-commerce, and competition policies. In terms of intellectual property protection, RCEP takes into account the varying development levels of member countries and has established a comprehensive and effective protection mechanism. However, due to differences in the legal systems between China and ASEAN countries, Guangxi's small and medium-sized enterprises (SMEs) and individuals may face greater risks in intellectual property issues when engaging in cross-border e-commerce transactions with ASEAN countries because they lack in-depth understanding of RCEP rules.

In the field of e-commerce, RCEP has formulated clear regulations on online personal information protection based on the domestic legal frameworks of its member countries. Given the differences in personal information protection policies and practices across ASEAN countries, Guangxi's cross-border e-commerce enterprises may face compliance risks if they do not fully understand the legal environment of these countries in advance, potentially leading to issues such as excessive data collection or improper handling of information. In the area of competition policy, the enforcement of RCEP further regulates competition in the cross-border e-commerce sector by strengthening anti-monopoly enforcement and severely penalizing illegal activities to promote fair market competition. Therefore, cross-border e-commerce enterprises need to be vigilant against potential risks such as price discrimination and market monopolies in their operations, ensuring that their business practices comply with legal requirements[12].

3.3 Lack of a Unified Cross-border E-commerce Payment System

Cross-border electronic payments, characterized by efficiency, convenience, and security, play a crucial role in promoting the rapid development of cross-border e-commerce between Guangxi and ASEAN. However, at present, online payment methods are not yet widely adopted in ASEAN countries, with a market penetration rate of only around 20%. This situation arises from two major factors: First, due to incomplete broadband network coverage and deficiencies in electronic payment security systems in some ASEAN countries, consumers tend to be cautious about using online payments. Second, the cooperation between Guangxi and ASEAN in the field of cross-border payments faces numerous challenges. In China, online payments have become a common practice in daily life, mainly through third-party platforms such as WeChat and Alipay. However, the penetration of these platforms in ASEAN countries is relatively low. Meanwhile, ASEAN countries are promoting their own third-party payment tools, such as ONEPAY and GOPAY, which differ significantly from China's payment systems, and there is no effective collaboration between the two. This results in a complicated payment process for cross-border e-commerce transactions, accompanied by high transaction fees, long refund cycles, and high time costs.

3.4 Insufficient Supply of Multi-skilled Cross-border E-commerce Professionals

With the rapid expansion of the cross-border e-commerce market, Guangxi faces a significant shortage of multi-skilled professionals in this field, particularly those targeting ASEAN markets. The imbalance between supply and demand has become a key obstacle to the industry's development. Since the Ministry of Education included cross-border e-commerce as an undergraduate major in 2019, only 49 universities across the country have offered this program, and only four universities in Guangxi have established it, resulting in a limited number of graduates entering the workforce.
The distinct legal policies, cultural norms, and social customs of ASEAN countries compared to China mean that cross-border e-commerce professionals need to possess not only expertise in market marketing and platform operations but also an understanding of local languages, consumer habits, and demands. This significantly increases the difficulty for universities in Guangxi to cultivate multi-skilled professionals in cross-border e-commerce. Moreover, some universities in Guangxi still prioritize theoretical teaching in their talent cultivation models for cross-border e-commerce, and the lack of practical experience makes it challenging for graduates to quickly adapt to industry needs.
Additionally, due to the relatively lower economic development level and enterprise compensation in Guangxi, cross-border e-commerce talent is increasingly gravitating towards economically prosperous regions such as Hangzhou, Guangzhou, and Shenzhen. This trend further widens the talent gap in Guangxi's cross-border e-commerce industry.

4 DEVELOPMENT STRATEGIES FOR GUANGXI'S CROSS-BORDER E-COMMERCE WITH ASEAN UNDER THE RCEP FRAMEWORK

4.1 Improving the Cross-border Logistics Network System

In the development of Guangxi's cross-border e-commerce with ASEAN, logistics serves as a core support, playing a crucial role. Therefore, Guangxi needs to accelerate the optimization and upgrading of its cross-border e-commerce logistics system.
First, leveraging the natural advantages of the BeiBu Gulf, Guangxi should fully capitalize on the cooperation opportunities brought by RCEP to deepen international logistics cooperation with ASEAN countries and build a comprehensive cross-border logistics system that encompasses land, air, sea, and railway transportation, achieving an integrated "land-sea-air" logistics network layout. At the same time, learning from the experiences of optimizing the healthcare logistics system would be beneficial in enhancing the efficiency and security of cross-border e-commerce logistics [13, 14].
Second, to enhance logistics efficiency and real-time logistics information tracking, Guangxi should promote the sharing of logistics information resources among various departments, expand the application scope of logistics informatization, and establish and improve logistics information exchange platforms to meet customer demands for logistics services[15].
Third, to promote the development of cross-border e-commerce, Guangxi should further deepen exchanges and cooperation with logistics enterprises in the member countries, jointly building a comprehensive logistics data-sharing network that covers cross-border e-commerce, international express delivery, and postal services. Finally, government departments should actively implement relevant policies to support the development of cross-border e-commerce logistics and simplify trade procedures in various stages of import and export, thereby effectively improving logistics speed and providing strong support for the sustainable and healthy development of Guangxi's cross-border e-commerce with ASEAN.

4.2 Optimizing the Regulatory and Service Systems for Cross-border E-commerce

To create a favorable business environment for cross-border e-commerce, the governments of Guangxi and ASEAN countries should deepen cooperation and jointly establish a comprehensive market regulatory system. First, both sides should work together to improve and innovate the regulatory mechanisms for cross-border e-commerce, formulating and promoting standardized regulatory rules. For bilateral and multilateral trade, the government should further strengthen regulatory oversight, build a comprehensive, efficient, and real-time information-sharing platform, streamline regulatory processes, and reduce regulatory costs.
Second, providing professional legal services for cross-border e-commerce is also crucial. Given the implementation of RCEP, cross-border e-commerce may face higher risks in a new business model, especially in key areas such as intellectual property protection and anti-monopoly enforcement[16]. Therefore, The Guangxi government should organize local cross-border e-commerce enterprises to participate in legal knowledge training, use diverse promotional methods to deepen enterprises' understanding of the rules of origin, and emphasize the importance of intellectual property rights. Similar legal protection is also crucial in the healthcare industry, especially in the cross-border trade of pharmaceuticals and medical services [17].The Guangxi government should actively play a leading role in promoting the establishment and healthy development of cross-border e-commerce industry associations. To ensure that cross-border e-commerce practitioners operate in compliance, industry associations should actively establish legal consulting mechanisms, providing services such as intellectual property protection, consumer rights protection, and contract review for practitioners. For potential anti-monopoly investigations, the association can offer risk assessments and compliance review services to ensure that practitioners adhere to anti-monopoly laws[18]. These measures aim to minimize the legal risks faced by enterprises in cross-border e-commerce and create a more stable and transparent

business environment for cross-border e-commerce cooperation between Guangxi and ASEAN countries.

4.3 Deepening Cooperation in Cross-border E-commerce Electronic Payments

Strengthening cooperation between Guangxi and ASEAN countries in the field of cross-border e-commerce electronic payments is of strategic importance for enhancing transaction convenience and promoting the internationalization of the Renminbi.

At the national level, the government should actively build and improve cross-border payment infrastructure, optimize the cross-border payment network system, and create a secure and stable network environment for electronic payments. It should also establish cross-border payment cooperation mechanisms with ASEAN countries to jointly promote the formulation of laws and regulations in the payment sector, information sharing, and payment risk prevention and control[19].

At the enterprise level, leading domestic cross-border payment institutions can either develop new payment applications for the international market or collaborate deeply with ASEAN countries' payment institutions, such as ONEPAY and GOPAY, to jointly develop new payment tools that meet the diverse needs of enterprises in cross-border trade, simplify cross-border transaction processes, and create a smoother and more efficient cross-border transaction experience for enterprises on both sides.

For Guangxi, the local government can actively promote the application of credit insurance in the cross-border e-commerce retail sector. By providing financial insurance to eligible enterprises, it can effectively reduce cross-border e-commerce payment costs and foreign exchange risks, thereby promoting the development of cross-border e-commerce in Guangxi.

At the consumer level, Alipay and WeChat have become mature payment methods in China. Introducing these platforms into the ASEAN market will significantly improve the cross-border payment experience for consumers, further promote the internationalization of the Renminbi, and expand Guangxi's cross-border e-commerce market towards ASEAN.

4.4 Accelerating the Cultivation of Multi-skilled Cross-border E-commerce Professionals

Under the RCEP framework, constructing and optimizing a talent cultivation system is crucial for promoting the prosperous development of Guangxi's cross-border e-commerce with ASEAN. First, the Guangxi government should play a leading role by establishing special funds and building cooperation platforms to actively promote exchanges and cooperation between Chinese and ASEAN experts and scholars in cross-border e-commerce. This will facilitate joint research and planning of talent cultivation strategies. Additionally, the Guangxi government can organize relevant lectures, seminars, and other events, inviting industry experts and successful entrepreneurs to share practical experiences in cross-border e-commerce, and introduce various policies, including financial support and tax incentives, to attract more talent to the cross-border e-commerce sector.

Second, Guangxi's universities should closely align with the economic and trade needs between China and ASEAN, optimizing curriculum settings and strengthening education in fields such as "e-commerce, trade exchanges, and international economics." They should also establish long-term and stable cooperative relationships with ASEAN universities and enterprises to jointly explore a cultivation model for multi-skilled talent proficient in "cross-border e-commerce + ASEAN languages + innovation and entrepreneurship"[20].

Moreover, deepening the integration of industry and education is key to providing talent support for Guangxi's cross-border e-commerce development. Guangxi universities can collaborate with leading enterprises such as Alibaba International and JD.com to build cross-border e-commerce training bases, providing students with platforms to understand the cross-border e-commerce industry and master practical skills. For graduates in this field, universities can actively encourage them to return to their hometowns for entrepreneurship and employment, leveraging local resource advantages to inject fresh vitality into the development of Guangxi's cross-border e-commerce.

Finally, cross-border e-commerce enterprises should place greater emphasis on employee training and talent development. Through systematic training and incentive mechanisms, they should continuously improve employees' professional competencies and innovation abilities, thereby providing a solid talent foundation for the sustainable development of enterprises.

5 CONCLUSION

In the context of the RCEP, Guangxi's cross-border e-commerce with ASEAN is poised for significant growth, presenting both opportunities and challenges. Guangxi must seize the opportunities presented by RCEP to further enhance its role in the regional cross-border e-commerce landscape. This requires a comprehensive approach, focusing on optimizing the logistics network, improving the regulatory and service systems, deepening cooperation in electronic payments, and cultivating a pool of multi-skilled professionals.

Addressing the existing issues, such as the lagging logistics system, increasing compliance risks, lack of a unified payment system, and shortage of specialized talent, is crucial for the sustainable development of cross-border e-commerce. By implementing these strategies, Guangxi can establish a more resilient and robust cross-border e-commerce ecosystem that not only strengthens its economic ties with ASEAN but also contributes to the broader economic development of the region.

Through collaborative efforts among government, businesses, and educational institutions, Guangxi can build a solid foundation for the continued prosperity and expansion of cross-border e-commerce, turning challenges into opportunities and fostering long-term, high-quality development in the region.

COMPETING INTERESTS

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REFERENCES

[1] Liu, Y, Zhao, C, Zhou, Y. The impact of the establishment of chest pain centers and optimized nursing procedures on the treatment outcomes of acute ST-segment elevation myocardial infarction. Journal of Youjiang Medical University for Nationalities, 2019, 4, 465-467.
[2] Zhou, Y, Zhuo, C, Tang, Q. A study on the mechanism of gallstone formation and the current status of diagnosis and treatment. Journal of Youjiang Medical University for Nationalities, 2019, 2, 203-206.
[3] Cheng Ningqian. Research on Accelerating the Upgrading and Development of International Cooperation Parks in Guangxi under the Background of RCEP. Guangxi Social Sciences, 2022, (05): 81-89.
[4] Guangxi Department of Commerce. “New” Movements in Guangxi: Towards ASEAN, Here’s the Highlight! 2024, July 26. http://swt.gxzf.gov.cn/zfxxgk/fdzdgknr/zwdt/gxsw/t18759493.shtml.
[5] Guangxi Department of Finance. Guangxi's Import and Export Volume Increased by 11.1% Year-on-Year in the First Seven Months, with Several Indicators Reaching Historical Highs. 2024, August13. https: //czt. gxzf. gov.cn/xwdt/gxyw/t18843219.shtml
[6] Zheng Chunfang, Zhang Yanqiu. Research on the Factors Influencing China’s Cross-border E-commerce Export and Its Potential. Journal of the Graduate School of the Chinese Academy of Social Sciences, 2021, (04): 63-72.
[7] Zhang Xiaheng. Promoting the New Development Pattern of Dual Circulation through Cross-border E-commerce: Theoretical Mechanisms, Development Ideas, and Relevant Measures. Contemporary Economic Management, 2021, 43(10): 59-65.
[8] Li Fuchang, Bao Yanna, Hu Xiaohui. RCEP Promotes the Integration Mechanism of Cross-border E-commerce Industry Chain and Supply Chain. Commercial Economic Research, 2022, (17): 158-163.
[9] Ma Yujie. Problems and Solutions in the Development of E-commerce Industry Clusters in China. Commercial Economic Research, 2024, (08): 178-180.
[10] Cui, X, Yang, M. The effect of nursing intervention based on the Rosenthal effect on stress response and emotional state of children with scoliosis. Journal of Youjiang Medical University for Nationalities, 2019, 6, 713-715.
[11] Xu Baochang, Xu Xiaoni, Sun yihan. Opportunities and Challenges Brought by RCEP’s Implementation for the High-quality Development of China-ASEAN Cross-border E-commerce. International Trade, 2022, (10): 53-59.
[12] Xu Na. Analysis of the Path for Promoting the Sustainable Development of China’s E-commerce under the New Development Pattern. Commercial Economic Research, 2024, (07): 113-115.
[13] Rao, Z, Chen, J, Zhao, L, et al. A comparative study of ultrasound-guided microwave ablation and laparoscopic resection in the treatment of benign thyroid nodules. Journal of Youjiang Medical University for Nationalities, 2018, 6, 583-585.
[14] Wang Songji, Han Rui. Ten Years of Progress, Problem Analysis, and Advancement Path of Trade Facilitation under the “Belt and Road” Initiative. Journal of Northwest University (Philosophy and Social Sciences Edition), 2024, 54(02): 54-64.
[15] Guo Xiaping. The Impact of Digital Trade Development of RCEP Member Countries on China’s Cross-border E-commerce Export. Commercial Economic Research, 2024, (15): 137-140.
[16] Wang Jian, Zhu Ziyi. The Impact of Hainan Free Trade Port’s Closure Operation on the Development of Cross-border E-commerce and Related Institutional Design. International Trade, 2024, (04): 36-44.
[17] Li, J, Leng, H. Clinical observation of the efficacy of respiratory muscle feedback training on respiratory and swallowing dysfunction in patients with post-stroke hemiplegia. Journal of Youjiang Medical University for Nationalities, 2018, 6, 586-589.
[18] Guo Yang. Research on the Development Level and Influencing Factors of China’s Cross-border E-commerce. Areal Research and Development, 2024, 43(03): 16-21.
[19] Feng Xiurong. Cross-border E-commerce Logistics Risk and Risk Avoidance Strategies—Review of “Research on Logistics Risk Management under the Background of Cross-border E-commerce.” Commercial Economic Research, 2024, (14): 2.
[20] Shi Lin, Jiang Meiling. Research on the Innovation of “Chinese + Cross-border E-commerce” Talent Training Model Targeting ASEAN under the “Belt and Road” Initiative. Guangxi Social Sciences, 2023, (08): 68-76.

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FISCAL MULTIPLIERS IN THE NEW KEYNESIAN MODEL: THE INFLUENCE OF GOVERNMENT SPENDING ON ECONOMIC OUTPUT

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Abstract: The thesis focuses on the influence of fiscal multipliers on economic output in the framework of New Keynesian, emphasizing the dominant position of government spending. By integrating the price concepts and wage stickiness, the analysis explores how fiscal policy may either stabilize or destabilize the economy, depending on the timing and nature of interventions. The research contrasts both short-term and long-term effects of government spending, considering interactions with monetary policy and the broader economic context. An insight into fiscal policy optimizing for enhancing stability of macroeconomic is provided in the thesis through both theoretical examination and case studies. The findings finally suggest that proper interventions do have ability to mitigate economic downturns and sustain the growth of output, making them essential tools for managing in modern macroeconomic.
Keywords: New Keynesian model; Fiscal multipliers; Government spending; Economic output; Price stickiness; Business cycle

INTRODUCTION

Fiscal policy, particularly government spending, plays an important role in influencing economic output and stabilizing the macroeconomy. Under the framework New Keynesian, the concept of fiscal multipliers—how government spending variation impact the demand of aggregate—offers vital insights into the effectiveness of such policies. In this thesis, a closer look will be taken at the intricate relationship between fiscal policies and economic growth. We'll be focusing on two key factors: price stickiness and the timing of policy implementation. The study aims to shed light on how fiscal policy can be optimized to achieve greater economic stability, especially during the economic fluctuation periods by theoretical perspectives and empirical evidence examination.

1 THE NEW KEYNESIAN MODEL: AN OVERVIEW

1.1 Core Principles of the New Keynesian Model

The New Keynesian model extends the traditional Keynesian framework by integrating microeconomic concepts like price and wage stickiness, which explain why output and employment can deviate from their natural rates during economic shocks. Price stickiness refers to the slow adjustment of prices, while wage stickiness results from long-term contracts and social norms that prevent quick wage changes. Expectations also play a crucial role in decision-making, as firms may increase production and hiring today based on anticipated future demand [1]). This forward-looking behavior distinguishes the New Keynesian model from the backward-looking nature of traditional Keynesian economics.

1.2 Fiscal Multipliers in the New Keynesian Context

The change in aggregate output resulting from a change in government spending or taxation is measured as fiscal multipliers. The unit however, usually are particularly significant when using the New Keynesian model as background, due to the presence of price and wage stickiness. When prices and wages cannot be timely changed (which represents most of the cases), the government spending will have a larger impact on the economy. Businesses and households aren't able to adjust right away, so changes in government policy can lead to a more significant shifts in things like output and employment.

The New Keynesian model incorporates fiscal policy tools through the lens of intertemporal optimization, where agents optimize their consumption and labor supply decisions over time, considering the effects of government spending and taxes. The model suggests that fiscal policy can be particularly effective during periods when monetary policy is constrained, such as at the zero lower bound of interest rates [2]. In such situations, fiscal multipliers tend to be larger, as government spending can directly increase aggregate demand without being offset by rising interest rates.

1.3 Interaction Between Fiscal and Monetary Policy

The New Keynesian model emphasizes the interaction between fiscal and monetary policy, where fiscal multipliers are influenced by interest rates. If the central bank targets inflation, increased government spending can raise inflation, prompting higher interest rates, which may reduce private investment and consumption, weakening fiscal stimulus [3].

However, when monetary policy is constrained, such as when interest rates are already low, fiscal policy becomes more effective, leading to a stronger and longer-lasting impact on output [4]. This underscores the importance of coordinating fiscal and monetary policies, especially during economic downturns.

2 THE IMPACT OF GOVERNMENT SPENDING ON ECONOMIC OUTPUT

2.1 Theoretical Analysis

In the New Keynesian framework, government spending influences aggregate demand, with short-term effects boosting output and employment, especially during recessions when idle capacity is high [5]. However, long-term effects depend on the nature of the spending (on consumption or investment), financing methods (through taxes or borrowing), and the economy's structural characteristics. While public investments may lead to sustained output growth by increasing the economy’s productive capacity, excessive spending, particularly when financed by debt, can raise interest rates, crowd out private investment, and potentially reduce long-term output growth.

2.2 Price Stickiness and Output Fluctuations

Price stickiness significantly impacts the effectiveness of fiscal multipliers, as it causes delays in price adjustments to changes in demand. This lag allows government spending to boost real demand, resulting in higher short-term output and employment [6]. However, price stickiness also risks inflation if spending continues without corresponding increases in productive capacity. Eventually, as prices adjust, inflationary pressures may reduce the real value of money and erode consumers' purchasing power, underscoring the importance of balancing short-term output gains with long-term inflation risks.

2.3 Empirical Evidence

Empirical studies provide mixed evidence on the impact of government spending on output, reflecting the complexity of fiscal multipliers. Research by [7]Auerbach and Gorodnichenko suggests that fiscal multipliers are larger during recessions, as government spending is more effective in stimulating demand when there is significant slack in the economy. Conversely, studies such as those by [8]Ramey highlight that the effects of government spending can be limited by crowding out effects, particularly when the economy is near full employment. Case studies, such as the 2008 global financial crisis, demonstrate that countries with substantial fiscal stimulus, like the United States and China, experienced stronger recoveries, underscoring the critical role of government spending during economic downturns [9].

3 FISCAL MULTIPLIERS AND ECONOMIC STABILIZATION

3.1 Government Spending During Economic Recessions

During economic recessions, fiscal policy, particularly through government spending, serves as a counter-cyclical tool to mitigate declines in output and employment. The New Keynesian model suggests that during periods of economic slack, fiscal multipliers are particularly large, as the increase in government spending directly raises aggregate demand without being offset by inflationary pressures or interest rate hikes [10]. This counter-cyclical role of fiscal policy is crucial in preventing deeper recessions and facilitating quicker recoveries.

For example, during the Great Recession, the American Recovery and Reinvestment Act (ARRA) of 2009 provided significant fiscal stimulus through increased government spending on infrastructure, education, and healthcare. Studies have shown that this stimulus played a key role in stabilizing output and employment in the U.S., demonstrating the effectiveness of fiscal multipliers in times of economic distress [11].

3.2 Government Spending in Overheated Economies

In overheated economies, where demand exceeds supply, expansionary fiscal policy can lead to inflation rather than increased output. The New Keynesian model suggests that fiscal multipliers are less effective in these contexts, with heightened risks of overheating and inflation [12]. For example, during periods of strong growth, increased government spending may result in higher interest rates as central banks tighten monetary policy to curb inflation, potentially crowding out private investment and reducing fiscal policy’s effectiveness. Therefore, fiscal interventions in overheated economies must be carefully managed to prevent exacerbating inflation and destabilizing the economy.

3.3 Policy Implications

The New Keynesian model and empirical evidence highlight the need for careful design of fiscal policy. The effectiveness of fiscal multipliers varies, being more impactful during recessions and less so during economic overheating [7]. To maximize their stabilizing effects, it is crucial to coordinate fiscal and monetary policies, ensuring government spending aligns with monetary objectives. Additionally, long-term factors like public debt sustainability and potential crowding out of private investment must be considered. Balancing these factors allows fiscal policy to contribute effectively to economic stabilization and sustained growth.

4 CASE STUDIES: FISCAL MULTIPLIERS IN PRACTICE

4.1 Case Study 1: The Global Financial Crisis (2008-2009)

The 2008-2009 Global Financial Crisis provided a unique opportunity to observe fiscal multipliers in action, as governments implemented large-scale stimulus measures. In the United States, the American Recovery and Reinvestment Act (ARRA) of 2009 allocated approximately $787 billion in government spending, tax cuts, and aid, significantly boosting economic output, with large fiscal multipliers observed as the economy was operating below potential [10]. In China, aggressive infrastructure investment led to a rapid recovery, showcasing the effectiveness of fiscal multipliers in large, emerging economies [13]. Conversely, European countries like Greece and Spain, with limited fiscal capacity, struggled to implement effective stimuli, resulting in prolonged recessions [14].

4.2 Case Study 2: Fiscal Policy in the Eurozone

A compelling case study for examining the role of fiscal multipliers in a monetary union is provided by the Eurozone, an organization where a common currency is shared but independent fiscal policies between members. Post-2008 crisis, fiscal policy coordination was challenging due to asymmetry in economic conditions. Germany, with a strong fiscal position, implemented significant stimulus, while Greece faced constraints due to high debt and austerity measures [12]. The centralized monetary policy complicated fiscal multipliers' effectiveness, as countries couldn't devalue their currencies, leading to divergent outcomes. Core countries maintained stable output, while peripheral nations faced recessions and unemployment, highlighting the need for coordinated fiscal responses to stabilize output in diverse economic environments [15].

4.3 Case Study 3: Emerging Markets and Fiscal Policy

Emerging markets face unique challenges in applying fiscal multipliers due to factors like institutional quality, financial market depth, and vulnerability to external shocks. In countries with strong institutions, such as Brazil, government spending during the global financial crisis effectively mitigated the downturn and supported a quick recovery [16]. However, in many emerging markets, issues like corruption, limited administrative capacity, and reliance on external financing hinder fiscal policy effectiveness, reducing fiscal multipliers. Additionally, external shocks, such as sudden stops in capital flows, can undermine fiscal interventions [17]. This highlights the need for tailored fiscal policies that consider emerging markets' unique characteristics to maximize government spending's impact on stability and growth.

5 SUMMARY OF FINDINGS

An analysis of the fiscal multiplier within the New Keynesian framework reveals that price and wage stickiness significantly amplify the impact of fiscal multipliers, especially during economic downturns. The effectiveness of fiscal policy varies, with larger multipliers observed during recessions and more limited effects in overheated economies. The interaction between fiscal and monetary policy is crucial, as coordinated efforts can better stabilize output. Case studies further emphasize that the fiscal multiplier effect differs across economic environments, underscoring the importance of institutional quality, policy coordination, and external factors. Overall, well-designed fiscal policies, considering timing, scale, and macroeconomic conditions, can significantly enhance economic stability and support sustained growth.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Woodford M. Interest and Prices: Foundations of a Theory of Monetary Policy. Princeton University Press, 2003.

[2] Eggertsson G B. What Fiscal Policy Is Effective at Zero Interest Rates? NBER Macroeconomics Annual, 2011, 25(1): 59-112.

[3] Gali J, Lopez-Salido J D, Valles J. Understanding the Effects of Government Spending on Consumption. Journal of the European Economic Association, 2007, 5(1): 227-270.

[4] Woodford M. Simple Analytics of the Government Expenditure Multiplier. American Economic Journal: Macroeconomics, 2011, 3(1): 1-35.

[5] Blanchard O, Perotti R. An Empirical Characterization of the Dynamic Effects of Changes in Government Spending and Taxes on Output. Quarterly Journal of Economics, 2002, 117(4): 1329-1368.

[6] Bernanke B S, Gertler M, Gilchrist S. The Financial Accelerator in a Quantitative Business Cycle Framework. Handbook of Macroeconomics, 1999, 1: 1341-1393.

[7] Auerbach A J, Gorodnichenko] Y.Measuring the Output Responses to Fiscal Policy. American Economic Journal: Economic Policy, 2012, 4(2): 1-27.

[8] Ramey V A. Can Government Purchases Stimulate the Economy? Journal of Economic Literature, 2011, 49(3): 673-685.

[9] Christiano L, Eichenbaum M, Rebelo S. When Is the Government Spending Multiplier Large? Journal of Political Economy, 2011, 119(1): 78-121.
[10] Blinder A S, Zandi M. The Financial Crisis: Lessons for the Next One. Center on Budget and Policy Priorities, 2015.
[11] Cogan J F, Cwik T, Taylor J B, et al. New Keynesian versus Old Keynesian Government Spending Multipliers. Journal of Economic Dynamics and Control, 2010, 34(3): 281-295.
[12] Blanchard O. Should We Reject the Natural Rate Hypothesis? Journal of Economic Perspectives, 2018, 32(1): 97-120.
[13] Chen S. China's Response to the Global Financial Crisis: Implications for Economic Growth and Stability. China Economic Review, 2011, 22(2): 183-193.
[14] Romer C D. Fiscal Policy in the Crisis: Lessons and Policy Implications. Business Economics, 2012, 47(3): 158-165.
[15] Corsetti G, Meier A, Müller G J. Fiscal Stimulus with Spending Reversals. Review of Economics and Statistics, 2012, 94(4): 878-895.
[16] Carvalho F A, Valli M. Fiscal Multipliers in Brazil: A Quantitative Assessment. Economic Modelling, 2013, 30: 495-510.
[17] Ilzetzki E, Mendoza E G, Végh C A. How Big (Small?) Are Fiscal Multipliers? Journal of Monetary Economics, 2013, 60(2): 239-254.

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AFFINE TERM STRUCTURE MODEL WITH MCMC

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Abstract: This paper develops a Bayesian Markov Chain Monte Carlo (MCMC) estimation method for multi-factor affine term structure models (ATSMs). ATSMs are popular, but efficient estimation methods for them are not readily available. Using simulated price data, the MCMC algorithms developed provide good estimates with their posterior distributions converge. With real historical data, the in-sample pricing errors obtained are significantly smaller than those obtained from alternative methods. A Bayesian forecast analysis documents the superior predictive power of the MCMC approach. Finally, Bayesian model selection criteria are discussed.
Keywords: Affine term structure model; Markov Chain Monte Carlo; Interest rate modeling

1 INTRODUCTION

Term structure models are essential building blocks for valuation, hedging and risk management of interest-rate-related derivatives. The yield curve conveys important macroeconomic information and play an important role for monetary policy transition, asset management, cross-border investment, etc. Among various term structure models, ATSMs are popular mainly because of their analytical tractability and flexibility.

To balance between the economic richness and computational cost for ATSMs, Dai and Singleton (2000) classify the n-factor affine family into $n+1$ non-nested sub-families: $A(m, n), m = 0, \cdots, n$[1]. The order m is the dimension of the restricted state variables that enter the diffusion matrix. To incorporate the investor's attitude toward factor risks, state variable dynamics are specified differently under the data-generating measure P and the risk-neutral measure Q. Different market price of risk specifications is proposed[1-3]. In this paper, we examine two models $A(0, 3)$ and $A(1,3)$, under the "extended affine" specification of Cheridito et al. (2007), which allows for more parameters and nests the "completely affine" specification of Dai and Singleton (2000), and "essentially affine" specification of Duffee (2002)[1-3]. It also imposes parameter constraints to impose no-arbitrage conditions.

Despite the analytical tractability of ATSMs, the estimation of these models is difficult. First, there is an issue of the stochastic singularity. The ATSMs are driven by low dimensional latent state vectors, whereas we observe cross-sectional yields with larger number of maturities. Measurement errors are added to the models to remove this singularity. However, the choice of the measurement error distribution is arbitrary. Many researchers assume that yields with n number of maturities are observed without error, where n is the dimension of the state variables[1, 3-5]. In contrast, other yields present observation errors. However, the underlying assumption is stringent. As pointed out by Piazzesi (2008), it is more plausible to assume all yields present observation errors[6]. With this alternative assumption, the state variables cannot be inverted but be estimated.

Second, for the majority of ATSMs, maximum likelihood estimation methods are difficult to apply, as there are no closed-form expressions for the transition densities of the state variables and parameters.

Finally, even in the rare cases where we do obtain closed-form expressions for the likelihood function, parameters enter such functions in a highly non-linear way. As there is no analytical expression for the maximum likelihood estimators (MLEs) in such cases, the MLEs require solving high-dimensional optimization problems by numerical methods. Some deterministic search algorithms are often applied to locate the MLEs[3]. However, choices such as termination criteria and initial parameter values can be non-trivial. Local maxima are frequent. Difficulties in estimation negatively affect the results of ATSMs.

There are several methods to estimate ATSMs. As the likelihood functions do not have closed-form expressions for most ATSMs, the first set of such methods attempt to approximate the likelihood function. One can apply the Euler discretization scheme for the stochastic differential equations (SDEs) of the state dynamics. Estimators obtained by maximizing the likelihood function based on the conditional Gaussian distribution are called quasi-maximum likelihood estimators, which is feasible for any ATSMs. However, the resulting estimators are not consistent except for the linear Gaussian dynamics. One can also numerically solve the forward Kolmogorov partial differential equations for conditional densities (Lo and MacKinlay (1988)). However, such methods face the curse of dimensionality. Yet another approach attempts to approximate the likelihood function using simulation techniques [7-9]. Such methods are also computationally costly, especially for multi-dimensional problems. Recently, Ait-Sahalia and Kimmel (2010) propose a maximum likelihood estimation method that relies on an approximation of the transition density of multi-dimensional state variables by Hermite polynomial expansions[4]. Most likelihood-based methods depend on the assumption that some yields are observed without error. There is little empirical evidence for this assumption. The presence of measurement noise in all yields requires the calculation of the filtered likelihood function, for which optimization is even more challenging. Another set of methods is based on moment matching (Hansen (1982)), using the feature that moments of affine diffusions are available in closed forms. However, one problem with this approach is that the states are never determined explicitly. Rather, it is possible to obtain state variables that lie outside of their domain [2].

The Bayesian inference analysis for ATSMs in this paper complements the previous analysis that resides in the frequentist domain. Specific to the ATSMs inference problem, the merits of Bayesian analysis can be exploited using MCMC methods. Within this framework, it is straightforward to relax the stringent assumption that an arbitrary set of yields are observed without error. This is empirically relevant. Our inference output based on market data indeed suggests that the measurement errors are of similar magnitude for yields across maturities. They also exhibit cross-sectional correlations. Now, with the relaxation of this assumption, the inversion method for state variables is not feasible.

In our MCMC framework, the latent states are inferred together with parameters. We use Gibbs samplers to alleviate the curse of dimensionality. They allow us to decompose the problem of sampling from the joint posterior distribution of parameters and latent states into a cycle of univariate sampling problems. Although the algorithm is designed to include the sampling of latent states, it can be readily applied to ATSMs with explicit states, such as moments extracted from yield data or macro factors[2,10]. Inference results on simulated yield data from different models show that our algorithm can closely replicate the observations. In the setting with explicit state variables, the algorithm generates samplers and likelihood values that converge to the true values. A common criticism against Bayesian analysis is the inclusion of prior distributions. We use diffuse prior distributions for most parameters. The performances on simulated yield data show that the algorithm is robust to disperse prior distributions.

We show that the MCMC algorithms also deliver good performances when applied to different market data sets. Data I consists of yields constructed from LIBOR and swap weekly observations for 1989.03.31 – 2007.03.02 for maturities 1, 3, 6, 9 and 12 months and 2, 3, 5, 7 and 10 years. Data II is the Fama-Bliss zero-coupon bond yields with monthly observations for 1972.01.31-2010.12.31 for maturities 1, 2, 3, 4 and 5 years. These two periods represent different economic episodes.

We document the strength of the MCMC methods in reconstructing yield data. The fitting errors, measured by the rooted mean square errors (RMSE), are smaller than that obtained by the inversion-MLE method and the model-free method in Collin-Dufresne et al. (2008)[10]. It is commonly thought that the principal component analysis (PCA) can produce small fitting errors that are hard to beat by affine models, as pointed out in Piazzesi (2008)[6]. Our results from the $A(1,3)$ model show that this is not necessarily the case. We obtain in-sample RMSEs that are comparable to that from the PCA.

We conduct an in-sample forecast analysis to identify missing data. The resulting pricing errors are within a few basis points (One basis point is 0.0001). Some other data construction methods such as Cubic splines, Nelson-Siegel and Svensson families are used in the industry[11-12]. These fitting methods explore the data in the cross-section but fail to consistently fit them in the time-series. Furthermore, these models, including PCA, lack probabilistic interpretations and no-arbitrage (NA) free. Our MCMC algorithms satisfy NA conditions by imposing parameter constraints provided in Cheridito et al. (2007)[3].

Finally, we can construct the short rates from the output. To fit the short end of the yield curve has been challenging because of seasonality and/or microstructure noise[6]. The inferred short rates from MCMC algorithms closely resemble the 1-month yield data, which are often used as a proxy for short rates.

Equipped with these efficient sampling schemes, we forecast future yield levels. For Data I, with the $A(0,3)$ and $A(1,3)$ models, we can forecast the 12- week-ahead yield levels with out-of-sample RMSEs within 5 basis points. We run a horse-race among several prediction methods. The Bayesian forecast performance of the $A(1,3)$ model dominates the OLS prediction and frequentist type prediction for all maturities. It also dominates the random walk prediction for all maturities greater or equal to one year.

We also conduct a full-fledged Bayesian model comparison for different ATSMs. The model mis-specification analysis from previous work has been exclusively based on goodness-of-fit tests[1,3]. Ait-Sahalia and Kimmel (2010) perform a model comparison based on the likelihood ratio test for (non)-nested models[4]. However, illustrative examples in Bishop (2007) show that estimation methods that perform well within the sample do not necessarily indicate a good predictive behavior because of over-fitting[13]. Various information criteria, such as AIC and BIC, have been proposed to penalize for over-parametrization, which often tend to favor simple models. From the Bayesian perspective, the problem of over-fitting can be avoided because the effective model complexity adapts automatically to the data. We find that the ranking of the two models by the model evidence is consistent with both in-sample fitting and out-of-sample forecast performances. Data I has the features of non-normality of yield distribution and a humped shape of yield change volatility. It ranks the models as $A(1,3)$ over $A(0,3)$. Data II also supports the non-normality feature but has a strong demand for the correlation between state variables. The $A(0,3)$ model is preferred by the data.

The MCMC analysis has been successfully applied to a wide range of stochastic volatility models. Jacquier et al. (1994) use MCMC methods to analyze the log stochastic volatility model, and then incorporate the leverage effect of stochastic volatilities [14-15]. Eraker et al. (2003) examine the Heston's volatility model by MCMC, and later extend the analysis to include jumps in volatility and return processes[16]. Johannes and Polson (2007) provide a review of recent developments regarding the application of MCMC in estimating various financial models[17].

In the multi-factor ATSMs literature, the MCMC analysis is relatively new. This might be due to the difficulty in evaluating the yields. In addition, state variable transition densities do not have closed-form expression for most ATSMs. Furthermore, the data-collection frequency in the literature prevents the usage of Euler discretization, which is common in other areas with wide application of MCMC. Early utilization of MCMC in ATSMs can be found in Chen and Scott (1993) and Hu (2005)[9,18]. Chen and Scott (1993) apply the extended Kalman filter for the multi-factor CIR model[9]. Hu (2005) conducts the MCMC analysis on multi-factor Vasicek and multi- factor CIR models[18]. As these models have limitations in capturing market data features, here we study more general models. Furthermore, we provide results for yield level forecasts and model comparison.

This chapter is organized as follows. In Section 2, we provide a brief introduction to MCMC methods. In Section 3, we apply the MCMC algorithms for ATSMs and investigate its performance with simulated data. Results of empirical studies on two sets of zero-coupon bond yield data are presented in Section 4. Section 5 concludes.

2 MCMC METHODS

In this section, we give a brief introduction to the MCMC methods applied in this paper. A thorough treatment of the theoretical foundations can be found in Robert and Casella (2004)[19]. The advantages of these methods rely mainly on two facts. First, they are useful in sampling random variables for which the conventional sampling scheme are not available. Second, they are beneficial in decomposing the problem of sampling from the high-dimensional density into a sequence of univariate sampling problems. Both features are helpful in addressing the inference problem for ATSMs.

Suppose that we observe data Y. The latent state variables X and the parameter set Φ are unknowns. The target is to infer Φ and X from the joint posterior distribution:

$$P(\Phi, X|Y). \tag{1}$$

Depending on the specific ATSM and the sample size, there are many parameters (approximately 40-80) to estimate, most of which enter the posterior density in a highly nonlinear way. As little is known about the density's properties, the traditional inversion and/or rejection-acceptance sampling schemes are not feasible. As discussed in the next paragraph, the Metropolis-Hastings (MH) algorithms are applied to sample these parameters. In addition to the parameter set Φ, we need to infer the latent states, which contribute 1000-3000 more random variables to sample, with the size depending on data window. The decomposition of high-dimensional problems into small units is extremely useful in reducing the complexity of the problem.

2.1 Metropolis-Hastings Algorithms

Suppose we want to sample a Markov chain $\{x^{(t)}, t = 1, 2, 3, \cdots\}$ with the stationary distribution $f(\cdot)$, the target density. Conditioning on $x^{(t)}$, we can use the MH algorithms and choose a conditional density $q(y|x)$, the proposal or candidate distribution, to help to sample $x^{(t+1)}$. The choice of $q(\cdot|x^{(t)})$ is delicate and needs to be tuned to specific problems. We will provide guidance in choosing this proposal density for ATSMs in the next section.

Step 1: Generate:

$$\begin{gathered} Yt \sim q\left(y|x^{(t)}\right), \\ u \sim U(0,1), \end{gathered} \tag{2}$$

where $U(0, 1)$ is the uniform distribution in $(0, 1)$.

Two special cases of MH algorithms, the independent MH algorithm and the random walk MH algorithm, are used in this paper. The former is useful when we have a good understanding of the target density and can propose efficient candidate densities. The latter explores the neighborhood of the Markov chain and gathers local information about the target stepwise. It is particularly useful for multi-dimensional densities.

2.2 The Independent Metropolis-Hastings Algorithm

Key: Candidate draws are independent of the previous states: $Y_t \sim q(y)$

For this algorithm, a good candidate density $q(\cdot)$ needs to fulfill two requirements. First, it needs to approximate the target density closely in the shape and location. With the close approximation, the acceptance probability for new samplers is high, and the sampling scheme is efficient. This requires us to be informative about the target density. Second, the candidate density should be diffusive to navigate through the entire support of the target density.

In many cases we have little information about the properties of the target density $f(\cdot)$, and thus it is hard to propose a good candidate density. The random walk MH algorithm provides an alternative approach.

2.2.1 The random walk Metropolis-Hastings algorithm

Key: Candidate draws are current state with a symmetric random walk perturbation: $Y_t \sim g(y - x_t)$.

Here $g(\cdot)$ is a symmetric distribution that is independent of x_t.

The two algorithms described above are helpful for the inference problem of the ATSMs. The other difficulty that affects the inference for ATSMs is that the posterior distribution is high-dimensional. The multistage Gibbs sampler described next is suitable for tackling this problem.

2.2.2 The Gibbs sampler[20]

Key: Joint densities are decomposed into iterations of conditional densities.

Denote $(X^{(t)}, \Phi^{(t)})$ as the samplers at the t-th entry in the Markov chain.

Step 1: Generate:

$$X^{(t+1)} \sim P_1(x|\Phi^{(t)}, Y). \tag{3}$$

Step 2: Generate:

$$\Phi^{(t+1)} \sim P_2(\phi|X^{(t+1)}, Y). \tag{4}$$

Here $P_1\left(x\middle|\Phi^{(t)}, Y\right)$ and $P_2\left(\phi\middle|X^{(t+1)}, Y\right)$ denote the distributions of each block of parameters or states conditioning on all others. Hammersley and Clifford (1971) prove the convergence of distributions $\left\{X^{(t+1)}, \Phi^{(t+1)}\right\}$ to the stationary joint distribution $P(X, \Phi|Y)$, as the number of iterations increases[21].

In the Gibbs sampling cycle, we decompose the target posterior distribution $P(\Phi, X|Y)$ into its full conditionals $P_1(x|\Phi^{(t)}, Y)$ and $P_2(\phi|X^{(t+1)}, Y)$. The distributions $P_1(x|\Phi^{(t)}, Y)$ and $P_2(\phi|X^{(t+1)}, Y)$ can be further decomposed into finer full conditional densities until efficient sampling methods are available.

2.3 The Kalman Filter and FFBS

The forward filtering backward sampling (FFBS) method is designed for the linear Gaussian model and is an efficient simulation version of smoothing recursions of the Kalman filter[22-23]. For the Gibbs sampler, we iterate through sampling latent states and parameters. In the first step, the FFBS algorithm samples the latent linear Gaussian states in a block. In this section, we first introduce the Kalman filter and then the FFBS algorithm.

Suppose that the state variables $\{X_t\}_{t=0}^{T}$ have a normal prior distribution at $t = 0$:

$$X_0 \sim X_p(m_0, G_0). \tag{5}$$

The observation equation and state equation follow the linear Gaussian system:

$$\begin{aligned} Y_t &= F_t X_t + v_t, v_t \sim N(0, V_t), \\ X_t &= G_t X_{t-1} + w_t, w_t \sim N(0, W_t). \end{aligned} \tag{6}$$

First, assume that the parameter set Φ in the (Ft, Vt, Gt, Wt) matrices is known. Denote the observations of $\{Y_s, s = 1 \cdots t\}$ as $Y_{1:t}$. Because of the linear Gaussian structure and normal prior, the filtered distribution $P(X_{t-1}|Y_{1:t-1}, \Phi)$ is normally distributed, hence is fully characterized by its mean and variance. The Kalman filter is a mechanism for recursively updating the mean and variance of $P(X_{t-1}|Y_{1:t-1}, \Phi)$.

2.3.1 The Kalman filter[24]

Suppose at $t - 1$, the distribution of $p(X_{t-1}|Y_{1:t-1}, \Phi)$ is:

$$p(X_{t-1}|Y_{1:t-1}, \Phi) \sim N(m_{t-1}, C_{t-1}). \tag{7}$$

The predictive distribution of $P(X_t|Y_{1:t-1}, \Phi)$ is Gaussian:

$$p(X_t|Y_{1:t-1}, \Phi) \sim N(a_t, R_t), a_t = G_t m_{t-1}, R_t = G_t C_{t-1} G_t^{'} + W_t. \tag{8}$$

The predictive distribution of $p(Y_t|Y_{1:t-1}, \Phi)$ is Gaussian:

$$p(Y_t|Y_{1:t-1}, \Phi) \sim N(f_t, Q_t), f_t = F_t a_t, Q_t = F_t R_{tF_t^{'}} + V_t. \tag{9}$$

The filtered distribution of $p(X_t|Y_{1:t}, \Phi)$ is Gaussian:

$$p(X_t|Y_{1:t}, \Phi) \sim N(m_t, C_t), m_t = a\_t + R_{tF_t^{'}Q_t^{-1}} e_t, C_t = R_t - R\_tF_t^{'}Q_t^{-1}F_t R_t, \tag{10}$$

where e_t is the predicting error:

$$e_t = Y_t - f_t. \tag{11}$$

Now we assume the parameter set Φ is unknown. Denote the latent states $\{X_s, s = 1 \cdots t\}$ as $X_{1:t}$. To sample from $P(\Phi, X_{1:T}|Y)$, we iterate through the full conditional decompositions:

$$P_1(X_{1:T}|\Phi, Y), P_2(\Phi|X_{1:T}, Y). \tag{12}$$

The first component is sampled by the FFBS algorithm. The second component is sampled by the random walk MH, independent MH, and/or other standard sampling schemes.

The target of interest is

$$P(X_{1:T}|Y_{1:T}, \Phi). \tag{13}$$

This joint distribution can be decomposed as:

$$P(X_{1:T}|Y_{1:T}, \Phi) = \Pi_{t=0}^{T} P(X_t|X_{t+1:T}, Y_{1:T}, \Phi). \tag{14}$$

Starting from $P(X_T|Y_{1:T}, \Phi)$, the last component in the forward iteration of filtered distribution in the Kalman filter, we iterate backward and sample sequentially:

$$P(X_t|X_{t+1:T}, Y_{1:T}, \Phi) = P(X_t|X_{t+1}, Y_{1:t}, \Phi), t = 1, \cdots, T - 1. \tag{15}$$

This last equality comes from the Markovian structure of the model.

2.3.2 The FFBS algorithm [22]

Initialization: Set:

$$P(X_T|Y_{1:T},\Phi) \sim N(m_T, C_T). \tag{16}$$

Backward iteration: For $t = T-1,\cdots,0$, we have:

$$p(X_t|X_{t+1},Y_{1:t},\Phi) \sim N(ht, Ht), h_t = m_t + C_t G'_{t+1} R^{-1}_{t+1}(X_{t+1} - a_{t+1}), H_t = C_t - C_t G'_{t+1} R^{-1}_{t+1} G_{t+1} C_t. \tag{17}$$

The MH sampling algorithms, Gibbs iterations, and the FFBS algorithm provide the essential building blocks for our MCMC algorithms for ATSMs. In the section of designing the MCMC algorithms, we tailor these algorithms to each ATSM.

2.4 The Model Comparison

A full Bayesian treatment of ATSMs involves a model-comparison analysis. Denote a specific ATSM by M. The posterior distribution is uniquely determined by the conditional probability of the unknowns given the observed data and the specific model:

$$P(\Phi, X|M,Y) = \frac{P(Y|\Phi,X,M)P(\Phi,X|M)}{Z}, \tag{18}$$

where $P(\Phi,X|M)$ is the prior distribution and $P(Y|\Phi,X,M)$ is the likelihood. The marginal likelihood Z is defined as:

$$Z \equiv P(Y|M) = \int\int P(Y|M,\Phi,X)P(\Phi,X|M)d\Phi dX. \tag{19}$$

The marginal likelihood Z is interpreted as the model evidence, as it measures the support for model M given data Y. The quantity Z carries information that allows us to make a model comparison from a Bayesian perspective. Such a comparison does not require alternative models to be nested. A detailed analysis of the advantages of Bayesian model comparison can be found in Kass and Raftery (1995)[25].

Direct computation of the marginal likelihood Z is not feasible, as it involves multi-dimensional integration over the parameters and latent states. Previously, the Schwarz information criterion (Schwarz (1978)) and the Laplace approximation method have been used to approximate the model evidence factor. The latter is the Bayesian inference criterion (BIC) in the frequentist framework[26]. As a quite different approach, the reversible-jump MCMC algorithm (Green (1995)) has been developed to incorporate different models as discrete parameters in the Gibbs iterations. The MCMC algorithm switches among different models during the iterations, and the model-comparison result is generated as an output of such algorithms. For the ATSMs inference problem, as we can efficiently sample from the posterior distribution, we can approximate the quantity Z by the harmonic mean of the likelihood values[27]:

$$\hat{Z} = \left[\frac{1}{N}\sum_{i=1}^{N}\frac{1}{P(Y|Xi,\Phi i)}\right]^{-1}, \tag{20}$$

where N is the number of simulations, and $\{X_i, \Phi_i\}$ are the i-th simulation from the joint posterior distribution $P(X,\Phi|Y)$.

3 MCMC ALGORITHMS FOR ATSMS

We study two classes of ATSMs: $A(0,n)$ and $A(m,n)$ with $m = 0,1$ and $n = 3$. We cast the analysis under the "extended affine" specification of Cheridito et al. (2007)[3]. In the $A(m,n)$ model, the dynamics of state variables:

$$dX = (O^p X_t + O^p_0)dt + diag[(C_i X_i + 1)^{0.5}]dW^P_t = (OX_t + O_0)dt + diag[(C_i X_i + 1)^{0.5}]dW^Q_t, \tag{21}$$

where $O^p, O \in R^{n\times n}$, $O^p_0, O_0 \in R^n$, and C_i is the i-th row of the matrix C with rank m. The parameter values are within the constraints that insure the existence, stationary and no-arbitrage conditions. The term W^P_t is an n-dimensional Brownian motion under the data-generating measure P, and W^Q_t is an n-dimensional Brownian motion under the risk-neutral measure Q.

The short rate process is a linear combination of state variables:

$$r_t = \delta_0 + \delta' X_t, \tag{22}$$

for some $\delta_0 \in R$ and $\delta \in R^n$.The observation equation is

$$Y_t = V'_b X_t - V_0 + \epsilon. \tag{23}$$

Here Y_t is a $T\times 1$ vector with the yields of T maturities at time t. V_b is a $n\times T$ matrix and V_0 is a $M\times 1$ vector. The terms V_b and V_0 solve Riccati-type ODEs in Duffie et al. (2000)[28]. In the $A(0,n)$ model, V_b can be solved explicitly. The measurement error, denoted by ϵ, has a normal distribution of $N(0,\Sigma)$, where Σ is a $T\times T$ symmetric and positive definite matrix.

For the $A(0,n)$ model, we simulate zero coupon yield data for 43 years with monthly observations. The maturities are 1, 2, 4, 6, 7, 8 ad 10 years. These specifications are chosen to match those frequently used in the literature. For the simulated data, the parameter values for different models are the estimation results in Cheridito et al. (2007) with slight modifications[3]. The parameter values are reported in Table 1 and 2.

Table 1 Parameter Inference Results, $A(0,3)$ with Explicit States

Parameter	True Value	Mean	Std. Dev.	95% Confidence Interval

η_0	0.0529	0.0537	0.0003	[0.0529, 0.0545]
η_1	0.0209	0.0194	0.0004	[0.0186, 0.0202]
η_2	0.0226	0.0222	0.0004	[0.0216, 0.0230]
η_3	0.0279	0.0272	0.0003	[0.0268, 0.0278]
OO_1	0.4349	0.2655	0.1118	[0.0598, 0.4985]
OO_2	0.2360	0.2977	0.0864	[0.1226, 0.4538]
OO_3	0.3454	0.3411	0.0174	[0.3056, 0.3735]
O_{11}	-0.8600	-0.4910	0.1136	[-0.7001, -0.3078]
O_{12}	-0.1600	-0.2641	0.0814	[-0.3956, -0.1125]
O_{13}	-0.3800	-0.2857	0.0626	[-0.4254, -0.1858]
O_{21}	-0.3200	-0.4955	0.0962	[-0.6477, -0.3325]
O_{22}	-0.6000	-0.4376	0.0679	[-0.6000, -0.3439]
O_{23}	-0.1200	-0.1194	0.0502	[-0.2026, -0.0434]
O_{31}	-0.1600	-0.1399	0.0220	[-0.1806, -0.0896]
O_{32}	-0.2400	-0.2754	0.0167	[-0.3018, -0.2313]
O_{33}	-0.4000	-0.4061	0.0122	[-0.4274, -0.3787]

*Note: This table reports the parameter inference results for the $A(0,3)$ model with explicit states. Monthly observations of zero-coupon bond yield data for 43 years with maturities 1 ,2, 4, 6, 7, 8 and 10 years are simulated with the true parameter values reported in the table.

Table 2 Parameter Inference Results, A(1,3) with Explicit States

Parameter	True Value	Mean	Std. Dev.	95% Confidence Interval
η_0	0.0529	0.0531	0.0003	[0.0526, 0.0536]
η_1	0.0209	0.0209	0.0002	[0.0205, 0.0213]
η_2	0.0226	0.0226	0.0001	[0.0224, 0.0227]
η_3	0.0279	0.0279	0.0000	[0.0278, 0.0280]
OO_d	1.2349	1.1259	0.0052	[1.0232, 1.2003]
OO_1	0.2360	0.3176	0.0022	[0.2836, 0.3715]
OO_2	0.3454	0.3350	0.0050	[0.3255, 0.3441]
O_{dd}	-0.8600	-0.8901	0.0427	[-0.9477, -0.7878]
O_{d1}	-0.3200	-0.2963	0.0357	[-0.3483, -0.2257]
O_{d2}	-0.1600	-0.1600	0.0106	[-0.1801, -0.1372]
O_{11}	-0.6000	-0.6053	0.0141	[-0.6345, -0.5738]
O_{12}	-0.1200	-0.1297	0.0074	[-0.1433, -0.1106]
O_{21}	-0.2400	-0.2379	0.0056	[-0.2505, -0.2260]
O_{22}	-0.4000	-0.3954	0.0031	[-0.4040, -0.3895]
C_1	0.3000	0.2532	0.0765	[0.4078, 0.7520]
C_2	0.3000	0.5229	0.0940	[0.1159, 0.3640]

*Note: This table contains the parameter inference results for the $A(1,3)$ model with explicit states. Monthly observations of zero-coupon bond yield data for 43 years with maturities 1, 2, 4, 6, 7, 8, and 10 years are simulated with the true parameter values reported in the table.

We denote the observation of yield data as $Y \equiv \{Y_t^\tau\}_{t=1}^T$ where τ is the maturity of zero-coupon bond. The state variables are denoted as $X \equiv \{X_t^\tau\}_{t=1}^T$. The parameter space is denoted as $\Phi \equiv \{\Phi^P, \Phi^Q\}$. Here Φ^P is the parameters governing the state dynamics under the data-generating measure P, and Φ^Q are the parameters under the risk-neutral measure Q. We sample the parameters and latent states from the posterior distribution:

$$P(\Phi^Q, \Phi^P, X|Y). \tag{24}$$

We can apply the Gibbs sampling to iterate through the full conditionals decomposition:

$$P(\Phi^P|\Phi^Q, X, Y), P(\Phi^Q|\Phi^P, X, Y), P(X|\Phi^P, \Phi^Q, Y). \tag{25}$$

In the sampling process for both Φ^P and Φ^Q, parameter constraints are imposed. The summary of parameter constraints for existence, stationarity, and boundary non-attainable conditions can be found in Ait-Sahalia and Kimmel (2010)[4]. The boundary non-attainable condition prevents arbitrage opportunities for the "extended affine" specification. Samplers falling out of such constraints are discarded.

In what follows, we first discuss sampling algorithms for posterior distributions $P(\Phi^P|\Phi^Q, X, Y)$ and $P(\Phi^Q|\Phi^P, X, Y)$. Then we introduce the sampling of latent states under different models.

3.1 Sampling Φ^P

As only Φ^Q enters the pricing formula, the yield data do not contain information directly for Φ^P . The data provide information for Φ^P indirectly through the channel of state variables X. To sample $P(\Phi^P|\Phi^Q, X, Y)$, we need to sample from the posterior distribution:

$$P(\Phi^P|X) = P(X|\Phi^P) \times P_0(\Phi^P), \tag{26}$$

where $P_0(\Phi^P)$ denotes the prior distribution for Φ^P. The posterior distribution of Φ^P cannot be sampled using conventional schemes. Therefore, the random walk MH algorithm is applied.
In the rest of the sections, we focus on the sampling of Φ^Q, as they are important for evaluating the performances of in-sample fitting, out-of-sample forecast, and model comparison.

3.2 Sampling Φ^Q

To sample $P(\Phi^Q|\Phi^P, X, Y)$, we explore information in both the state variables X and yield data Y. To sample the total parameter set, we further break $P(\Phi^Q|\Phi^P, X, Y)$ down to the full conditional decomposition of each parameter. Here we abbreviate $P(\theta|\cdot)$ as the full conditional decomposition for the parameter θ. Only few parameters, δ_0, O_b^0 and Σ, have conjugate posterior distributions that can use conventional sampling algorithms. The two distributions, $P(\delta_0|\cdot)$ and $P(O_b^0|\cdot)$, are sampled from the normal distributions. The distribution $P(\Sigma|\cdot)$ is sampled from the Wishart distribution. Further information about the choice of conjugate distributions can be found in Bishop (2007)[13]. As there are no standard posterior distributions for the rest of the parameters, they are sampled from the random walk MH algorithms.
In the first simulation exercise, we set state variables X as known and only sample parameters. We refer the models where the state variables are known as models with explicit states. The inferred parameters can be used to reconstruct the yield data. We compare the (simulated) true yield data and the yield data reconstructed with the inferred parameters. In Table 3, the “Exp” column reports the in-sample pricing errors for the two models measured by RMSE in bps. As we can see, the in-sample errors are indeed small, which indicates that our algorithm can generate parameter samplers that closely reconstruct the yield data. This table also reports the simulated and true log-likelihood values, which approach the true maximal value.

Table 3 In-Sample Fitting Performances with Simulated Data

	$A(0,3)$		$A(1,3)$	
	Exp	Latent	Exp	Latent
		RMSE (bps)		
1-Year	0.72	29.45	0.27	36.38
2-Year	1.67	20.67	0.39	24.42
4-Year	1.94	13.89	0.64	5.97
6-Year	1.54	11.30	0.75	6.21
7-Year	1.04	10.50	0.87	7.43
8-Year	1.13	9.86	1.40	8.85
10-Year	3.02	8.89	2.00	10.71
		Log Likelihood		
True	23267.4	23265.5	23262.2	23298.1
Simulated	21822.0	20900.0	23254.0	22599.0

*Note: This table reports the in-sample pricing errors and log-likelihood values of the inference output from the simulated data. Monthly observations of zero-coupon bond yield data for 43 years are simulated with the true parameter values and maturities reported in Table 1-2.

3.3 Sampling X in $A(0, n)$

In this section, we describe the sampling scheme for latent states in the $A(0, n)$ model. Specifically, the state variables have the dynamics:

$$dX_t = O_p X_t dt + dW_t^P = (O_{bb}Xt + O_b^0)dt + dW_t^Q. \tag{27}$$

Denote the time interval between the time indices t and $t+1$ as Δ. In the $A(0, n)$ model, conditioning on X_{t-1}, X_t has a Gaussian transition density:

$$X_t \sim N\left((e^{O_{bb}\Delta}X_{t-1} + \int_{t-1}^{t} e^{O_{bb}(t-s)}O_b^0 ds\,, \int_{t-1}^{t} e^{O_{bb}(t-s)}\, e^{O_{bb}^{'}(t-s)}ds\right). \tag{28}$$

As the state variables follow a linear Gaussian dynamic and enter observation equation linearly, the FFBS algorithm can be applied to simulate $P(X|Y, \Phi^Q)$[22,23,29].
Closely related to the FFBS algorithm is the Kalman filter. The Kalman filter gives a mechanism to recursively evaluate the Gaussian predictive, filtering and smoothing distributions when the parameters are known. In particular, the Kalman smoother provides a backward recursion mechanism to compute the conditional distribution of $P(X_t|Y, \Phi^Q)$ for $t = T, \cdots 1$. Instead of recursively sampling $P(X_t|Y, \Phi^Q)$, $t = T \cdots 1$ backwards, the FFBS algorithm simulates X from $P(X|Y, \Phi^Q)$ in one block.
In the simulation exercise, we apply the MCMC algorithms described for the inference of parameters and latent states for the $A(0, 3)$ model. Table 3 reports RMSEs and log-likelihood values. Based on the results, we can see that the algorithm produces inferred parameters and latent states that replicate the in-sample data closely and
log-likelihood value that approaches the true maximal value.

3.4 Sampling X in $A(1, n)$

In the $A(1,n)$ model, the state variables in the first dimension are restricted to be positive. This state variables drive conditional volatilities and thus compensate for the counterfactual assumption of constant conditional variances in the $A(0,n)$ model. Denote the restricted state variables as $X_0 \equiv \{X_t^0\}_{t=1}^T$ and the unrestricted state variables as $X1 \equiv \{X_t^1\}_{t=1}^T$. The dynamics of the restricted state variables are

$$dX_t^0 = (O_{dd}\, X_t^0 + O_0)dt + \sqrt{X_t^0} dW_{0,t}^Q. \tag{29}$$

For $n = 3$, the unrestricted state variables are two-dimensional with the dynamics:

$$dX_t^1 = \left(O_{bd}\, X_t^0 + O_{bb} X_t^1 + O_b^0\right)dt + \begin{pmatrix} \sqrt{c_1 X_t^0 + 1} & 0 \\ 0 & \sqrt{c_2 X_t^0 + 1} \end{pmatrix} dW_{1,t}^Q. \tag{30}$$

The posterior distribution we want to sample is $P(\Phi^Q, \Phi^P, X^0, X^1|Y)$.

In the Gibbs sampling process, we iterate through the cycle of the full conditional decomposition of the posterior distribution:

$$p(\Phi^Q|X^0, X^1, \Phi^P, Y),\ p(\Phi^P|X^0, X^1, \Phi^Q, Y),\ p(X^0|X^1, \Phi^Q, \Phi^P, Y),\ p(X^1|X^0, \Phi^Q, \Phi^P, Y). \tag{31}$$

As we have discussed about sampling parameters Φ^P and Φ^Q, we focus on sampling of the latent states in this section.

3.4.1 Sampling X^0

The restricted state variables $\{X_t^0\}_{t=1}^T$ enter the pricing formula linearly but have a non-linear dynamic. We can apply the Gibbs samplers to further decompose the vector X^0 into the cycle:

$$P\left(X_t^0 \middle| X_{t-1}^0, X_{t+1}^0, Y_t, X_{t-1}^1, X_t^1, X_{t+1}^1, \Phi^Q\right), t = 1, \cdots T \tag{32}$$

Even with this decomposition, we still cannot draw the univariate state variable X_t^0 directly. However, we can propose an efficient candidate density in the independent MH algorithm by exploiting the linearity of X_t^0 in the observation equation and its dynamics. For the independent MH algorithm, an efficient candidate density needs to closely resemble the shape and location of the target density in equation (3) for each t. In the following analysis, the parameter set Φ^Q is omitted for notational clarity. The target posterior density in (3) can be further decomposed:

$$P\left(X_t^0 \middle| X_{t-1}^0, X_{t+1}^0, Y_t, X_t^1, X_{t+1}^1, X_{t+1}^1\right) \propto P(Y_t|X_t^0, X_t^1) \times P(X_{t-1}^0, X_t^0, X_{t+1}^0, X_{t-1}^1, X_t^1, X_{t+1}^1). \tag{33}$$

The component $P\left(X_{t-1}^0, X_t^0, X_{t+1}^0, X_{t-1}^1, X_t^1, X_{t+1}^1\right)$ can be decomposed as:

$$P\left(X_{t-1}^0, X_t^0, X_{t+1}^0, X_{t-1}^1, X_t^1, X_{t+1}^1\right) \propto P(X_{t+1}^0|X_t^0) \times p(X_t^0|X_{t-1}^0) \times P(X_{t+1}^1|X_t^0, X_{t+1}^0, X_t^1) \times P\left(X_t^1 \middle| X_{t-1}^0, X_t^0, X_{t-1}^1\right) \tag{34}$$

With the decomposition above, the posterior distribution in equation (3) has the expression:

$$P\left(X_t^0 \middle| X_{t-1}^0, X_{t+1}^0, Y_t, X_t^1, X_{t-1}^1, X_{t+1}^1\right) \propto e^{-0.5\left(Y_t + V_0 - X_t^0 V_d - X_t^1 V_b\right)' \Sigma^{-1}\left(Y_t + V_0 - X_t^0 V_d - X_t^1 V_b\right)} \times P_X\left(\Delta, X_{t+1}^0 \middle| X_t^0, O_{dd}, O_d^0\right) \times$$
$$P_X\left(\Delta, X_t^0 \middle| X_{t-1}^0, O_{dd}, O_d^0\right) \times \frac{e^{-\frac{\left(X_t^1 - e^{O_{bb}\Delta} X_t^1 - m_1\right)^2}{2\sigma_1^2}}}{\sqrt{\sigma_1^2}} \times \frac{e^{-\frac{\left(X_t^1 - e^{O_{bb}\Delta} X_{t-1}^1 - m_0\right)^2}{2\sigma_{01}^2}}}{\sqrt{\sigma_0^2}}. \tag{35}$$

Here $P_X(\Delta, x|x_0, O_{dd}, O_d^0)$ denotes the transition density of the restricted state variable:

$$P_X\left(\Delta, x \middle| x_0, O_{dd}, O_d^0\right) = c \times e^{-v-u} \left(\frac{v}{u}\right)^{\frac{q}{2}} I_q\left(2(u \times v)^{0.5}\right), \tag{36}$$

with $q = 2O_d^0 - 1, c = \frac{-2O_{dd}}{1 - e^{O_{dd}\Delta}}, u = cx_0 e^{O_{dd}\Delta}$ and $v = cx$. I_q is the modified Bessel function of the first kind of order q. The terms (m_0, σ_0^2) and (m_1, σ_1^2) have the following expressions:

$$\begin{aligned} m_0 &= \left[O_{bd} X_t^0 + O_0^b + e^{O_{bb}\Delta}(O_{bd} X_{t-1}^0 + O_0^b)\right]\frac{\Delta}{2}, \\ \sigma_0^2 &= \left[C_{bd} X_t^0 + O_0^b + e^{2\times O_{bb}\Delta}(O_{bd} X_{t-1}^0 + O_0^b)\right]\frac{\Delta}{2}, \\ m_1 &= \left[O_{bd} X_{t+1}^0 + O_0^b + e^{O_{bb}\Delta}(O_{bd} X_t^0 + O_0^b)\right]\frac{\Delta}{2}, \\ \sigma_1^2 &= \left[C_{bd} X_{t+1}^0 + O_0^b + e^{2\times O_{bb}\Delta}(O_{bd} X_t^0 + O_0^b)\right]\frac{\Delta}{2}. \end{aligned} \tag{37}$$

Now we are ready to choose the candidate density to sample the posterior distribution of equation (3). First, conditioning on Y_t, X_t^0 follows the distribution:

$$X_t^0 | Y_t \propto (U_t, V_t), \tag{38}$$

with

$$U_t = V_t^{-1}\left(V_d' \Sigma^{-1}(Y_t + V_0 - X_t^0 V_d - X_t^1 V_b)\right), V_t^{-1} = V_d' \Sigma^{-1} V_d. \tag{39}$$

Conditioning on X_{t-1}^0, the distribution $P(X_t^0|X_{t-1}^0)$ is approximately normally distributed as $N(U_t^1, V_t^1)$ with:

$$U_t^1 = X_{t-1}^0 + \left(O_{dd} X_{t-1}^0 + O_d^0\right)\Delta, V_t^1 = X_{t-1}^0 \Delta. \tag{40}$$

Conditioning on X_{t+1}^0, the X_t^0 can be approximated to be normal $N(U_t^2, V_t^2)$, with

(41)

$$U_t^2 = \frac{X_{t+1}^0 - O_d^0\Delta}{1 + O_{dd}\Delta}, V_t^2 = \frac{X_{t+1}^0\Delta}{(1 + O_{dd}\Delta)^2}.$$

Combining the three normal distributions, we can propose the candidate density that approximates the target density in equation (3) closely. Denote $q1(\cdot)$ and $q2(\cdot)$ as the candidate densities with the following definitions:

$$\tilde{q} \sim N\left(\frac{V_t^1V_t^2U_t + V_tV_t^2U_1 + V_tV_t^1U_2}{V_tV_t^1 + V_tV_t^2 + V_t^1V_t^2}, \frac{V_tV_t^1V_t^2}{V_tV_t^1 + V_tV_t^2 + V_t^1V_t^2}\right). \tag{42}$$

In the experiment where we set the parameters and the unrestricted state variables as known, and sample only the restricted states, the acceptance rate for the independent MH algorithm is around 99%, which indicates that the candidate density $\tilde{q}(\cdot)$ is indeed efficient.

3.4.2 Sampling X^1

The last step in the Gibbs cycle is to sample:

$$P(X^1|X^0, \Phi^Q, \Phi^P, Y). \tag{43}$$

Without loss of generality, we consider the $A(1, 2)$ model. For $A(1, 3)$, the algorithm applies, and we only need to adjust the matrix calculations accordingly. Conditioning on $X1$, the state variable $X1$ can be solved by:

$$X_t^1 = e^{O_{bb}\Delta}X_{t-1}^1 + \int_{t-1}^{t} e^{O_{bb}(t-s)}\left[\left(O_{bd}X_s^0 + O_b^0\right)ds + \sqrt{c_1X_s^0 + 1}dW_s^Q\right]. \tag{44}$$

Conditioning on X^0, the integrals can be approximated as:

$$\int_{t-1}^{t} e^{O_{bb}(t-s)}\left(O_{bd}X_s^0 + O_b^0\right)ds = \left(O_{bd}X_t^0 + O_b^0 + e^{O_{bb}\Delta}\left(O_{bd}X_{t-1}^0 + O_b^0\right)\right)\frac{\Delta}{2},$$
$$\int_{t-1}^{t} e^{O_{bb}(t-s)}\sqrt{C_{bd}X_s^0 + 1}\,dW_s^Q \sim \left(0, \left(C_{bd}X_t^0 + 1 + e^{O_{bd}\Delta}\left(c_1X_{t-1}^0 + 1\right)e^{O_{bb}'\Delta}\right)\frac{\Delta}{2}\right). \tag{45}$$

Based on this approximation, X_t^1 resumes the linear Gaussian structure:

$$y_t^1 = X_t^1V_b + N(0, \Sigma),$$
$$X_t^1 = e^{O_{bb}\Delta}X_{t-1}^1 + D_t + N(0, V_t), \tag{46}$$

with

$$y_t^1 = Y_t - X_t^0V_d + V_0,$$
$$D_t = \left(O_{bd}X_t^0 + O_b^0 + e^{O_{bb}\Delta}\left(O_{bd}X_{t-1}^0 + O_b^0\right)\right)\frac{\Delta}{2},$$
$$V_t = \left(c_1X_t^0 + 1 + e^{O_{bb}\Delta}\left(c_1X_{t-1}^0 + 1\right)e^{O_{bb}'\Delta}\right)\frac{\Delta}{2}. \tag{47}$$

The FFBS algorithm can be applied to sample X^1 in a block.

Table 3 reports the performance of the algorithm for $A(1,3)$ based on simulated data. The pricing errors, being bigger than the models with explicit states, are within good precision ranges. The log-likelihood value approaches the true maximal value. The increase in pricing errors comes from the fact that, in addition to the parameters, we have 1548 state variables for $A(1, 3)$ to sample. To access the efficiency of the candidate density for the restricted state variables, the acceptance rate is 60%-70% for all restricted states. This indicates that the candidate density we propose is efficient.

4 THE EMPIRICAL ANALYSIS

In this section, we apply the MCMC algorithms on two market data sets of different economic episodes and show that it can replicate the yield data and forecast future yield levels. Then we perform a model comparison analysis for each of the two data sets.

4.1 The Data

We use two sets of zero-coupon bond yield data. Data I consists of weekly observations of zero-coupon bond yield with a sample period 1989.03.31-2007.03.02. The data are like that used in Collin-Dufresne et al. (2008)[10]. The zero-coupon bond prices are constructed by bootstrapping the LIBOR rates with maturities 1, 3, 6, 9 and 12 months and the swap rates with maturities 2, 3, 5, 7 and 10 years. The 9-month LIBOR rates are not available for the period of 1989.03.31-1991.05.31. The linear interpolation method is applied to obtain the missing data.

Data II consists of zero-coupon bond yield data with maturities 1, 2, 3, 4, and 5 years from the CRSP monthly treasury file. The sample period is 1972.01.31-2010.12.31. We trace the data sets used in Ait-Sahalia and Kimmel (2010) and Cheridito et al. (2007) as closely as possible[3-4]. We can only obtain data with five maturities from CRSP. To have similar sample size, we use a longer sample period of 39 years.

The two yield data sets cover different economic episodes and exhibit different empirical features. During the sample period of Data I, Piazzesi (2008) suggests that there is evidence of "a return to normality" and constant conditional second moments seem to be enough to describe the state dynamics[6]. Data II covers the two regimes of extreme volatility movements: the oil price shock in 1974 and monetary experiment in 1979-1982. The conditional second moments of yields exhibit peaks corresponding to these two regimes. We exam these two empirical facts from a Bayesian perspective. For Data I, $A(1,3)$ dominates the other model. For Data II, $A(0,3)$ model outperforms better.

4.2 The In-Sample Fitting Performance

We study the in-sample fitting and forecasting performances of the MCMC algorithms applied on Data I. Parameters and latent states inferred from the MCMC algorithms can be used to replicate the in-sample yield data closely. Table 4 reports the in-sample fitting performance for Data I with $A(0,3)$ and $A(1,3)$ models.

Table 4 In-Sample Fitting Performances-Data I

	$A(0,3)$		$A(1,3)$	
	Mean	RMSE	Mean	RMSE
1-Month	0.42	5.83	-0.10	5.99
3-Month	1.13	4.98	0.69	4.52
6-Month	-0.08	4.54	0.18	4.40
9-Month	-1.28	4.86	-0.36	4.60
12-Month	-2.19	6.01	-0.88	4.92
2-Year	1.29	7.32	2.33	6.01
3-Year	1.64	6.64	1.62	6.03
4-Year	0.18	6.06	-0.44	5.56
5-Year	0.69	5.95	0.04	5.78
7-Year	-0.50	6.68	0.26	6.01
10-Year	-0.56	8.29	0.86	6.92

*Note: This table reports the in-sample fitting performances of the $A(0,3)$ and $A(1,3)$ models for Data I: weekly observations of zero-coupon bond yield data of maturities 1, 3, 6, 9 and 12 months, 2, 3, 4, 5, 7, and 10 years from 1989.03.31 – 2007.03.02.

The in-sample fitting performance is evaluated by two measures: the average pricing errors and RMSEs for each maturity. To compare the RMSEs, we use the results reported in Table III and V in Collin-Dufresne et al. (2008) as a benchmark[10]. Data I is similar to the data used in their paper. It turns out that for both $A(0,3)$ and $A(1,3)$ models, our in-sample pricing errors are smaller than those from their model-free estimation method for all maturities.

For the in-sample fitting performance, the PCA is a benchmark hard to beat. We provide a comparison between MCMC with the PCA decomposition. As suggested by the fitting performance of the models in Data I, we choose $A(1,3)$ model for this comparison. We also assume that the measurement error is uncorrelated across maturities. We could gain more precision in in-sample fitting. As shown in Table 5, the in-sample errors are marginally bigger than but comparable to that implied by the PCA.

Table 5 In-Sample Pricing Errors, $A(1,3) -$ Data I

	PCA	$A(1,3)$		
	In-sample fit	In-sample fit	Out-sample forecast	In-sample forecast
			RMSE	
1-Month	2.96	8.71	2.07	7.32
3-Month	2.96	4.61	3.34	6.19
6-Month	2.01	0.63	5.10	5.28
9-Month	2.12	2.53	5.53	4.96
1-Year	2.00	3.93	5.11	5.18
2-Year	1.83	1.92	6.62	6.77
3-Year	2.01	1.49	6.63	6.50
4-Year	1.44	1.06	8.00	5.78
5-Year	1.31	1.22	7.71	5.73
7-Year	1.11	1.25	6.88	5.82
10-Year	1.28	3.94	4.99	8.25

*Note: This table reports the in-sample fitting and forecast performances of the $A(1,3)$ model for Data I.

We also conduct an in-sample forecast analysis. We apply the MCMC algorithms on yield data with nine maturities from Data I, while leaving out yields of maturities 2 and 10 years. With the inferred parameters and latent states, we reconstruct the yield data. In addition, we "interpolate" the yield of 2 years, and "extrapolate" the yield of 10 years. Results are reported in Table 4. As we use 9 maturities compared with the previously 11 maturities, the smaller sample size results in bigger pricing errors. The pricing errors for yields of 2 and 10 years are marginally larger compared with the RMSEs of other maturities. Other yield construction methods, such as the Cubic spline and the Nelson-Siegel families, are often used in the industry. These methods, together with PCA, fit the yield data in the cross-section but fail to consistently provide fitting in the time-series. Furthermore, these methods do not rule out arbitrage opportunities. By contrast, the MCMC method consistently fits yield data in both time-series and cross-section and satisfies the no-arbitrage condition. In addition, the probabilistic characterization of parameters and latent states in MCMC allows us to make a Bayesian forecast about future yield levels.

At last, we show that our algorithm can construct the short rates closely. The $A(0,n)$ and $A(1,n)$ models have the problem that the implied short rates can be negative. Furthermore, the fitting errors for short-end yields from ATSMs are usually big for the reasons of seasonality and microstructure noises [10]. As reported in Collin-Dufresne et al. (2008), the RMSEs for 1-month yield are around 14 basis points for both $A(0,3)$ and $A(1,3)$ models, even though the 3-month yield data are used for inversion[10]. We use the inferred parameters and latent states to construct the short rates, and compare it with the 1-month yield, which is often used as a proxy for short rates. The inferred short rates are positive and closely resemble the 1-month yield data with a correlation of 99.75% and the in-sample RMSE of 5.99 basis points.

In conclusion, the MCMC algorithms deliver good in-sample fitting and in-sample forecast performances. They also construct the short rates that closely resemble the short-end yield data. In this next section, we explore the out-of-sample forecast performance of the MCMC algorithms.

4.3 The Out-of-Sample Forecast Performance

In this section, we exam the forecast performance of each model for Data I. Denote Y_t as the yield data observations up to time t. As current yield data reflect the market's expectation of future, we want to forecast the future yield level given current information of Y_t. We accomplish this task by characterizing the conditional expectation of $E(Y_T|Y_t)$ with marginalization of parameters and latent states:

$$E(Y_T|Y_t) = \int\int Y_T P(\Phi^Q, X|Y_t) dX d\Phi^Q. \tag{48}$$

We sample $\{\Phi^Q, X\}$ from the posterior distribution $P(\Phi^Q, X|Yt)$, simulate Y_T, and apply to Monte Carlo integration to obtain $E(Y_T|Y_t)$. Here we see the power of the MCMC algorithms. They allow us to sample the high-dimensional posterior density $P(\Phi^Q, X|Y_t)$ efficiently.

Table 6 reports the forecast performances of $A(0,3)$ and $A(1,3)$ models for Data I for a prediction period of 12 weeks. The $A(1,3)$ model has the best forecast performance. The maximal mean error is 4.28 basis points and the maximal RMSE is 4.98 basis points.

Table 6 Forecast Performances and the Model Evidence for Data I

	$A(0,3)$		$A(1,3)$	
	Forecast (bps)			
	Mean	RMSE	Mean	RMSE
1-Month	0.67	0.72	-2.27	2.61
3-Month	-0.21	0.75	-4.18	4.42
6-Month	-0.26	1.97	-4.28	4.75
9-Month	-0.02	3.05	-3.04	4.12
1-Year	0.45	3.82	-1.04	3.47
2-Year	-4.82	6.65	0.27	4.09
3-Year	-6.98	8.33	1.51	4.57
4-Year	-8.68	9.69	-1.02	4.29
5-Year	-7.16	8.29	-0.10	4.30
7-Year	-3.52	5.28	-1.56	4.45
10-Year	1.01	3.86	-2.92	4.98
	Model Comparison			
Model Evidence	68177.4		68922.0	
AIC	117698.0		132501.0	
BIC	93173.0		111580.0	

*Note: The first panel reports the out-of-sample forecast performances of the $A(0,3)$ and $A(1,3)$ models for Data I. The second panel reports the logarithm of the Bayesian model evidence and information criteria: AIC and BIC.

We also compare the Bayesian forecast performance with three alternative methods: the RW method, the OLS method, and the frequentist method. The first two methods are often used as benchmarks in evaluating the forecast performances[2,30]. The RW method uses last observations of in-sample data as the forecast. The OLS uses the linear regression to forecast. The dependent variable is the difference between the future and current yield data, and the regressor is the difference between the 5-year and 3-month yield data. Note the choice of the 5-year and 3-month is merely for being the same with Duffee (2002)[2]. Yield forecasts are computed with the simulated future states and parameters.

Table 7 compares the forecast performances of these methods. The random walk method has the best performance for yields with short-term maturities ($\tau < 1$), whereas the Bayesian forecast with $A(1,3)$ renders the best performance for longer maturities ($\tau \geq 1$). The gain of the Bayesian forecast with $A(1,3)$ is substantial. The RMSEs is around 60% to those of the random walk approach, which is the second-best method. This improvement is larger compared with the improvement of the arbitrage-free Nelson-Siegel forecast over the random walk method (Table 5 in Christensen et al. (2011))[30]. It is also larger compared with that of the "essentially affine" model forecast over the random walk method (Table VIII in Duffee (2002))[2]. The reason that the random walk performs best in the short end is that the short-end yields are extremely flat in the prediction period.

Table 7 Forecast Performances-Data I

	Forecast (bps)					
	RW	OLS	Freq. $A(0,3)$	Freq. $A(1,3)$	Bay. $A(0,3)$	Bay. $A(1,3)$
1-Month	0.00	4.53	4.81	8.80	7.17	2.61
3-Month	0.40	5.59	3.09	5.90	7.52	4.42
6-Month	1.56	6.86	5.62	4.61	1.97	4.75
9-Month	2.84	7.78	7.80	5.02	3.05	4.12
1-Year	3.49	7.98	9.74	6.25	3.82	3.47
2-Year	7.06	9.16	21.68	6.42	6.65	4.09
3-Year	7.35	8.18	29.78	7.29	8.34	4.57
4-Year	7.91	8.16	36.49	6.17	9.70	4.29
5-Year	7.80	7.41	40.02	6.29	8.29	4.30
7-Year	8.00	7.31	43.66	5.92	5.28	4.45
10-Year	8.39	7.48	44.50	5.67	3.86	4.98

*Note: This table reports the out-of-sample forecast performances of several methods for Data I.

The comparison between the frequentist and Bayesian forecast methods reveals the advantage of the latter. As reported in Table 7, the frequentist forecast with $A(0,3)$ performs worst, whereas the frequentist forecast with $A(1,3)$ dominates the Bayesian forecast with $A(0,3)$ for some maturities. However, this pattern is not persistent. With different simulated trajectories of future states, the forecast performance by the frequentist forecast method changes. The Bayesian forecast method is advantageous in that it averages the future yield level over simulated state paths and parameters. We find that $A(1,3)$ model has a better out-of-sample forecast performance compared with the $A(0,3)$ model. This is in contrast with Duffee (2002) who finds that $A(0,3)$ is better[2]. A question arises as how to choose the best model that delivers good in-sample fitting and out-of-sample forecast performances. In the next section, we exam the model comparison from a Bayesian perspective.

4.4 The Model Comparison

A full treatment of Bayesian inference includes a model-comparison analysis. We evaluate the relative performance of each model using the measure of the model evidence $Z = P(Y|M)$. This quantity is approximated by the harmonic mean of likelihood values[25]:

$$Z \approx \left(\frac{1}{N}\Sigma_{i=1}^{N}\frac{1}{P\left(Y\middle|X_i,\Phi_i^Q\right)}\right)^{-1}, \tag{49}$$

where N is the number of simulations and the pair $\{X_i,\Phi_i^Q\}$ is the i-th simulated parameters and latent states from the posterior distribution. The efficient MCMC algorithms for posterior densities make this feasible.

Table 6 reports the logarithm of the model evidence for each of the two models examined for Data I. The ranking is coherent with both the in- sample fitting and out-of-sample forecast performances of each model.

For Data I, there is a dominance of $A(1,n)$ over $A(0,n)$. The restricted state variables introduce stochastic volatilities and induce fat tails to the yield distribution. For Data II, model ranking is different from that of Data I[31-32]. As shown in Table 8, the model evidence suggests a ranking of $A(0,3), A(1,3)$ in descending order.

Table 8 Fitting & Forecast Performances and the Model Evidence for Data II

	$A(0,3)$		$A(1,3)$	
	Fit	Forecast (3m)	Fit	Forecast (3m)
	RMSE (bps)			
1-Year	20.75	12.46	20.80	21.27
2-Year	16.23	7.62	19.11	20.44
3-Year	15.90	13.92	17.44	9.52
4-Year	16.29	21.57	17.70	22.25
5-Year	15.49	26.04	19.50	45.75
	Model Comparison			
Model Evidence	13837.0		13688.0	
AIC	11225.1		10966.0	

BIC	3002.8	2701.0

*Note: The first panel reports the in-sample fitting and out-of-sample forecast performances or Data II. The second panel reports the logarithm of the Bayesian model evidence and information criteria: AIC and BIC.

The reason could be, for the $A(1, 3)$ model, the two unrestricted state variables can support large negative correlations and the unrestricted state variables can support the non-normality property. However, $A(0, 3)$ cannot support the non-normality property.

5 THE CONLUSION

We develop MCMC algorithms to conduct a Bayesian inference analysis for multi- factor term structure models. We apply the algorithms on two market data sets with different regimes. The in-sample pricing errors are smaller than those in the literature with the similar sample. We also conduct a Bayesian forecast analysis on future yield levels. With the $A(1, 3)$ model, the Bayesian forecast performance dominates the OLS forecast and frequentist forecast approaches for all maturities. It also dominates the random walk forecast for maturities greater or equal to one year. We study the Bayesian model comparison for the two market data sets. The model evidence delivers a ranking consistent with the in-sample fitting and out-of-sample forecast performances for each model. Data I supports the non-normality of the yield change distribution and a humped shape of yield volatility. The model evidence ranks the models as $A(1, 3)$, $A(0, 3)$ in descending order. Data II supports the non-normality feature but demands a strong correlation between state variables. As a result, the model ranking is $A(0, 3)$ and $A(1, 3)$ in descending order.
Future research can explore the MCMC algorithms of the $A(m, n)$ model for $m \geq 2$. Also, it is interesting to analyze the model comparison across different market price of risk specifications.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Q Dai, KJ Singleton. Specification analysis of affine term structure models. Journal of Finance, 2000, 55(5): 1943–1978.
[2] GR Duffee. Term premia and interest rate forecasts in affine models. Journal of Finance, 2002, 57(1): 405–443, .
[3] P Cheridito, D Filipovic, RL Kimmel. Market price of risk specifications for affine models: Theory and evidence. Journal of Financial Economics, 2007, 83(1): 123–170.
[4] Y Ait-Sahalia, RL Kimmel. Estimating affine multi factor term structure model using closed-form likelihood expansions. Journal of Financial Economics, 2010, 98(1): 113–144.
[5] JD Hamilton, JC Wu. Identification and estimation of Gaussian affine term structure models. Journal of Econometrics, 2012, 168(2): 315–331.
[6] M Piazzesi. Affine term structure models. In Handbook of Financial Econometrics. Elsevier, 2008.
[7] AR Pedersen. A new approach to maximum likelihood estimation for stochastic differential equations based on discrete observations. Scandinavian Journal of Statistics, 1995, 22(1): 55–71.
[8] MW Brandt, P Santa-Clara. Simulated likelihood estimation of diffusions with an application to exchange rate dynamics in incomplete markets. Journal of Financial Economics, 2002, 63(2): 161–210.
[9] RR Chen, L Scott. Multi-factor Cox-Ingersoll-Ross models of the term structure: Estimates and tests from a Kalman filter model. Journal of Fixed Income, 1993, 3 (3): 14–31.
[10] P Collin-Dufresne, RS Goldstein, CS Jones. Identification of maximal affine term structure models. Journal of Finance, 2008, 63(2)743–795.
[11] Nelson-Siegel term structure models. Journal of Econometrics, 2011, 164(1): 4–20.
[12] LEO Svensson. Estimating and interpreting forward interest rates: Sweden 1992-1994. NBER Working Papers 4871, National Bureau of Economic Research, Inc., 1994.
[13] CM Bishop. Pattern Recognition and Machine Learning (Information Science and Statistics). Springer, 2nd edition, 2007.
[14] E Jacquier, NG Polson, PE Rossi. Bayesian analysis of stochastic volatility models. Journal of Business and Economic Statistics, 1994, 12(4): 371–389.
[15] E Jacquier, NG Polson, PE Rossi. Bayesian analysis of stochastic volatility models with fat-tails and correlated errors. Journal of Econometrics, 2004, 122(1): 185– 212.
[16] B Eraker, M Johannes, N Polson. The impact of jumps in volatility and returns. Journal of Finance, 2003, 58(3): 1269–1300.

[17] M Johannes, N Polson. MCMC methods for continuous-time financial econometrics. In Handbook of Financial Econometrics. Elsevier, 2007.
[18] H Hu. Markov chain Monte Carlo estimation of multi-factor affine term-structure models. Unpublished doctoral dissertation, University of California, Los Angeles, 2005.
[19] CP Robert, G Casella. Monte Carlo Statistical Methods. Springer, 2nd edition, 2004.
[20] S Geman, D Geman. Stochastic relaxation, Gibbs distributions, and the Bayesian restoration of images. IEEE Transactions on Pattern Analysis and Ma- chine Intelligence, 1984, 6(6): 721–741.
[21] JM Hammersley, PE Clifford. Markov random fields on finite graphs and lattices. Unpublished manuscript, 1971.
[22] CK Carter, R Kohn. On Gibbs sampling for state space models. Biometrika, 1994, 81(3): 541–553.
[23] S Fruwirth-Schnatter. Data augmentation and dynamic linear models. Journal of Time Series Analysis, 1994, 15(2): 183–202.
[24] RE Kalman. A new approach to linear filtering and prediction problems. Transactions of the ASME-Journal of Basic Engineering, 1960, 82(1): 35–45.
[25] RE Kass, AE Raftery. Bayes factors. Journal of the American Statistical Association, 1995, 90(430): 773–795.
[26] L Tierney, JB Kadane. Accurate approximations for posterior moments and marginal densities. Journal of the American Statistical Association, 1986, 81(393): 82–86.
[27] MA Newton, AE Raftery. Approximate Bayesian inference with the weighted likelihood bootstrap. Journal of the Royal Statistical Society. Series B (Methodological), 1994, 56(1): 3–48.
[28] D Duffie, J Pan, KJ Singleton. Transform analysis and asset pricing for affine jump-diffusions. Econometrica, 2000, 68(6): 1343–1376.
[29] N Shephard, S Kim. Bayesian analysis of stochastic volatility models: Comment. Journal of Business and Economic Statistics, 1994, 12(4): 406–410.
[30] JHE Christensen, FX Diebold, GD Rudebusch. The affine arbitrage-free class of C.R. Nelson and A.F. Siegel. Parsimonious modeling of yield curves. Journal of Business, 1987, 60(4): 473–489.
[31] CP Robert, G Casella. Introducing Monte Carlo Methods with R. Springer Verlag, 2009.
[32] D Duffie, R Kan. A yield-factor model of interest rates. Mathematical Finance, 1996, 6(4): 379–406.