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Preface

The 2nd International Conference on Management Research and Economic Development (ICMRED 2024) is an annual conference focusing on research areas including economy, finance, and business studies. It aims to establish a broad and interdisciplinary platform for experts, researchers, and students worldwide to present, exchange, and discuss the latest advance and development in economy, finance, and business studies.

This volume contains the papers of the 2nd International Conference on Management Research and Economic Development (ICMRED 2024). Each of these papers has gained a comprehensive review by the editorial team and professional reviewers. Each paper has been examined and evaluated for its theme, structure, method, content, language, and format.

Cooperating with prestigious universities, ICMRED 2024 organized five workshops in London, Galati, Murcia, Birmingham and Beijing. Dr. Canh Thien Dang chaired the workshop "Accounting Practices and Corporate Governance in Firms Exposed to Cryptocurrency", which was held at King's College London. Professor Dr. Habil. Florian Marcel Nuţă chaired the workshop "Green Development for Urban Communities", which was held at Danubius University from Galaţi. Dr. Javier Cifuentes-Faura chaired the workshop "Identifying the Explanatory Variables of Public Debt and Its Importance on The Economy", which was held at University of Murcia. Dr. Chinny Nzekwe-Excel chaired the workshop "Exploring the 'Gem' of Executive Education as an Alternative to Traditional Degree Pathways", which was held at Birmingham City University. Prof. Xuezheng Qin chaired the workshop "The 3rd International Conference on Applied Economics and Policy Studies", which was held at Peking University.

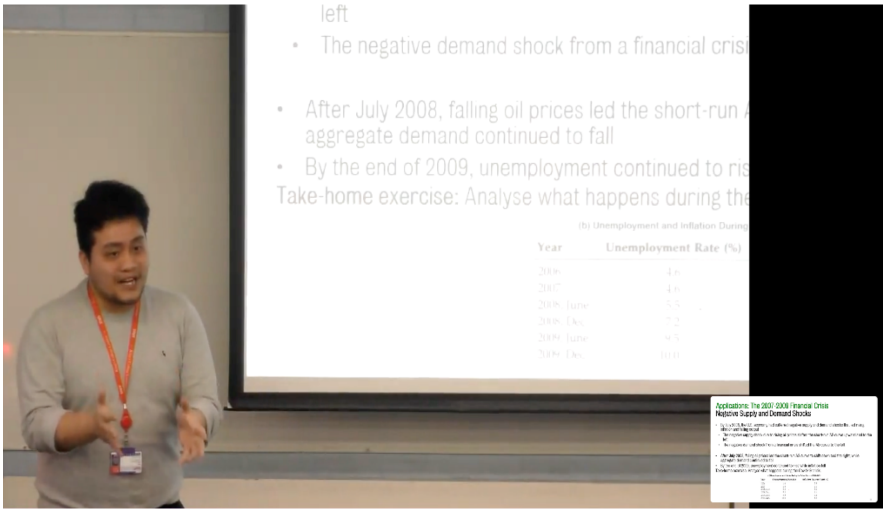
Besides these workshops, ICMRED 2024 also held an online session. Eminent professors from top universities worldwide were invited to deliver keynote speeches in this online session, including Dr. Ruth Badru from University of Bristol, Professor Dr. Habil. from the Danubius University from Galaţi, Dr. Javier Cifuentes-Faura from University of Murcia, etc. They have given keynote speeches on related topics of economy, finance, and business studies.

On behalf of the committee, we would like to give sincere gratitude to all authors and speakers who have made their contributions to ICMRED 2024, editors and reviewers who have guaranteed the quality of papers with their expertise, and the committee members who have devoted themselves to the success of ICMRED 2024.

Dr. Canh Thien Dang
General Chair of Conference Committee

Workshop

Workshop – London: Accounting Practices and Corporate Governance in Firms Exposed to Cryptocurrency



May 30th, 2024 (GMT+1)

King's Business School, King's College London

Workshop Chair: Dr. Canh Thien Dang, Lecturer in King's College London

Workshop – Galati: Green Development for Urban Communities

May 15th, 2024 (GMT+3)

Faculty of Economics and Business Administration, Danubius University from Galaţi

Workshop Chair: Professor Dr. Habil. Florian Marcel Nuţă, Professor Dr. in Danubius University from Galaţi

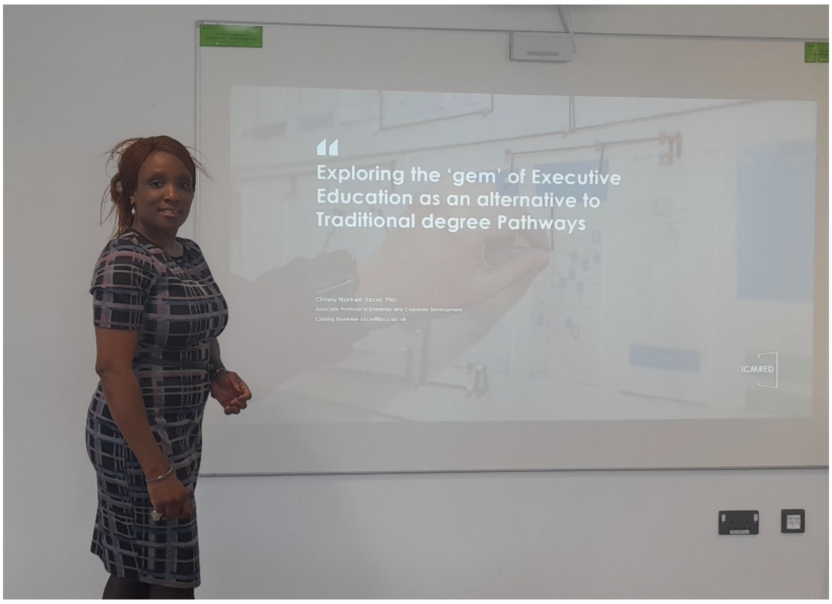
Workshop – Murcia: Identifying the Explanatory Variables of Public Debt and Its Importance on The Economy

June 17th, 2024 (UTC+2)

Department of Financial Economics and Accounting, University of Murcia

Workshop Chair: Dr. Javier Cifuentes-Faura, Researcher in University of Murcia

Workshop – Birmingham: Exploring the ‘Gem’ of Executive Education as an Alternative to Traditional Degree Pathways



July 25th, 2024 (GMT+1)

Department of Management, Birmingham City University

Workshop Chair: Dr. Chinny Nzekwe-Excel, Associate Professor in Birmingham City University

Workshop – Beijing: The 3rd International Conference on Applied Economics and Policy Studies

July 20th, 2024 (GMT+8)

Peking University Research Center for Market Economy, Peking University

Workshop Chair: Prof. Xuezheng Qin, Professor in Peking University

The 2nd International Conference on Management Research and Economic Development

ICMRED 2024

Table of Contents

Committee Members

Preface

Workshop

Research on Hedging Ratio of Stock Index Futures to ETF Fund ········· 1
Jiahao Wu

TOD Development in Shenzhen Rail Transit Based on SWOT Model ········· 8
Hangyi Zhu

Study of Factors Influencing U.S. Treasury Yields Based on Time Series Linear Regression Models ········· 19
Cheng Jiang, Xin Liu, Tianhan Zhang

Macroeconomic Policy Adjustments on Environmental Protection Effectiveness Research - Based on the DSGE Model ········· 27
Liyang Peng

Comparative Analysis of SVR and LSTM in Stock Price Forecasting Across Market Cycles ··· 40
Weimeng Liu

Research on the Innovative Practices of Tourism Platform in Web3.0 - Taking Ctrip Trekki NFT Project as an Example ········· 51
Jingyang Chen, Zimeng Hui, Qingke Jiang

Whether Silver Serves as a 'Safe-Haven' for Crude Oil ········· 59
Keyu Chen

Stock Prices Forecasting and Optimization Strategies Based on Support Vector Machines ···· 66
Junyuan Qiu, Jiahao Xu, Zirui Yu

A Financial Analysis and Valuation on Disney ········· 77
Xindi Zhao

Research and Analysis of the Development of Live E-commerce on Xiaohongshu ········· 85
Yang Wang

A Study of the Capital Structure Characteristics Across Diverse Industries ········· 93
Changxin Shi

A Study of the Relationship Between Capital Structure and Corporate Performance ········· 99
Kaiyuan Deng

An Empirical Study on the Impact of Investor Gambling Factors on Stock Cross-Sectional Returns ········· 106
Zhongxuan Du, Jinsheng Li, Yangxuan Lu

A Financial Analysis and Valuation of Energy Transfer LP ······ 118
Xiaohan Yao
The Impact of Industrial Clusters on Supply Chain Resilience: The Moderating Role of Supply Chain Concentration ······ 125
Ruomeng Shi
The Impact of COVID-19 Pandemic on the Private Equity Valuation ······ 132
Yuheng Guo, Penghao Li
The Combined Effects of Financial and Market Indicators on the Valuation of New Listings: Evidence from the Biopharmaceutical Sector ······ 141
Xianzhe Ji
A Study on the Performance of Mergers and Acquisitions in the Context of State-Owned Enterprise Reform: The Case of Ansteel and Benxi Steel ······ 149
Yushan Cai
The Study of an Urban Social Resilience Evaluation Index System under the Context of Public Health Emergencies ······ 157
Li Li, You Wu
Does Failure Tolerance of the Board of Directors Affect Investment Efficiency? ······ 164
Chunyan Zhu, Jia Song
The Relationship Between AI and Unemployment Rate and the Solution ······ 171
Yichen Cao, Yanzhe Pan, Chenrui Tao

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Research on Hedging Ratio of Stock Index Futures to ETF Fund

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Abstract: Exchange Traded Funds (ETF) can largely avoid non-systematic risk, but investors often cannot avoid systemic risk, and the hedging function of stock index futures can do this. Therefore, hedging ETF with stock index futures has become a good investment strategy. Based on the trading data of the China Securities Index (CSI) 300 stock index futures and CSI 300 Exchange-Traded Fund (ETF), this paper analyzes the optimal hedging ratio of CSI 300 stock index futures by Ordinary Least Squares (OLS) and dynamic Error Correction Model - Generalized Autoregressive Conditional Heteroskedasticity (ECM-GARCH) model and compares the hedging performance predicted by the model to avoid the systematic risk of ETF. The results show that the hedging effect of the dynamic hedging model is better than that of the static model, and the ability to avoid systemic risk is also better. The predictions of both models show that stock index futures hedge ETFs very well. The dynamic model is more able to reduce the heteroscedasticity of the transaction data.

Keywords: CSI 300 stock index futures, hedging ratio, ETF, ECM-GARCH

1. Introduction

Exchange-traded funds (ETFs), use a completely passive indexation investment strategy to track and fit a representative underlying index. Because ETFs sell portfolios, fluctuations in individual bonds have less impact on bond ETFs. At the same time, the fund invests in bonds with excellent qualifications and good liquidity, so the returns of bond ETFs are relatively stable. Therefore, the fund can effectively avoid the non-systematic risk of individual stocks, to obtain a rate of return similar to the index. However, the huge systemic risk in the stock market brings unavoidable risks to investors. Stock index futures are a hedging tool for investors, and shorting stock index futures can achieve the purpose of avoiding systemic risks.

When investors invest in financial assets, to ensure considerable returns and avoid market risks, they usually hedge through hedging [1]. Nowadays, a large number of investors participating in ETF trading will use stock index futures, a financial derivative, to hedge, avoid systemic risks and improve returns. Therefore, how to hedge ETF through stock index futures has research significance.

The hedge ratio refers to the mathematical relationship that exists between the amount of assets used for hedging and the amount of assets being hedged. Among them, the optimal hedging ratio refers to the hedging ratio in which the combination of hedging can eliminate the risk caused by the change in spot value [2]. To maximize the realization of asset hedging, it is very necessary to study the optimal hedging ratio. The more commonly used method is the minimum variance hedge ratio,

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whose goal is to minimize the fluctuation of the entire hedging portfolio return, which is specifically manifested as the minimization of the hedging return.

At present, there are many models for hedging ratio research, the time series model is the most extensive prediction, and there are also many studies on the hedging ability of China Securities Regulatory Commission (CSI) 300. For the static hedging model, that is, the hedging ratio does not change with time, the Ordinary Least Square (OLS) is better than other models in terms of prediction accuracy and operation difficulty [3]. When the hedging ratio changes in the long-term financial time series, the dynamic hedging model is used. The univariate Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) model cannot estimate the covariance between variables or carry out error correction, while the Error Correction Model-Generalized AutoRegressive Conditional Heteroskedasticity (ECM-GARCH) model not only considers the cointegration relationship between futures price and spot price but also considers the heteroscedasticity problem existing in the price series fluctuations of the two prices [4]. So consider estimating and forecasting with these two models.

However, there are not many studies on the hedging effect of combining CSI 300 stock index futures and ETF funds with real-time data.

This paper selects the recent data of CSI 300 stock index futures and Harvest 300ETF and analyzes the effect of using stock index futures on ETF hedging by constructing static and dynamic hedging models.

Based on the static and dynamic hedging models, this paper discusses the necessity of avoiding the systemic risk of the market through the literature research and analysis of ETF risk and finds that the investment choice of stock index futures can reduce the systemic risk. Then taking CSI 300 stock index futures and Harvest 300ETF as an example, the optimal hedging ratio and hedging performance of stock index futures on ETF are predicted, the hedging effect of the two models is compared, and the hedging effect of stock index futures on ETF is studied.

2. Research Review

In recent years, there have been many precedents for the hedging of stock index futures. Wang Jing used the simple portfolio hedging model to conclude that ETFs in the rising channel need not be hedged for temporary periodic adjustment because the transaction cost of hedging transaction is not necessarily lower than the adjustment loss [5]. Gu uses OLS, Bayesian-Vector Autoregressive(B-VAR), Error Correction Model (ECM), and ECM-GARCH models to determine the hedging ratio of CSI 300 index futures and spot data, and finds that hedging technology has a great impact on hedging performance under daily data. Under 5 min frequency data, increasing information efficiency can make up for the defect of technical efficiency [6]. Zhong took Harvest 300ETF and CSI 300 stock index futures as sample data and found that the VAR model had the best hedging performance through the OLS model, vector autoregression model, and error correction model [7]. Sun Yanhong et al. established the exponential weighted moving average model (EWMA model) and GARCH model combined with volatility under the principle of minimum VAR. Among them, the method combining EWMA and Cornish-Fisher expansion achieves the best hedging effect [8].

Ederington studied the hedging effect of US Treasury bond futures based on Makowitz's portfolio theory and found that the optimal hedging ratio calculated was due to the hedging ratio of 1, and the hedging method was a special case of portfolio theory [9]. Ghosh considered the cointegration relationship between the two time variables, and based on this, used the ECM model to study the stock hedging ratio and effect, and found that the effect was better than the hedging ratio obtained by ordinary OLS [10]. Hsu proposed a series of estimation models of optimal hedging ratio based on

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GARCH, including traditional static GARCH, constant conditional correlation GARCH, and dynamic conditional correlation GARCH [11].

According to a large number of hedging examples and the empirical work of Fama et al., except for very few futures commodities, the basis volatility of most commodities is quite violent, and the basis risk is sometimes no less than the price risk. In addition, the model assumes either full or no hedging of spot positions, ignoring the ability of many hedgers to anticipate price fluctuations and the feasibility of flexibly adjusting hedging decisions based on expectations.

3. Algorithm Principle and Research Method

3.1. Description of ETF Systemic Risk

According to the Capital Asset Pricing Model (CAPM), the value of assets in inefficient markets can be assessed as follows:

$$R_j = \alpha_j + \beta_j R_m + \varepsilon_j \tag{1}$$

R_j is the return rate of the JTH asset, R_m is the market return rate, and the variance relationship can be obtained:

$$\sigma_j^2 = \beta_j^2 \sigma_m^2 + \sigma_\varepsilon^2 \tag{2}$$

Consider variance as a measure of risk, total risk, $\beta_j^2 \sigma_m^2$ is systematic risk, and unsystematic risk determined only by the asset or firm is σ_ε^2. Then the proportion of systemic risk θ_j is:

$$\theta_j = \frac{\beta_j^2 \sigma_m^2}{\sigma_j^2} \tag{3}$$

Here, $\beta_j = \dfrac{Cov(R_j, R_m)}{Var(R_m)} = \dfrac{\sigma_{jm}}{\sigma_m^2}$.

If I plug in, $\theta_j = \dfrac{\beta_j^2 \sigma_m^2}{\sigma_j^2} = \dfrac{\sigma_{jm}^2}{\sigma_j^2 \sigma_m^2}$.

3.2. Determination of Hedging Ratio

3.2.1. Static Hedging Model (The Hedging Ratio is Fixed)

The OLS hedging model:

The least squares regression model is established to estimate the hedging ratio, and the model is as follows: $\triangle S_t = \alpha + \beta \triangle F_t + \varepsilon_t$.

Variance of spot portfolio returns $Var(R_p) = Var(\Delta S_t) + h^2 Var(\Delta F_t) - 2hCov(\Delta S_t, \Delta F_t)$,The hedging efficiency is the highest when the variance of the spot portfolio return rate is the smallest, take the derivative concerning h, let the derivative be zero, and get $\beta = h^* = Cov(\triangle S_t, \triangle F_t) / Var(\triangle F_t)$.

Where, ΔS_t and ΔF_t are the return rate of spot price and the return rate of futures price respectively, and ε_t is the random disturbance term. The slope β is the optimal hedging ratio, $\beta = h^* = Cov(\triangle S_t, \triangle F_t) / Var(\triangle F_t)$.

3.2.2. Dynamic Hedging Model

The estimation model of the static hedge ratio is established, and the estimated optimal hedge ratio does not change with time. However, time series data often have heteroscedasticity. When the risk level of the futures market and the spot market changes over time, the hedging ratio changes over time [4].

The ECM-GARCH model:

For financial time series with high volatility, it is necessary to introduce a GARCH model that the variation of spot price variance over time. Due to the possible ARCH effect of the ECM model, the obtained residual may have heteroscedasticity, thus affecting the estimation of the hedging ratio, which can be overcome by the ECM-GARCH model:

Establish the mean equation:

$$\Delta S_t = C_s + \beta_s Z_{t-1} + \varepsilon_{st} \tag{4}$$

$$\Delta F_t = C_s + \beta_f Z_{t-1} + \varepsilon_{ft} \tag{5}$$

$Z_{t-1} = S_{t-1} - \beta F_{t-1}$. is the residual term in the long run, and here is the error correction term.

And $\varepsilon_{st}, \varepsilon_{ft} \sim N(0, H_t)$, $H_t = \begin{pmatrix} h_{ss,t} & h_{sf,t} \\ h_{sf,t} & h_{ff,t} \end{pmatrix}$, h_{ss}, h_{ff} is the conditional variance of the random error term and h_{sf} is the covariance of ε_{st}, and ε_{ft}.

The conditional variance equation is:

$$H_t = \begin{pmatrix} C_{ss} & 0 \\ 0 & C_{ff} \end{pmatrix} + \begin{pmatrix} \alpha_{ss} & \alpha_{sf} \\ \alpha_{sf} & \alpha_{ff} \end{pmatrix} \begin{pmatrix} \varepsilon_{s,t-1}^2 & \varepsilon_{s,t-1}\varepsilon_{f,t-1} \\ \varepsilon_{s,t-1}\varepsilon_{f,t-1} & \varepsilon_{f,t-1}^2 \end{pmatrix} + \begin{pmatrix} \lambda_{ss} & \lambda_{sf} \\ \alpha\lambda_{sf} & \lambda_{ff} \end{pmatrix} \begin{pmatrix} h_{ss,t-1} & h_{sf,t-1} \\ h_{sf,t-1} & h_{ff,t-1} \end{pmatrix} \tag{6}$$

It is estimated that the optimal hedge ratio:

$$h^* = \frac{Cov(\varepsilon_{st}, \varepsilon_{ft})}{Var(\varepsilon_{ft})} = \frac{h_{sf,t}}{h_{ff,t}} \tag{7}$$

3.3. Hedging Performance

For the hedging effect under all optimal hedging ratios, some index is applied to measure the hedging effect. In this paper, HP is the proportion of portfolio return variance reduction before and after hedging to measure the hedging effect:

$$HP = \frac{Var(U) - Var(H)}{Var(U)} = \frac{X_s^2 \sigma_s^2 - (X_s^2 \sigma_s^2 + X_f^2 \sigma_f^2 + 2 X_s X_f \sigma_{sf})}{X_s^2 \sigma_s^2} \tag{8}$$

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HP minimum, $HP_{\min} = \dfrac{\sigma_{sf}^2}{\sigma_s^2 \sigma_f^2}$.

(Xs is the spot holding position, Xf is the stock index futures holding position, Var(U) is the variance of spot return before hedging, and Var(H) is the variance of portfolio return after hedging.)

4. Empirical Analysis

4.1. Hedge Ratio

Harvest 300 ETF is selected as the spot for hedging CSI 300 stock index futures. The data of the two are selected because Harvest 300 ETF was listed earlier and has a large market share. CSI 300 stock index futures have sufficient data, low risk, and high return, which are similar to stock market operations and easy for investors to understand. The experimental data range from January 2, 2022, to July 2, 2023, 355 trading days of Harvest 300ETF and CSI 300 stock index futures contract closing prices. The data are obtained from the Choice financial terminal. The regression analysis of the above model is done on the sample data through MATLAB.

(1) OLS Model

Table 1: Parameter estimates from the OLS model

α	β	R^2	P value (F-test)
-6.164073	0.894320	0.9836	0

It can be seen from Table 1 that $\Delta S_t = -6.164073 + 0.894320 \Delta F_t, R^2 = 0.9836$ the model has a high degree of fit and the regression effect is significant. The hedging ratio is 0.894320. Under F test, the P value is 0<0.5, and the regression fitting degree is good.

(2) ECM-GARCH Model

The ECM-GARCH model was established by MATLAB programming according to the formula $h^* = \dfrac{Cov(\varepsilon_{st}, \varepsilon_{ft})}{Var(\varepsilon_{ft})} = \dfrac{h_{sf,t}}{h_{ff,t}}$ The dynamic hedge ratio is derived.

Table 2: Predicted results of the ECM-GARCH model

model	Mean value	Maximum	Minimum	Standard deviation
ECM-GARCH	0.9123	0.9564	0.7543	0.0340

It can be seen from Table 2 that the hedge ratio under this model is stable at 0.9123. Among them, $R^2 = 0.9263$, the regression effect is better.

4.2. Hedging Performance

Based on, $HP = \dfrac{Var(U) - Var(H)}{Var(U)} = \dfrac{X_s^2 \sigma_s^2 - (X_s^2 \sigma_s^2 + X_f^2 \sigma_f^2 + 2 X_s X_f \sigma_{sf})}{X_s^2 \sigma_s^2}$.

The HP of the two models is calculated and the following results are obtained (Table 3).

Table 3: Hedging performance of the two models

model	Hedging performance(%)
OLS	90.6448
ECM-GARCH	91.2689

It can be seen that the hedging efficiency of the two models is 90.64% and 91.27% respectively, and the hedging effect is relatively high, and both models can avoid more than 90% of the risk of spot ETF portfolio. However the dynamic ECM-GARCH model performs a little better in risk aversion than the static OLS model.

After this study, the dynamic ECM-GARCH model studies long-term financial series, which can better overcome the large volatility of data series, prevent some data from being too high and some data from being too low, and make the hedging ratio more stable and better [4]. Therefore, it also shows that the hedging ratio is dynamically adjusted. For investors holding ETFs in the future, the OLS model with simple operation can be used to operate, and the hedging strategy of stock index futures can be used to reduce systemic risk as much as possible. However, the study also shows that the hedging ratio is dynamically adjusted, and investors should adjust the optimal hedging ratio. To get more revenue. In addition, the recent data of Harvest 300ETF are selected in this study, but the data of some funds with long sample periods, such as Shanghai and Shenzhen 300ETF, are not selected, so the prediction effect is not too universal. The hedging ratio of the same model is dynamically adjusted, which may cause a high cost of position adjustment [3]. Therefore, it is necessary to comprehensively examine the hedging effect of static and dynamic hedging ratio models from the perspective of cost, to make stock index futures fully play the role of risk aversion.

5. Conclusion

This paper puts the hedging of stock index futures into ETF to study and summarize and selects a static and dynamic hedging model. This can reduce the systematic risk of ETF for investors, and it is of great significance to learn from domestic and foreign literature to study the hedging of stock index futures under ETF. The results show that stock index futures have high hedging ability, and the hedging effect reflected by the dynamic hedging model is better than that of the static model. When constructing the spot investment strategy, investors can determine the optimal hedging strategy according to the trading volume data of spot and stock index futures, and obtain the optimal number of futures contracts. However, it should be clear that investors can only reduce part of the risk with stock index futures, not achieve complete hedging, but also combine the actual situation, the optimal hedging and investment.

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TOD Development in Shenzhen Rail Transit Based on SWOT Model

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Abstract: In today's urban planning field, Transit-Oriented Development (TOD) has become a crucial research topic. With the acceleration of urbanization and increasing population density, traffic problems have become key factors affecting urban development and living quality of residents. Therefore, discussing how to effectively plan urban traffic and realize the harmonious coexistence between traffic and city has become the focus of urban planning scholars and practitioners. However, there is still a lack of unified understanding regarding the role of railway TOD planning in urban development. Therefore, this paper takes Shenzhen as an example and adopts a SWOT analysis to examine the TOD development mode of Shenzhen's railways, based on the city's structure, railway layout, and development strategy. This paper finds that the polycentric urban development pattern of Shenzhen is closely connected to its railway planning. The foundation for Shenzhen's railway TOD construction is relatively solid, and the prospects for development are optimistic. However, many issues in the future development space and planning design still need to be addressed.

Keywords: TOD, urban planning, railway, SWOT

1. Introduction

Urbanization and urban renewal around the world have integrated sustainable development into their governance and planning as a fundamental goal. The rapid expansion of urbanization has led to consequences such as insufficient urban infrastructure, traffic congestion, and environmental deterioration. Concepts of sustainable, green, and harmonious urban renewal have gained widespread attention across all sectors of society. Transit-Oriented Development (TOD) is defined as an integrated development model of transportation systems and land use, and it is an effective sustainable planning strategy [1].

In recent decades, TOD planning has begun to gain popularity globally, with many TOD projects emerging in North America, Europe, and the Asia-Pacific region. Similarly, the TOD model is also thriving in China. Shenzhen is one of the first Chinese cities to introduce and implement the TOD development model. According to the "Transit-Oriented Development Framework and Planning Strategies in Shenzhen" released by the Shenzhen Urban Transport Planning Center, as early as 2011, Shenzhen had established a complete TOD framework system and planning strategy [2]. Over the past decade, Shenzhen's TOD model has mainly gone through three development stages: a rapid urban construction phase driven by TOD, a Special Economic Zone integrated development phase promoted by TOD and a stage of guiding the development of key areas with TOD [3]. Since the "Thirteenth

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five-year plan," Shenzhen has built a high-quality comprehensive transportation system, setting a new benchmark for the charm of mega-city transportation governance [4].

Shenzhen has now entered a new phase of development with the "Fourteenth five-year plan." In the past five years, most research on Shenzhen's TOD development model has focused on subways, buses, and the urban slow traffic system, with less emphasis on Shenzhen's railway construction and railway hubs. In the studies on Shenzhen's railway system, there is little mention of the TOD development model based on railway hubs. Issues such as the insufficient positioning of passenger hubs, the imperfect functioning of external passages, and the weak railway services in the western part of Shenzhen exist [5]. In the "Shenzhen Metropolitan Area Development Planning" document, the Shenzhen government explicitly proposed the construction requirements for vigorously promoting the integrated development of rail stations and cities [6]. Therefore, discussing the TOD development model of Shenzhen's railway transportation system is significant to the future development of Shenzhen's comprehensive transportation system.

This study is based on the Shenzhen Rail Transit Network Planning [7] and the Shenzhen National Land and Space Master Plan [8], among other related materials, to sort out the overall development pattern of Shenzhen's railway transportation, combining the railway network planning with Shenzhen's urban development planning. Employing the SWOT analysis method, the study investigates the urban planning pattern of Shenzhen and the development pattern of its railways, analyzing the strengths and weaknesses, opportunities, and threats of Shenzhen's railway transportation TOD development model. The study also offers suggestions for the future comprehensive development of Shenzhen's railway transportation in conjunction with the TOD model.

2. Introduction to Shenzhen's TOD Development Model Based on Railway Transportation Hubs

2.1. Introduction to the Current State and Spatial Structure of Shenzhen's Railway System

Shenzhen currently has eight existing railway lines: the Guangzhou-Shenzhen Railway, the Guangzhou-Shenzhen-Hong Kong Railway, the Guangzhou-Shenzhen Intercity, the Shenzhen-Dongguan Intercity, the Shenzhen-Shanwei Intercity, the Shenzhen-Maoming Railway, the Shenzhen-Huizhou Railway, and the Xiamen-Shenzhen Railway. There are nine railway passenger stations in total: Shenzhen Station, Futian Station, Shenzhen North Station, Shenzhen East Station, Guangmingcheng Station, Xili Station, Airport East Station, Yantian Station, and Pingshan Station, as shown Figure 1. The two most central railway lines in Shenzhen are the Guangzhou-Shenzhen Railway and the Guangzhou-Shenzhen-Hong Kong Railway. The Guangzhou-Shenzhen Railway runs approximately 24 kilometers within the Shenzhen territory and is a national first-class trunk line with a mainline consisting of four tracks (two quasi-high-speed tracks and two conventional-speed tracks); the Guangzhou-Shenzhen-Hong Kong Railway spans 32 kilometers within Shenzhen and is a trunk railway line connecting Guangzhou, Shenzhen, and Hong Kong, forming part of the national railway's main thoroughfare.

From the perspective of stations, the Shenzhen railway network is centered around Shenzhen Station, expanding, and building outwards towards the east, west, and north, while simultaneously promoting the construction of stations in surrounding satellite cities within the core urban area. From the railway lines, the Shenzhen railway network uses the Guangzhou-Shenzhen Railway and the Guangzhou-Shenzhen Intercity as its vertical axis, linking the lateral Shenzhen-Maoming Railway, Xiamen-Shenzhen Railway, and Shenzhen-Shanwei Intercity, thus constructing a multi-centered, radial railway network.

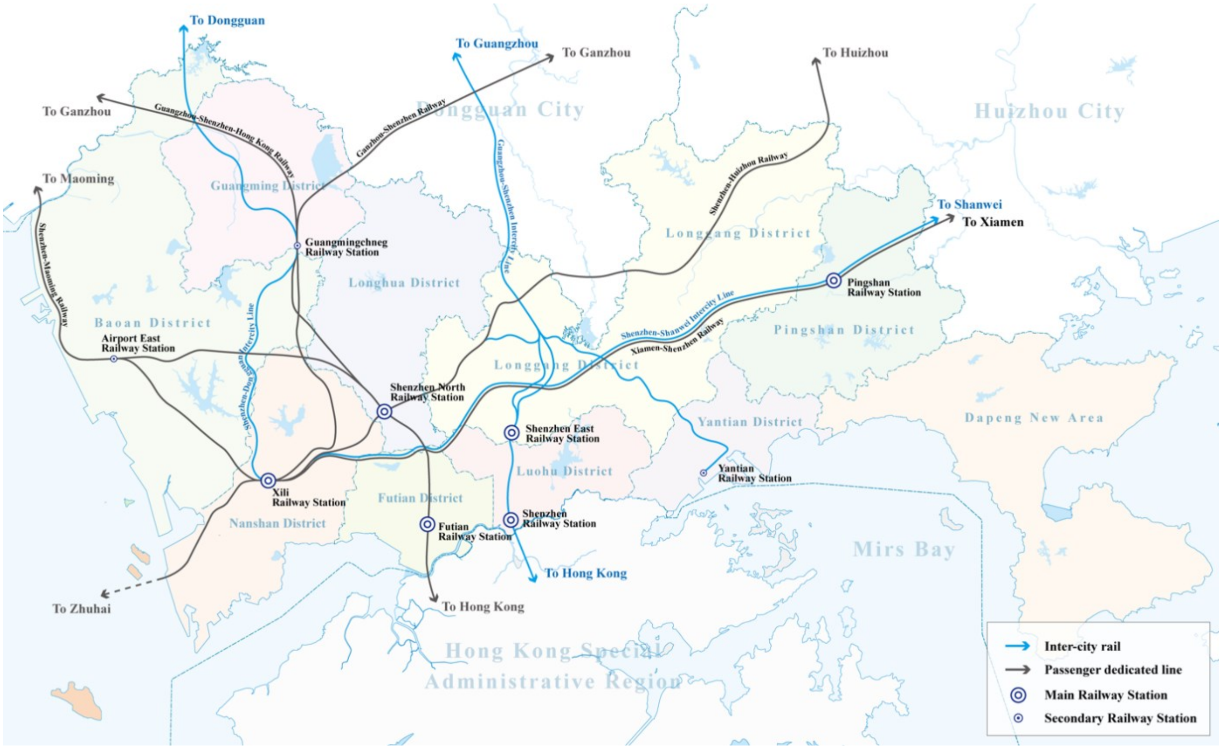

Figure 1: Shenzhen passenger rail network.

2.2. Shenzhen's Multi-Centric Urban Development Pattern

Shenzhen City has long insisted on a multi-centric spatial structure in urban spatial planning [9]. The earliest version of the "Shenzhen Special Economic Zone Master Plan" from 1986 established a spatial structure of "multiple points advancing together" and "belt-based clusters". Later, the 1996 "Shenzhen Urban Master Plan" introduced a development strategy of "expanding across the territory and advancing in gradients", constructing a "network-based cluster" spatial structure. The 2010 "Shenzhen Urban Master Plan" proposed a "north-south penetration, east-west expansion" spatial structure with "three axes, two belts, and multiple centers". The latest round of land and space planning introduces a "multi-centric, networked, and clustered" spatial structure. Ultimately, Shenzhen has formed a spatial development pattern of "north-south penetration, east-west expansion, central polarization, and wings stretching", dividing the urban space into five differentiated development zones, creating a three-tiered center system composed of the main center, sub-centers, and cluster centers, as shown figure 2, composed of clusters radiating between various urban centers [10].

After years of exploration, Shenzhen has essentially formed a consensus on using hubs as the focal points for urban development elements to promote the formation of cluster centers, allowing industry, land, population, capital, and other urban development elements to aggregate and disperse in different regions. Under the requirements of successive urban planning layouts, the development of Shenzhen's railway system TOD model has become a significant factor in supporting the formation of a multi-centric system.

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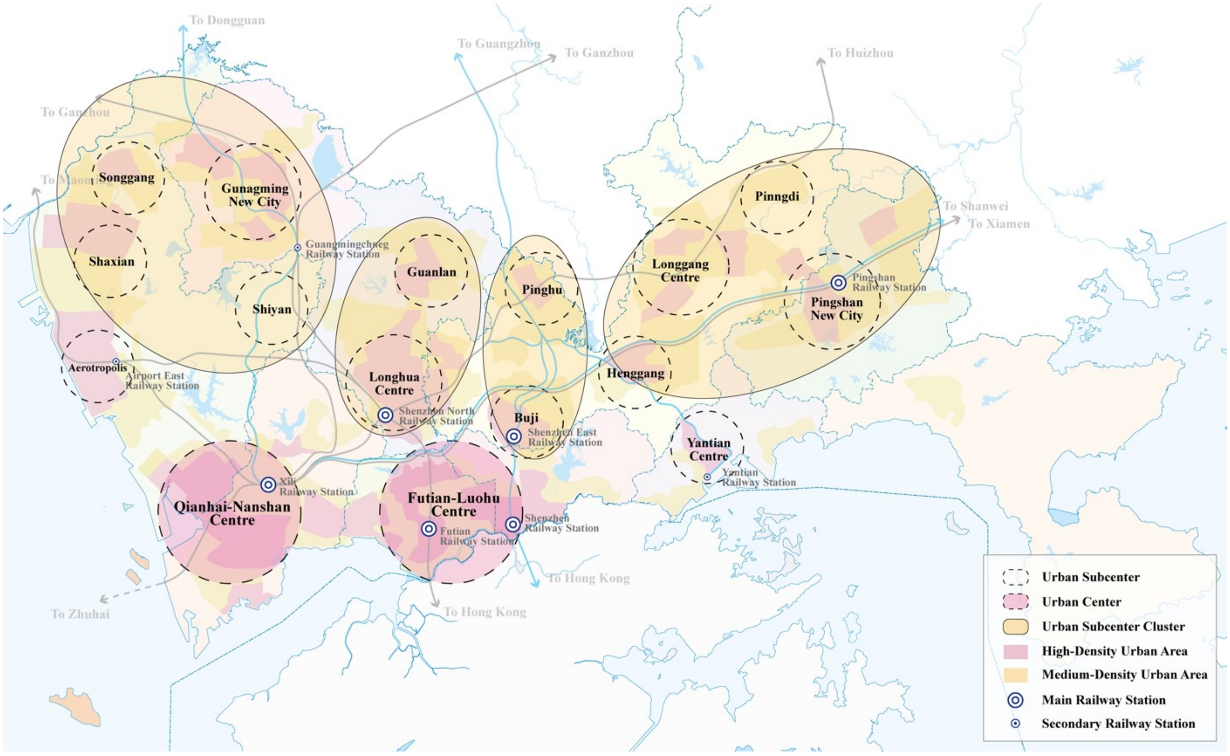

Figure 2: Shenzhen urban spatial structure.

2.3. Shenzhen Railway TOD Development Strategy Integrating Urban Layout

As a central city in the Guangdong-Hong Kong-Macao Greater Bay Area (hereinafter referred to as "the Greater Bay Area"), Shenzhen's main urban center should have the capability to radiate across the Pearl River Delta region encompassing the Guangzhou-Shenzhen-Hong Kong metropolis. Therefore, the regional intercity railway hub's anchoring in the main urban center is particularly vital [11]. Shenzhen's urban sub-centers should serve as specialized functional service agglomerations and cover the surrounding secondary urban areas; sub-centers are also regions where a large influx of population aggregates, hence national railway hubs should be prioritized in these areas. The functions of other secondary urban cluster centers and some key areas are to serve the city's internal production and life, driven by small railway hubs and the layout of other transportation facilities [11].

According to the aforementioned planning principles, the layout of Shenzhen's railway hubs presents a hierarchy of "main hubs - sub-hubs". The main urban centers, such as Bao'an, Luohu, and Futian, feature regional passenger stations like Airport East Station, Shenzhen Station, and Futian Station as railway hubs. They connect intercity railways that radiate across the Greater Bay Area with medium and short-distance conventional railways, taking on the function of business transfers between cities. Sub-centers such as Buji, Longhua, and Pingshan New City, serviced by national passenger stations like Shenzhen East, Shenzhen North, and Pingshan Station, and combined with the Xiamen-Shenzhen, Shenzhen-Maoming, and Guangzhou-Shenzhen railways, form comprehensive railway transfer functions that serve the nation. The remaining secondary city centers are mainly served by city-wide passenger stations that undertake hub functions, focusing on serving the city's internal passenger flow, mainly undertaking the transfer functions of the city's internal rail transit and bus passenger flow. They are coupled with the city's main and sub-centers and some key areas, undertaking the nurturing function of cluster centers and key regions [11].

Therefore, it is evident that the development layout of Shenzhen's various urban centers fundamentally reflects the integrated development concept of rail and city, achieving the city's

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railway TOD development model. Constructing railway hubs at different radiation scale levels drives the coordinated and stable development of Shenzhen's three-tiered urban layout.

3. Exploring the TOD Development Model of Shenzhen's Railway Transportation Based on the SWOT Model

3.1. Strength Analysis

3.1.1. Central Railway Hub Position in the Greater Bay Area

The Greater Bay Area, located in the Pearl River Delta region, is one of China's three major city clusters alongside the Yangtze River Delta and the Beijing-Tianjin-Hebei region. Currently, the Greater Bay Area's urban planning structure mainly presents Guangzhou and Shenzhen as dual centers, with the eastern and western banks of the Pearl River mouth being the focus. In terms of railway hubs, a dual-center railway network layout centered around Guangzhou and Shenzhen is evident. From the perspective of the Greater Bay Area, Shenzhen's railway hub is the convergence point for various railway lines on the eastern bank of the Pearl River, introducing coastal railway corridors and inland rail networks into the Pearl River Delta in a Y-shaped structure and extending west across the Pearl River to connect with the southwest corridor. At the same time, Shenzhen's railway hub is situated midway along the railway connection between mainland China and Hong Kong, serving as an important port of entry into Hong Kong. Therefore, Shenzhen occupies a central railway hub position within the city cluster of the Greater Bay Area, linking north to south and east to west, with significant strategic importance, thus bringing great advantages to its railway TOD development.

3.1.2. Relatively Developed Passenger Railway Infrastructure

Over the years since the Reform and Opening Up, Shenzhen has developed a relatively complete passenger railway network. Shenzhen has three main railway lines: the Guangzhou-Shenzhen Railway, the Guangzhou-Shenzhen-Hong Kong Railway, and the Xiamen-Shenzhen Railway, as well as two railway branch lines; the Shenzhen-Maoming Railway and the Shenzhen-Huizhou Railway, forming a "double cross" hub. In addition, the Ganzhou-Shenzhen High-Speed Railway and the Guangzhou-Dongguan-Shenzhen Intercity Railway are under construction. Spatially, the Guangzhou-Shenzhen Railway and the Guangzhou-Shenzhen-Hong Kong Railway run north-south, while the Xiamen-Shenzhen Railway runs east-west, converging at the Xili Railway Station through the Shenzhen-Maoming Railway and the Shenzhen-Huizhou Railway branch lines. In terms of railway stations, Shenzhen Station and Shenzhen North Station are the main passenger stations within the hub, with Shenzhen East Station, Shenzhen West Station, Futian Station, and Xili Station serving as auxiliary passenger stations. Furthermore, the intercity railway lines within the Shenzhen metropolitan area are shorter in length, designed for lower speeds, and feature smaller average distances between stations, which is more conducive to urban development along the railway lines. In summary, Shenzhen has a comprehensive railway planning structure, a long operational mileage, numerous railway stations, and a wide coverage area, providing a solid foundation for railway TOD development and a significant advantage.

3.1.3. Mature TOD Development Planning Experience

Shenzhen was one of the first cities in China to introduce and implement the TOD development model and possesses mature TOD planning concepts. Around 2010, Shenzhen established new districts such as Longhua, Guangming, and Dapeng, incorporating the TOD comprehensive development model

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into the construction of these districts. In 2011, leveraging the opportunity of hosting the 26th Summer Universiade, Shenzhen promoted the city-wide connectivity of its subway network, with five lines totaling 178 kilometers, effectively driving the development of urban sub-centers such as Bao'an Central District, Longgang Central District, and Longhua New Town. In 2014, Shenzhen proposed the important development concept that "building rail transit is equivalent to building a city," adopting the TOD model as a strategic urban transportation development approach.

Based on the fundamental network of urban rail transit, Shenzhen timely promoted the adjustment of the third phase of rail construction and the planning of the fourth phase, beginning to focus on supporting the guided development of key areas. Based on these key areas, the city implemented the integration and coordination of urban rail with urban space and activities, supporting TOD construction in key areas such as Qianhai Cooperation Zone, Shenzhen Bay Tech-Eco Park, Shenzhen Bay Headquarters Base, Liuxiandong Headquarters Base, and the International Low Carbon City [3]. In conclusion, Shenzhen has widely applied the TOD development concept in its planning and construction over the past decade and has gained valuable successful experiences from various aspects, bringing experience advantages to the TOD development of Shenzhen's railways.

3.2. Weaknesses Analysis

3.2.1. Fragmented Urban Planning Pattern

Over the past 30 years, Shenzhen has been committed to promoting a multi-center, group-style spatial layout, which has alleviated the traffic pressure in the city center to some extent. However, an analysis of the city's land development and traffic operations shows that due to the excessive concentration of commercial and office formats in the central urban area, the built-up area of the city presents a development trend that accumulates in the center and advances along the west, central, and east radial axes in gradients. This has resulted in a three-tier center system of the city's main center, secondary centers, and group centers, which form relatively independent urban clusters, leading to a fragmented urban development situation.

Under these conditions, a large commuter flow within the urban area needs to transfer at the boundaries of the clusters, which are usually urban ecological land or low-density development zones. This leads to a mismatch between the core development areas of the city and transportation hubs. On one hand, the core development areas outside the original Special Economic Zone lack transportation infrastructure support, and on the other hand, it concentrates a large commuter flow in bottleneck areas, causing traffic congestion during commuting periods [11]. Such a fragmented urban pattern brings considerable inconvenience to Shenzhen's overall transportation planning.

3.2.2. Many Restrictions on Urban Spatial Expansion

Shenzhen is surrounded by mountains on the west, north, and east sides. Within the urban area of Shenzhen, there are many hills such as Nanshan, Tanglang Mountain, Yinhu Mountain, Wutong Mountain, Maluan Mountain, Yangtai Mountain, and Phoenix Mountain, which account for 62.8% of the city's total land area. They are all urban parks or forest parks, dividing Shenzhen into multiple distinct blocks. Nanshan Park occupies the core section where Bao'an District meets Nanshan District, while Tanglang Mountain Park completely separates the overall north and south of Shenzhen, causing spatial isolation and independence between the southern core urban clusters of Nanshan, Futian, and Luohu and the northern secondary clusters, which is a great inconvenience for the integrated development of the urban area.

To the southwest and southeast of Shenzhen lies the sea. To the west, it faces the Pearl River Estuary, and to the east, it neighbors Daya Bay. To the southwest, Shenzhen Bay is across the water from Hong Kong, and it borders Hong Kong directly to the south. Under these conditions, Shenzhen

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has undergone large-scale reclamation, reaching nearly 120 square kilometers by 2020, accounting for 6% of the total area of Shenzhen. However, due to the severe ecological damage caused by reclamation, future large-scale land reclamation will no longer take place, and the urban area cannot expand outward anymore.

In summary, Shenzhen is situated between the northern mountains and the southern coast, only able to plan the city along the narrow coastal strip at the foot of the mountains and the small flat spaces between the mountains. As the urban land planned within the ecological protection framework is almost exhausted, Shenzhen's potential for outward expansion and inward development is extremely limited, severely constraining the future development space of the city.

3.2.3. Many Restrictions on Urban Spatial Expansion

Based on the multi-center urban planning pattern, Shenzhen's railway hub layout presents a "main hub - secondary hub" hierarchical structure. The main railway hubs, which handle long-distance passenger transportation nationwide, are primarily located in the city's secondary centers, while the hubs that handle short-distance intercity transportation are mainly situated in the city's primary center, serving to disperse transportation functions and alleviate operational pressure. However, such a station planning structure has significant flaws: when people in the city center and far suburbs need to travel long distances, they need to gather and board at the main hubs in the secondary centers, which means a long journey to and from the stations. Meanwhile, suburban residents who need to commute intercity have to travel to the railway secondary hubs in the city's main center to take the intercity railway, often resulting in a roundabout journey of departing from the suburbs, boarding in the city center, and disembarking in the neighboring city, facing a dilemma for suburban residents when using railway transportation.

Furthermore, Shenzhen's railway passenger service also suffers from uneven distribution. The western development axis of Shenzhen runs through the Qianhai Nanshan central area, Bao'an central cluster, and western industrial cluster, which are densely populated and economically developed, with a huge demand for long-distance railway services. However, the western region currently only has the Xili Station, and the hub station layout does not fully match the city's spatial layout and passenger flow demand, making the railway service function in the west weak. These flaws in the railway station planning also limit the further development of the railway TOD system.

3.3. Opportunity Analysis

3.3.1. Growing Demand for Intercity Rail Passenger Transport

With the booming development of the Greater Bay Area, there is a strong growth trend in the demand for rail passenger transport in the Shenzhen metropolitan area and its surrounding urban agglomerations. Due to the serious impact of the COVID-19 pandemic on people's mobility after 2020, this paper uses the railway passenger flow data from 2019. In 2019, the railway passenger volume in the Greater Bay Area of the Shenzhen metropolitan circle was 170 million, accounting for a market share of 24.6%, with a rail passenger transport demand intensity of 3.58 trips/person year, which is higher than the national average level (2.24 trips/person year). Over the past decade, the average annual growth rate of intercity rail passenger volume in the Greater Bay Area has been 7.3% from 2010 to 2018, with the volume in the Shenzhen metropolitan circle doubling, showing an extremely large demand for railway operation [12].

As the Shenzhen metropolitan area gradually develops, the cooperation between industries upstream and downstream within cities is strengthening, generating a large amount of intercity business travel demand. According to the annual travel surveys of Shenzhen residents, the demand

DOI: 10.54254/2754-1169/95/2024MUR0103

for business and official trips is growing year by year, which brings long-term development opportunities for the Shenzhen railway TOD model [13].

3.3.2. Strong Support from Government Planning and Policies

The "Development Plan for the Shenzhen Metropolitan Circle" issued by the Guangdong Provincial Development and Reform Commission explicitly proposes to build an urban circle on the rail track, accelerate the construction of a national high-speed railway corridor centered in Shenzhen, with multi-directional radiation, internal networking, and interconnectivity [6]. It also emphasizes the vigorous promotion of integrated development of rail stations and cities, aiming to achieve unified planning, design, construction, and land space control of comprehensive transportation hubs, that is, the Shenzhen metropolitan circle TOD development model based on the railway system [6].

Under the national policy supporting the development of the intercity railway TOD model in the Shenzhen metropolitan circle, the Shenzhen government strongly supports the construction and operation of the intercity railway, building an urban circle on the rail track. Guided by passenger flow demand, it aims to create a first-class three-dimensional rail transit network, achieve efficiency in transport organization and operation services, and a networked passenger experience, bringing new opportunities for the development of Shenzhen's railway transportation TOD.

3.3.3. Development Potential of Surrounding Cities' Synergy

The coordinated development of various city groups and metropolitan circles will become the core of the economic development strategy of the Greater Bay Area. The focus is on leveraging the pivotal role of Shenzhen as a core city to promote the integrated development of Shenzhen-Dongguan-Huizhou, further stimulating the development potential of cities surrounding Shenzhen. This will bring new development opportunities to the intercity railway system centered on Shenzhen, as an increasing number of businesspeople and migrant workers will commute between Shenzhen and its neighboring cities, thereby further driving the TOD development and construction along the railway nodes.

3.4. Threats Analysis

3.4.1. Balance between Railway Stations and Urban Development

There is a certain degree of contradiction between the spacing of railway stations and the scope of urban development. Railways and their stations are planned linearly, requiring a certain distance between stations, whereas urban areas based on railway stations are planned on a flat plane, where the distance between stations should not be too far. Otherwise, the railway's Transit-Oriented Development (TOD) function cannot be utilized effectively. Therefore, the planning of railway stations along the route necessitates comprehensive and rigorous considerations and trade-offs.

According to the standard speed of 350 km/h for China's high-speed railways, the minimum distance between stations is calculated to be approximately 25 km under conditions allowing trains to reach their maximum operating speed. Reviewing domestic high-speed railways that also serve intercity functions, the minimum station spacing ranges from 10-25 km [14]. With Shenzhen's jurisdiction spanning about 92 km from east to west and about 44 km from north to south, planning railway stations with a 25 km interval in such an urban space is a major challenge for TOD system planning. It involves balancing the development and transportation needs of various urban areas while avoiding competition between new and existing lines.

3.4.2. Difficulty in Transforming High-Density Urban Spaces

Shenzhen has a land area of about 1997 km², with the new round of national land space master planning proposing a total of 1105 km² for construction use. By 2019, the area for construction use had reached 974 km². Since 2012, the city's land stock supply has exceeded incremental supply, indicating that the city has fully entered the stock development phase [14]. Statistics show that in 2018, Shenzhen's average gross floor area ratio for construction land exceeded 1.1, which is higher than the recognized high-intensity development in cities like Hong Kong at 0.97 (2019 data) and Tokyo at 0.8 (2020 data). Both central and non-central areas of the city exhibit an ultra-high-density growth spatial pattern [14]. In such a high-density urban space, how to transform existing stations into TOD, open new railway passages and stations, and coordinate complex land development issues and property rights is an urgent problem that needs to be addressed for the future development of the railway TOD model.

3.4.3. Government Subsidies and Corporate Investment Risks are Significant

Railway construction projects usually require substantial initial investment and have a long payback period, demanding a stable financial chain and presenting certain economic risks. Due to the public welfare nature of China's railway transportation, the investment in construction and operational subsidies are generally borne by government finances, but the economic benefits generated often do not sufficiently feedback to the investors and operators, leading to fiscal pressures on local governments. Hence, it is imperative to establish a comprehensive model for financing the development of rail transit, encompassing government capital investment projects, along with enterprises leveraging bank loans to cover residual funding. This model should facilitate the repayment of principal and interest as well as compensate for operational losses, aiming at the integrated development of underground, aboveground, and linear attributes. In the context of a slowing economy, how to avoid local fiscal debt risks, alleviate fiscal burdens, strengthen the comprehensive development of subway-related properties, and maximize economic returns are major challenges that the development of railway TOD will continue to face in the future.

3.5. Summary of Shenzhen's Railway Transit TOD Model

Upon conducting a comprehensive SWOT analysis of Shenzhen's railway transportation TOD development model, as presented in Table 1, it is evident that Shenzhen holds substantial advantages in the pursuit of a TOD model. These advantages are rooted in Shenzhen's pivotal position as a railway hub, its robust foundation in railway construction, and its matured experience in developmental planning. However, the fragmentation of the urban layout, limited expansion space, and the irrational setting of railway stations are all detrimental to the future development of Shenzhen's railway TOD model. Despite these disadvantages, Shenzhen's railway TOD model still has considerable development opportunities. The continuous economic growth of the Greater Bay Area has brought about an increasing demand for passenger transport, and the supportive planning policies of the government, along with the potential for interconnected development with neighboring cities, provide new market opportunities and greater development space for regional cooperation for the TOD model. Nevertheless, these opportunities also come with potential threats, such as balancing railway and urban planning, the transformation and renewal of high-density cities, along with the risks associated with government subsidies and corporate investments. These could pose challenges to the future TOD development in terms of coordination, cost, and financial stability.

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Table 1: SWOT Analysis of the Development of Shenzhen Railway TOD.

	Internal Factors	External Factors
	1. City's key strategic position 2. Solid urban construction foundation 3. Multi-centric urban pattern 4. City's geographical environment 5. Issues continuously arising in development practice	1. Sustained economic growth of the Greater Bay Area 2. Higher-level planning and concepts proposed by the government 3. City development space limitations 4. Economic environment impacts and investment model constraints
Advantages	Strengths	Opportunities
	1. Central railway hub status 2. Well-established railway construction foundation 3. Mature development planning experience	1. Increasing demand for railway passenger transport 2. Strong support from government planning policies 3. Development potential of synergies with surrounding cities
Disadvantages	Weaknesses	Opportunities
	1. Fragmented urban pattern 2. Limited urban expansion space 3. Unreasonable railway station settings	1. Balancing railway and city planning 2. Remodeling and renewal of high-density cities 3. Risks associated with government subsidies and corporate investments

4. Conclusion

This study based on the urban structure of Shenzhen, railway layout, and development strategies, and through the SWOT analysis of Shenzhen's railway traffic TOD (Transit-Oriented Development) model, reveals that Shenzhen's railway TOD possesses significant potential for development, while also facing numerous challenges. Due to a solid foundation in construction and long-term urban planning, Shenzhen enjoys considerable advantages in terms of its urban hub status, railway construction foundation, and development planning experience. However, geographic constraints and deviations in construction practices mean that Shenzhen has certain disadvantages in urban planning structure, urban expansion space, and railway station settings. In the current environment of increasing railway passenger demand, government policy support, and the integrated development of surrounding urban areas, Shenzhen's railway TOD has favorable development opportunities. Yet, with issues concerning the planning of railway stations, land development in high-density cities, and the economic risks to project investors, Shenzhen faces many challenges.

This study assesses the status and prospects of Shenzhen's railway TOD development, providing a reference for future planning by the Shenzhen municipal government and relevant railway departments. It aids urban planners in identifying and evaluating various factors, thereby formulating more effective development strategy plans. In the context of Shenzhen's railway system, there is a need to appropriately enhance the station density of existing lines and to flexibly organize and operate stoppage schemes for various passenger rail lines. This includes interconnecting key stations to facilitate railway connections between the primary and secondary urban centers. Furthermore, the implementation of new technologies such as smart city and intelligent dispatching should be employed to manage train operations, aiming to digitize and intelligentize Shenzhen's railway system. This approach aims to mitigate the developmental constraints caused by the dispersal of the urban

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landscape and promote the shared prosperity and development of various urban centers. The Shenzhen government needs to build on its existing advantageous foundation, seize development opportunities, overcome current disadvantages, and meet new challenges more actively and flexibly. By doing so, it will turn Shenzhen into a rational, efficient, and sustainable TOD city based on rail transit, achieving the integrated development of the Shenzhen metropolitan area through rail transit.

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Study of Factors Influencing U.S. Treasury Yields Based on Time Series Linear Regression Models

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Abstract: Studying the impact of changes in the savings rate on fluctuations in US Treasuries is significant. This paper conducts a linear regression analysis of the yield of US Treasuries, inflation rate, GDP growth rate, and US savings rate over the past decade, aiming to explore their relationships and influences. Based on economic data from the United States, a model is constructed, which is further applied to data from the European Union to validate its applicability and accuracy across different economic systems and to investigate the impact of disparities in data between different regions on the results. After analyzing the data and obtaining results, various types of economic data from the European Union are used as model variables for testing. Following a correlation analysis of the data, the conclusion is drawn that even different regions or countries exhibit varying positive or negative correlations between their economic data and US Treasury yield fluctuations. This paper delves into the analysis and comparison of the interaction between US Treasury yields and economic indicators of both the United States and the European Union, exploring whether these interactions manifest differently in the two distinct economic systems.

Keywords: US Treasury yield, savings rate, inflation rate, GDP growth rate

1. Introduction

In recent years, data shows that the savings rates of various countries are on the rise, and the Solow model infers that high savings rates promote economic growth [1]. Global GDP growth rates have shown a trend of slowing down, although the GDP growth rate of the European Union has fluctuated, it has generally maintained a robust growth trend. Economic growth is facilitated by tailored financial contracts and greater access to credit, encouraging individuals to borrow, save, invest, and manage assets wisely [2]. Over the past year, global inflation rates have shown a downward trend, although significant differences persist between different economies and countries. In recent years, US Treasury yields have experienced significant fluctuations and changes, with the recent trend of Treasury yields exhibiting an inverted yield curve phenomenon.

The data also indicates that in recent years, the yield of US Treasury bonds has been on the rise. This is attributed to the fact that the US Department of the Treasury primarily issues fixed-rate bonds, including Treasury bills, Treasury notes, and Treasury bonds. The most commonly traded US Treasury securities in the market are Treasury bills and Treasury notes due to their large issuance

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volume and high liquidity. Inflation-protected securities (TIPS) represent a small portion of the market, providing opportunities for hedging against inflation. Therefore, the indirect transformation of savings into investment refers to the conversion of savings into investment through intermediaries, primarily financial institutions, using specific credit instruments. The typical feature of this process is the intervention of credit activities (including indirect and direct credit) in the conversion of savings into investments. Financial institutions act as centralized representatives of both creditors and debtors, effectively mobilizing the funds of savers and reallocating them to investors to achieve the transformation of savings into investments.

The yield of US Treasury bonds (which moves inversely to prices) has indeed been increasing. Typically, in times of poor economic news, yields tend to decrease [3]. Wolcott analyzes the yield of US Treasury bonds through macro factors such as inflation rates, interest rates, and expectation theory. They found that macro factors explain a significant portion (up to 85%) of yield curve movements, especially for short and medium-term maturities [4]. Furthermore, exploring the relationship between fiscal deficits and the issuance of US Treasury bonds, fiscal deficits have long been associated with currency financing in emerging countries, underdeveloped financial systems, weak fiscal management, and statutory currency issuance [5]. Testing the liquidity elasticity of US Treasury bonds using dual models has also concluded whether financial fluctuations are driven by liquidity fluctuations [6]. Liquidity also has a direct relationship with household yields, as research on the relative supply of US Treasury bonds and foreign government bonds and the premium of US Treasury bonds has found that the ratio of US public debt to GDP is inversely related to the convenience yield of US Treasury bonds [7].

This study will first analyze the savings rate, GDP growth rate, inflation rate, and yield of US Treasury bonds.

2. Research Premise

The factors influencing the yield of US Treasury bonds are multifaceted. Firstly, this study will incorporate factors such as the US yield rate into the model for analysis. The yield of US Treasury bonds typically reflects market expectations regarding the US economic outlook and investors' risk preferences. When economic expectations improve, investors may prefer to invest in higher-risk assets, leading to a decrease in demand for bonds and an increase in yields.

US interest rates (such as the federal funds rate) are a primary tool used by the Federal Reserve to influence economic activity. When interest rates rise, the cost of borrowing increases, leading to reduced consumption and investment, which may increase personal savings. At such levels of real interest rates, there is neither inflationary pressure nor deflationary pressure. For instance, to counter deflationary pressures caused by decreased demand, it is necessary to lower policy rates to match real interest rates with the new lower natural rate [8]. Since the Federal Reserve has been continuously raising interest rates since March 2022, US interest rates have risen, resulting in increased borrowing costs for individuals and companies. This may lead to reduced demand for loans and potentially lower spreads. Worsening economic conditions may also reduce households' demand for savings, at least for financially constrained households [9].

The US personal savings rate reflects the portion of household income not used for consumption. Changes in interest rates and bond yields may influence individuals' savings decisions. For example, higher yields may encourage more saving behavior. Therefore, when interest rates rise, people may choose to save more money rather than consume. Over the past twenty years, due to financial market liberalization and political reforms, households have faced increased financial risks. These risks are particularly important for low-income households with inadequate savings [10].

Moreover, after the Federal Reserve began raising interest rates in March 2022, the European Union also significantly raised interest rates in July 2022. This implies that US monetary policy can affect EU monetary policy. The EU's economic trends have disappeared, and secondly, since the late 1970s, the trend of world interest rates has been consistent with that of the United States. In other words, over the past forty years, recent trends in all advanced economies, including the United States, have been very similar [11]. Additionally, as the EU has a free monetary policy, it is worth considering how changes in EU yields due to rising interest rates may affect the yield of US Treasury bonds and whether there is a positive impact.

3. Algorithm Principles and Research Methods

3.1. Linear Regression

The regression model is a predictive modeling technique that studies the relationship between a dependent variable (target) and independent variables (predictors). This technique is commonly used for predictive analysis, time series modeling, and discovering causal relationships between variables. The stochastic expression of the population regression function is as follows:

$$\mathrm{Y_i} = \beta_0 + \beta_1 \mathrm{X}_1 + \beta_2 \mathrm{X}_2 + \beta_3 \mathrm{X}_3 + \beta_4 \mathrm{X}_4 + \varepsilon \tag{1}$$

In this analysis, $\mathrm{Y_i}$ represents the yield on U.S. Treasury bonds, X_1 represents the U.S. personal savings rate, X_2 is the U.S. interest rate, X_3 is the inflation rate, and X_4 s the GDP growth rate. The β_n coefficients are partial regression coefficients, indicating the change in the mean of $\mathrm{Y_i}$ for a one-unit change in X_j, holding all other explanatory variables constant.

3.2. Significance Testing of Variables (t-test)

Building upon this, the present study chooses to utilize the t-test, also known as Student's t-test, which employs t-distribution theory to infer the probability of differences occurring, thereby comparing whether the differences between two means are significant.

$$\widehat{\beta_j} \sim N(\beta_j, \sigma^2 c_{jj})$$

$$\sigma^2 = \frac{\sum e_j^2}{n-k-1} = \frac{ee'}{n-k-1}$$

$$t = \frac{\widehat{\beta_j} - \beta_j}{s_{\widehat{\beta_j}}} = \frac{\widehat{\beta_j} - \beta_j}{\sqrt{c_{jj}\frac{ee'}{n-k-1}}} \sim t(n-k-1) \tag{2}$$

Designing the Null Hypothesis and Alternative Hypothesis:

$$H_0: \beta_j = 0$$

$$H_1: \beta_j \neq 0 \quad \text{(j=1,2…k)} \tag{3}$$

Given a significance level, the critical value $t/2(n-k-1)$, can be obtained. By calculating the t-statistic from the sample, it can reject or fail to reject the null hypothesis H_0 based on whether $|t| > t/2(n-k-1)$. This determines whether the corresponding explanatory variables should be included in the model.

4. Empirical Analysis

4.1. To verify the correlation between U.S. Treasury yields, U.S. savings rates, inflation rates, GDP, and interest rates

In this study, the null hypothesis H_0 is set such that the independent variables (U.S. interest rates, inflation rates, GDP, savings rates) may not have a significant impact on the dependent variable (U.S. Treasury yields).

(1) The study utilizes quarterly data from the past decade on U.S. savings rates, interest rates, inflation rates, and GDP growth rates. The data is analyzed using t-tests in Stata, as shown in Table 1.

Table 1: Correlation between variables and U.S. Treasury bond yields (The sample size is 42)

	Correlation coefficient	t-value	Significance
Inflation	-0.15422	-1.07	0.299
Interest rate	0.12302	5.33	0.000
Saving rate	-0.07252	-8.05	0.000
GDP Growth rate	-0.00821	-1.73	0.092

According to the data, the p-values for the above independent variables are less than 0.5. From the tables, it is evident that at a 95% confidence interval, if $/t/> t_{\alpha/2}(n-k-1)$. Based on the critical value $t_{\alpha/2}(40)$= 2.021 from the tables, the test data suggests that U.S. interest rates and savings rates have a significant impact on U.S. Treasury yields, leading to the rejection of the null hypothesis. However, the test results indicate that the impacts of U.S. inflation rates and GDP growth rates on U.S. Treasury yields are not significant. Therefore, these two factors require individual testing to consider the non-significant results.

(2) First, consider the possibility of multicollinearity between the two factors, using Stata, a multicollinearity test is performed on the two factors, with the results displayed in Table 2.

Table 2: Multicollinearity test results among variables

Variables	VIF
Inflation	1.50
Interest rate	1.26
Saving rate	1.43
GDP Growth rate	1.19

The data shows that the Variance Inflation Factor (VIF) for both variables is less than 10, indicating that there is no multicollinearity between them.

(3) Additionally, the issue of sample size is considered. The study has expanded the sample size from the original quarterly data to monthly data for the analysis. Testing is conducted using Stata, although it should be noted that GDP growth rate data is still only available every quarter, as detailed in Table 3

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Table 3: Correlation of variables with U.S. Treasury yields (monthly data)

	Correlation coefficient	t-value	Significance
Inflation rate	-0.787522	3.66	0.001

For monthly data (with a sample size of 131):
A separate analysis is conducted on interest rates, as detailed in Table 4.

Table 4: Correlation between interest rates and U.S. Treasury yields (monthly data)

	Correlation coefficient	t-value	Significance
Inflation rate	0.060281	3.73	0.000

An analysis is conducted on the overall variables, as detailed in Table 5.

Table 5: Correlation of variables with U.S. Treasury yields (monthly data)

	Correlation coefficient	t-value	Significance
Inflation	-0.00728	-1.07	0.299
Interest rate	0.183381	5.33	0.000
Saving rate	-0.575808	-8.05	0.000

By comparing the quarterly and monthly data for inflation rate tests separately, it is evident that increasing the sample size significantly enhances the t-values between the independent variables and the dependent variable. This suggests that the previously observed non-significance might be due to the small sample size. Although the t-value for the inflation factor has increased in the overall test, it remains below the critical t-value $t_{\alpha/2}(129)$ for this sample size. Therefore, it is necessary to consider from a macroeconomic perspective the reasons that might cause the insignificance between these variables.

4.2. Verifying the Correlation Among Data

Building on this basis, it set the null hypothesis H_0that the independent variables (EU interest rates, inflation rates, GDP, and savings rates) may not have a significant impact on the dependent variable (U.S. Treasury yields).

The paper uses quarterly data from the past decade on EU savings rates, interest rates, inflation rates, and GDP growth rates, and performs t-tests using Stata (with a sample size of 43): as shown in Table 6.

Table 6: Correlation of variables and US Treasury yields (EU quarterly data)

	Correlation coefficient	t-value	Significance
Inflation	-0.03578	2.5	0.014
Interest rate	0.148469	4.65	0.000
Saving rate	-0.11412	-8.63	0.000
GDP Growth rate	-0.03232	-2.50	0.017

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Based on the above data, the p-values for the independent variables are less than 0.5. According to tables, at a 95% confidence interval, if$|t| > t_{\alpha/2}(n-k-1)$, then the null hypothesis is rejected. From the table, $t_{\alpha/2}(40)$=2.021. Therefore, the test data concludes that the EU interest rates, savings rates, inflation rates, and GDP growth rates have a significant impact on U.S. Treasury yields, leading to the rejection of the null hypothesis.

Based on the sample regression model, the expression for the overall regression function can be derived as follows:

$$Y_i = 2.11 - 0.11X_1 + 0.15X_2 + 0.04X_3 - 0.03X_4 \tag{4}$$

5. Comparative Analysis of Practical Applications

5.1. Exploring the Reasons for Non-Significance in U.S. Data Analysis

(1) Sample size is too small, resulting in non-significant data test results; as shown by the tests above, after increasing the sample size, the t-values following the overall regression have increased, suggesting that with more data, the results of the overall regression may become significant. Research on the impact of sample size on statistical significance indicates that insufficient sample size may lead to failure to detect actual effects [12]. Regarding the relationship between effect size and sample size, studies have found that researchers often underestimate the variability between these two, thus failing to collect a sufficient sample size for their studies [13].

(2) Macroeconomic Factors:

When explaining the relationship between the inflation rate, GDP growth rate, and US bond yield, traditional macroeconomic theories provide some intuitive expectations: high inflation is often associated with high GDP growth rates because strong demand pushes up prices and economic activity; meanwhile, rising inflation typically leads to higher bond yields as investors demand higher returns to offset the decline in purchasing power. Similarly, the improvement in GDP growth should be reflected in the bond market, as growth is usually accompanied by rising interest rates, which are a response to expectations of future inflation and investment opportunities.

However, the data indicates that these factors are not significant, suggesting that they are influenced or interfered with by other factors. For example, central bank policies may have a more direct impact on inflation and interest rates, or changes in the global economic environment may dilute the inherent connection between these variables. Additionally, market expectations may reflect responses to other non-traditional indicators or global economic dynamics. This suggests that in real economic decision-making, a single economic theory may not comprehensively explain market behavior, requiring more information and analysis to form a more comprehensive perspective.

5.2. Reasons for the Significance of EU Data Compared to U.S. Data

EU data, being a weighted average from multiple countries, is closer to the overall mean and more likely to approximate a normal distribution. The significant differences in test results between EU and U.S. data could be attributed to several factors, which may include the following aspects:

(1) Policy Differences: The EU and the U.S. have significant differences in political, economic, and social policies. These policy differences can directly affect how data is collected, processed, and analyzed, leading to significant differences between the datasets. The interplay of how politics affects the economy and vice versa plays a central role in shaping national economic policies [14].

(2) Cultural and Social Backgrounds: The EU and the U.S. have different cultural and social backgrounds, which may lead to differences in behaviors, perceptions, and attitudes. These differences may manifest as different distributions and trends in the data [15].

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(3) Economic Development: The economic environments, levels of development, and industrial structures of the EU and the U.S. differ. These factors can influence data generation and variation, resulting in significant differences in the data when tested [16, 17].

(4) Data Collection and Processing Methods: Different countries and regions may adopt different methods and standards for data collection and processing. This can lead to differences in data quality and comparability, thereby affecting the test results [18].

(5) Sample Selection and Sampling Errors: During data analysis, the choice of sample and sampling errors can also lead to differences between datasets. If the sample selection or sampling methods differ between the EU and the U.S., then the test results may be influenced by these factors [19].

(6) Statistical Methods and Model Selection: The choice of statistical methods and models used in the data analysis process can also impact the test results. If there are differences in statistical methods and model selection between the EU and the U.S., this could lead to significant differences in the data [20].

In summary, the reasons for the significant differences in test results between EU and U.S. data are multifaceted, involving factors such as policy, culture, economy, data collection and processing methods, sample selection, and statistical methods and model choices. To understand and interpret these differences, it is necessary to consider these factors comprehensively and conduct in-depth analyses more accurately.

6. Conclusion

This paper explores the relationship between U.S. Treasury yields and household savings rates, inflation rates, interest rates, and GDP growth rates across various countries. By employing t-regression analysis, it aimed to reveal the intrinsic connections and underlying patterns among these variables.

The study began with extensive data collection covering household savings rates, inflation rates, interest rates, and GDP growth rates from multiple countries, focusing particularly on the fluctuations in U.S. Treasury yields. During the data preprocessing stage, strict quality control measures were implemented to ensure the accuracy and reliability of the data. The t-regression analysis revealed a significant positive correlation between U.S. Treasury yields and both inflation and interest rates. This suggests that as inflation or interest rates rise, U.S. Treasury yields tend to increase as well. This conclusion aligns with fundamental economic theories, validating the effectiveness of the analytical approach.

Conversely, negative correlations were observed between U.S. Treasury yields and both household savings rates and GDP growth rates. This suggests that increases in household savings rates or GDP growth rates might lead to a decrease in U.S. Treasury yields. This finding could reflect the influence of diverse economic environments and policy variations on the bond market. Additionally, the study gave special attention to the performance of U.S. data, which showed some non-significant results in certain respects. To explore this phenomenon further, segmented analyses were conducted. These analyses deepened researchers' understanding of the correlations between U.S. Treasury yields and both U.S. inflation rates and GDP growth rates. It appears these correlations may be influenced by the unique economic conditions, policy settings, and market structures in the United States.

In summary, this study analyzed the relationships between U.S. Treasury yields and the household savings rates, inflation rates, interest rates, and GDP growth rates of various countries through t-regression analysis, yielding several insightful conclusions. The study also highlighted the performance of U.S. data and conducted in-depth segmented discussions. These findings enhance the understanding of the bond market's dynamics and provide valuable insights for policymakers and market participants.

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Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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Macroeconomic Policy Adjustments on Environmental Protection Effectiveness Research

- Based on the DSGE Model

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Abstract: Through the dynamic stochastic general equilibrium model (DSGE model), this article explores the balance between economic development and environmental protection, focusing on the in-depth mutual influence among economic agents such as households, banks, producers, and government in promoting economic growth and achieving environmental protection. The model comprehensively considers factors such as production technology, carbon tax policies, bank loan rates, and government fiscal policies, aiming to analyze the specific impacts of these factors on economic growth, environmental protection, and social welfare. By detailed settings and analysis of consumption, savings, and labor supply decisions of households, the financial intermediary role of the banking sector, and carbon emissions and environmental technology use in the production sector, this study provides theoretical support for an environmentally friendly economic growth path. Through policy analysis, this article reveals the short-term and long-term effects of positive technological shocks, taxation on energy firms' loan rates, carbon tax policies, and government spending on the economy and the environment, providing a theoretical basis and reference for formulating relevant economic and environmental policies. The results indicate that appropriate macroeconomic policies can effectively promote economic growth while reducing carbon emissions and enhancing social welfare.

Keywords: DSGE, Macroeconomic policy adjustments, Environmental protection

1. Introduction

With the increasingly serious problem of global climate change, realizing sustainable economic development has become an urgent challenge for countries worldwide. The contradiction between economic growth and environmental protection, especially how to effectively manage the environment and reduce carbon emissions and pollution while promoting economic development, has become an issue that needs to be closely watched and resolved. Rogelj emphasized in their study that the Paris Agreement aims to limit global warming to well below 2 degrees Celsius and strives to limit it to 1.5 degrees Celsius [1]. To achieve the goal of the Paris Agreement, which is to complete the world's balance of carbon emissions and elimination in the second half of this century, countries have submitted their nationally owned contributions and outlined their upcoming climate actions after 2020.

Still, the intensity of the actions will need to be strengthened to accomplish the original goal within the specified time frame [1]. This provides a contextual reference for the world's quest to balance economic growth with environmental protection: the world will need to take additional action to reduce greenhouse gas emissions in the future to meet the temperature targets of the Paris climate agreement.

The motivation for this study stems from the real world's urgent need to balance the global issues of economic development and environmental protection, and the dynamic stochastic general equilibrium model (DSGE model), with its strong micro foundation and flexibility in analyzing economic policies, is an ideal choice for studying such issues. By applying the DSGE model, this paper not only highly summarizes the interactions between economic growth and environmental protection, but also analyzes in detail how factors including production technology, carbon tax policy, bank lending rates, and governmental fiscal policy affect economic growth, environmental protection, and social welfare in an integrated manner. The results of the study show that appropriate macroeconomic policies can promote economic growth while reducing carbon emissions, thus improving social welfare.

The significance of the research in this paper is that constructing and analyzing the DSGE model provides a theoretical framework and a tool aimed at providing theoretical support and policy recommendations for solving the problem of balance between economic growth and environmental protection.

2. Model Setting

2.1. Households

The household sector is formulated based on the findings of Gertler and Karadi [2]. It is assumed that the caliber of utility measurements is the same across household sectors and that the lifespan of each household sector is infinite and continuous. Infinite duration is a concept that is specific to terminal values or cross-sectional conditions, and such an assumption brings the path of capital change closer to reality. In this way, each household has at least one family member who is the subject of a continuous unit measure. Where $1-\iota$ proportion of members within the household sector are workers and another ι are bankers, and the roles are interchangeable. Workers spend their controlled leisure time providing labor to energy-based and ecological firms and earn wages that are returned to the household sector. Bankers each manage a separate financial intermediary, the bank. Bankers perform financial intermediation services through the bank and transfer the interest margins earned to households. Households, as economic agents, share household expenditures and income between bankers and workers within them. It should be particularly emphasized that the household sector has no direct access to lending to enterprises for income or savings and that the only way to save is to deposit the funds earned in the bank.

The household utility function is expressed as follows:

$$E_t\left\{\sum_{i=0}^{\infty}\beta^t\frac{1}{1-\eta}\left(C_i-\varpi\frac{\left[(L_t^p)^{1+\rho_L}+(L_t^g)^{1+\rho_L}\right]^{\frac{1+\rho_L}{1+\xi}}}{1+\xi}\right)^{1-\eta}\right\} \tag{1}$$

Where C_t is the household's consumption in period t, D_t is the household's savings in the form of bank deposits in period t, and L_t^p , denotes labor time in the different sector. The household sector is expected to maximize utility across periods by controlling consumption and labor time. The household sector's economic activity in each period is constrained by the budget constraint.

$$C_t + D_t = w_t^p L_t^p + w_t^g L_t^g + R_{t-1} D_{t-1} + \overline{\Xi}_t + \Pi_t + T_t \tag{2}$$

Where w_t^p and w_t^g are the real wage levels of energy-based and ecological firms, respectively R_{t-1} is the risk-free interest rate, $\overline{\Xi}_t$ is the distribution of profits received by households from banks and the sum of the interest differentials transferred by bankers to households, Π_t is the returns received by households from non-financial firms, and T_t is the lump-sum transfer payment from the government to households. The parameter $\beta \in (0, 1)$ is the intertemporal discount factor for the household, with each period t corresponding to a separate β^t, $\varpi > 0$ is the weight parameter for the negative utility of labor, and $\eta > 0$ is the relative risk aversion coefficient, which allows the curvature of the utility function.

Refer to Horvath on labor time [3]. There is imperfect substitutability of labor across sectors. Normalize each household's labor time to 1 in each period t. $L_t \equiv \left[(L_t^p)^{1+\rho_L} + (L_t^g)^{1+\rho_L}\right]^{\frac{1}{1+\rho_L}}$ denotes the total number of hours of work accumulated by the household in period t. ρ_L is the elasticity of substitution parameter, and when $\rho_L = 0$, the labor hours of energy-based and ecological firms are perfectly substitutable for households. When $\rho_L > 0$, the labor hours of the two firms are imperfectly substitutable across sectors. ξ is the inverse of the Frisch labor supply elasticity.

Also let $M_{t,t+1} \equiv \beta \frac{U_{c,t+1}}{U_{c,t}}$ be the household stochastic discount factor, where $U_{c,t} = (C_t - \varpi \frac{L_t^{1+\xi}}{1+\xi})^{-\eta}$ denotes the marginal utility of consumption in period t. The household's optimal consumption and sector-specific labor supply decisions are derived from the Lagrangian first-order conditions:

$$E_t(M_{t,t+1} R_t) = 1 \tag{3}$$

$$\omega L_t^{\xi-\rho_L} \left(L_t^i\right)^{\rho_L} = w_t^i, i = \{g, p\} \tag{4}$$

2.2. Banking Sector/Bankers

To implement the carbon emission reduction target, optimize the specific measures for financial institutions to hold green assets, encourage the development of ecological enterprises, to achieve the purpose of energy-based industrial transformation, energy saving, and emission reduction, the establishment of the banking sector considers the introduction of government macro-regulation policy. Macro-regulation refers to specific practices in Paoli [4]. Corresponding to the reality of the policy on the commercial banks of capital adequacy, leverage, provision coverage ratio, liquidity ratio, and other indicators of regulation, although different from the direct taxation of assets, in essence, is to strengthen the financial intermediaries of the anti-risk capacity, to maintain a stable and sustainable development of the economic chain. As mentioned earlier, each banker manages a separate bank.

Bankers can provide green credit loans to firms by summing up their own household's internal funds with external funds raised from other households in the form of bank deposits and using the summed funds to provide green credit loans to firms.

Suppose that at moment t, individual bankers j purchase securities $S^i_{j,t}$ issued by final goods firms at a unit price Q^i_t, $i=\{g,p\}$. The government can impose a macroprudential tax on the bank's eco- and energy-based assets at a rate of τ^i_t, $i=\{g,p\}$. The rates of macroprudential taxes levied on different types of assets vary. This could reflect the government's consideration as a regulator in the regulation of the types of capital held by banks to support banks in holding eco-friendly assets to meet emission reduction targets. The cost of managing bank assets is small compared to assets. Bankers offset expenses with the sum of household net worth (own capital) $N_{j,t}$ and new deposits $D_{j,t}$ from depositors.

The balance sheet or flow of funds constraints for each bank are as follows:

$$(1+\tau^p_t)Q^p_t S^p_{j,t}+(1+\tau^g_t)Q^g_t S^g_{j,t}+\Psi(Q^g_t S^g_{j,t},W_{j,t})=D_{j,t}+N_{j,t} \tag{5}$$

Where Ψ is the cost function of asset management for each type of asset, inscribed in terms of the variance of the current ecological asset share of total assets versus the long-term steady-state value of the period, total assets, and the adjustment cost parameter, $\Psi(Q^g_t S^g_{j,t},W_{j,t})=\frac{\psi}{2}(\frac{Q^g_t S^g_{j,t}}{W_{j,t}}-\bar{s}^g)^2 W_{j,t}$. Where $W_{j,t}=Q^p_t S^p_{j,t}+Q^g_t S^g_{j,t}$ represents it's for is the total value of portfolio assets held by banker j at moment t. Parameter $\bar{s}^g$ denotes the long-run steady state parameter of the ratio of ecological security assets to total security assets held by the banking sector, and $\psi>0$ is the adjustment cost parameter. In calibration, the administrative costs are small and they are set up so that the bank's steady-state portfolio choice is deterministic. $R^p_{k,t}$ and $R^g_{k,t}$ denote the bank's energy-based and ecological asset returns, respectively. t is the period in which the moment of total return is realized.

The asset accumulation equation for bank j, managed by banker j, is as follows:

$$N_{j,t+1}=R^p_{k,t+1}Q^p_t S^p_{j,t}+R^g_{k,t+1}Q^g_t S^g_{j,t}-R_t D_{j,t} \tag{6}$$

According to Gertler and Karadi, making banks endogenously financially risky and introducing a moral hazard problem for bankers to limit each bank's ability to obtain external funding [2]. Normalizing all assets held by a bank to 1, after raising deposits and purchasing assets at time t, a banker managing an independent bank can choose to supply part κ of the exogenous portion of the total assets for his use, with κ being the proportion of funds that can be misappropriated, or it can be a financial friction factor that means that the assets are diverted to the banker's household sector. The cost of this behavior is that if the misappropriation of assets becomes known to the various depositors, the bank immediately declares bankruptcy and begins liquidation, and each depositor closes the bank after recovering the remaining part $1-\kappa$ of the assets in proportion to the deposits made. Depositors need to be aware of the possibility of ethical problems with bankers. Depositors will consider saving with bank j only if they are informed that the misappropriation of assets by banker j is unprofitable and if they are assured of the integrity of banker j. $V_{j,t}$ denotes the value of the bank's going concern at the end of period t. The following incentive constraints must be satisfied if depositors are to be willing to deposit with banker j.

$$V_{j,t} \geq \kappa(Q_i^p S_{j,t}^p + Q_i^g S_{j,t}^g) \tag{7}$$

The above equation expresses that the present value of the bank's going concern value $V_{j,t}$ discounted future honest operating profit is greater than the gain from misappropriation of funds, which satisfies the condition that depositors are willing to deposit funds with bankers. The endogenous risk of the bank can be reflected in the fall in the price of assets will lead to a surplus on the liability side of the bank, which will lead to a reduction in the supply of loans to enterprises, bringing financial risk and triggering a downturn in the economy. However, the above equation always holds in equilibrium, so banks do not go into liquidation and bankers do not misappropriate funds.

To make it impossible for banks to operate exclusively with bankers' funds, assume that at the end of each period t, bankers exit the banking industry with exogenous probability $1-\gamma$, while the transformation of a worker into a banker has the same exogenous probability. Upon exit, the banker transfers retained earnings to his household in cash and becomes a worker. The continuing banker reinvests all of the assets he or she currently owns. The ultimate goal of the banker is to maximize the expected present value of his or her wealth. The banker chooses to maximize the summed asset holdings of securities $S_{j,t}^i$, $i = \{g, p\}$, and deposits $D_{j,t}$, in the production sector consisting of energy-based and ecological firms. Since bankers belong to households, the ultimate equity holders of the bank are the household sector, and the problem of maximizing the discounted terminal value is written in the form of Bellman's equation as follows for a discounting operation using the household stochastic discount factor:

$$V_{j,i} = E_t \left\{ \sum_{\tilde{\tau}=t+1}^{\infty} (1-\gamma)\gamma^{\tilde{\tau}-t-1} M_{t,\tilde{\tau}} N_{j,\tilde{\tau}} \right\} \tag{8}$$

The meaning expressed at the right end of the above equation is the sum of the multiplication of the probability of surviving previously and exiting the banking sector in the current period with the discounted value it receives in each period. Where the household stochastic discount factor $M_{t,\tilde{\tau}} = \beta^{\tilde{\tau}-t} \frac{U'_{c,\tilde{\tau}}}{U'_{c,t}}$, $s_t^g = \frac{Q_t^g S_{j,t}^g}{W_{j,t}}$ denotes the ecological asset share of the total portfolio. where the total assets held by the banker are $W_{j,t}$ and the share of ecological assets in the total portfolio is s_t^g in each period.

Referring to most of the literature, the bank value is assumed to be linear for the banker's assets, with the following expression:

$$V_{j,t} = \varphi_t N_{j,t} \tag{9}$$

Where $\varphi_t \geq 1$ is the coefficient of own assets on the value of the bank.

Combining (7) (9) the incentive constraint is expressed as:

$$Q_{j,t}^p S_{j,t}^p + Q_{j,t}^g S_{j,t}^g \leq \frac{\varphi_t}{\kappa} N_{j,t} \tag{10}$$

The above equation indicates that the social demand for bank loans $Q_{j,t}^{p}S_{j,t}^{p}+Q_{j,t}^{g}S_{j,t}^{g}$ receives the bank net worth N_t constraint, and the exogenous shocks will have an effect by affecting the bank's net worth.

The following equation determines the total capital requirements of polluting and non-polluting firms, where the proportion of green capital to total capital is:

$$s_t^g=\frac{E_t\left\{\Omega_{t+1}\left[\left(R_{k,t+1}^g-R_{k,t+1}^p\right)-\left(\tau_t^g-\tau_t^p\right)R_t\right]\right\}}{\psi E_t\left[\Omega_{t+1}R_t\right]}+\overline{s}^g \tag{11}$$

In the above equation $\Omega_{t+1}=M_{t,t+1}\left(1-\gamma+\gamma\varphi_{t+1}\right)$ is the bank's stochastic discount factor, and the right-hand side of the equal sign in the above equation represents the discounted excess return of ecological corporate capital over energy corporate capital. When τ_t^p rises and τ_t^g falls, the share of ecological capital in total capital will rise. Thus changes in government taxes can affect the market share of capital held by ecological and energy-based firms.

Suppose that the initial working capital of all new banks joining the banking industry is $\frac{\zeta}{1-\gamma}\sum_{i=\{g,b\}}Q_t^iS_t^i$. where the total assets of the banking sector are determined by the following equation:

$$N_{t+1}=\gamma\left[\sum_{i=\{g,b\}}R_{k,t+1}^iQ_t^iS_t^i-R_tD_t\right]+\zeta\sum_{i=\{g,b\}}Q_t^iS_t^i \tag{12}$$

The bank pays households a profit is as follows:

$$\Xi_{t+1}=\left(1-\gamma\right)\left[\sum_{i=\{g,b\}}R_{k,t+1}^iQ_t^iS_t^i-R_tD_t\right]+\zeta\sum_{i=\{g,b\}}Q_t^iS_t^i \tag{13}$$

Define total leverage in the banking sector as the ratio of total capital to bank net worth, i.e., $lev_t=\frac{Q_t^bS_t^b+Q_t^gS_t^g}{N_t}$. Similarly, the bank's loan premium is the difference in the yields of different types of assets over the risk-free asset, i.e., $spread_t^i=E_t\left(R_{k,t+1}^i-R_t\right)$

2.3. Final Product Enterprises

Two types of firms are assumed to produce final goods, the energy-based firms produce requiring emissions as by-products, while the eco-based firms have no by-products. Both production sectors depend on the banking sector for funds to purchase capital or means of production.

2.3.1. Production Technology

It is assumed that carbon emissions hurt the productivity of both ecological and energy-based firms. Both types of firms use a C-B production function and invest in capital K_{t-1}^i and labor L_t^i.

$$Y_t^i = \left[1 - d(X_t)\right] A_t (K_{t-1}^i)^{\alpha^i} (L_t^i)^{1-\alpha^i}, 0 < \alpha^i < 1 \tag{14}$$

where X_t is the stock of carbon emissions, $d(X_t)$ ∈ (0, 1) is the increasing loss function, α^i is the weight of the share of capital in the output, and A_t is the Total Factor Productivity (TFP) shock for the aggregate economy, which is consistent with:

$$\log A_t = \rho_A \log A_{t-1} + \sigma_A \varepsilon_{A,t}, \varepsilon_{A,t} \sim N(0,1) \tag{15}$$

There is an imperfect substitution between eco-commodities and energy commodities. The amount of product Y_t that eventually circulates to the market for consumption is a CES elasticity of aggregation of outputs in each sector.

$$Y_t = \left[(\pi^p)^{\frac{1}{\rho Y}} (Y_t^p)^{\frac{\rho Y - 1}{\rho Y}} + (1-\pi^p)^{\frac{1}{\rho Y}} (Y_t^g)^{\frac{\rho Y - 1}{\rho Y}} \right]^{\frac{\rho Y}{\rho Y - 1}} \tag{16}$$

where $\rho Y > 0$ is the elasticity of substitution parameter for the two intermediate goods, and π^p is the proportion of energy-based goods in the final goods. The demand functions for the two types of output are:

$$Y_t^p = \pi^p \frac{Y_t}{\left(p_t^p\right)^{\rho \gamma}}, Y_t^g = (1-\pi^p) \frac{Y_t}{\left(p_t^g\right)^{\rho \gamma}} \tag{17}$$

Where p_t^p and p_t^g denote the relative prices of energy-based and ecological commodities, respectively, and normalized to 1 for final consumer goods.

2.3.2. Energy-based Enterprises

The production of energy-based firms requires carbon emissions as a by-product. The stock of carbon emissions X_t is expressed as follows:

$$X_t = \delta_X X_{t-1} + e_t + e_t^{row} \tag{18}$$

where e_t denotes domestic emissions in the current period and e_t^{row} is emissions from the rest of the world. Domestic emissions depend on the amount of production in the energy-based sector Y_t^p and the proportion of emission reductions μ_t

$$e_t = (1 - \mu_t) h(Y_t^p) \tag{19}$$

The abatement cost Z_t is set up as $Z_t = f(\mu_t) Y_t^p$. Referring to the approach of Nordhaus and Heutel, the exponential function form of the carbon emission elasticity with respect to output, $h(Y_t^p) = (Y_t^p)^{\delta}$, and the abatement cost function, $f(\mu_t) = \theta_1 \mu_t^{\theta_2}$ [5, 6]. Since energy-based firms do not internalize the impact of the carbon emission stock X_t and the associated damages $d\left(Xt\right)$ in their production on total output, an externality from the environmental point of view arises.

It is assumed that at the end of period t, the final goods firms of the energy-based firms purchase capital K_t^p from the capital goods manufacturers at the market price Q_t^p. Referring to Gertler and Karadi, firms finance their capital purchases by issuing financial securities S_t^p to banks [2]. Each unit of the security has the same price Q_t^p as the corresponding unit of capital such that $Q_t^p K_t^p = Q_t^p S_t^p$. When production ends at moment t + 1, the firm can sell depreciated capital $(1-\delta^p)K_t^p$ in the market for Q_{t+1}^p. At the same time, firms offer a payoff $R_{k,t+1}^p$ on securities held by banks conditional on their profitability status.

The energy-based firm is constrained by the carbon tax rate τ_t^e imposed by the government. Then its profit function in period t is:

$$\Pi_t^p = p_t^p Y_t^b - \tau_t^e e_t - Z_t - w_t^p L_t^p - R_{k,t}^p Q_{t-1}^p K_{t-1}^p + \left(1-\delta^p\right) Q_t^p K_{t-1}^p \tag{20}$$

The payoff first-order conditions for labor L_t^p, emission reductions μ_t, and energy-based assets with respect to the profitability state condition are as follows:

$$w_t^p = (1-\alpha^p)\frac{Y_t^p}{L_t^p}\left[p_t^p - f(\mu_t) - \tau_t^c(1-\mu_t)h'(Y_t^p)\right] \tag{21}$$

$$\tau_t^e h\left(Y_t^p\right) = Y_t^p f'\left(\mu_t\right) \tag{22}$$

$$R_{k,t}^p = \frac{\alpha^p \dfrac{Y_t^p}{K_{t-1}^p}\left[p_t^p - f\left(\mu_t\right) - \tau_t^c\left(1-\mu_t\right)h'\left(Y_t^p\right)\right] + (1-\delta^p)Q_t^p}{Q_{t-1}^{p_{t-1}}} \tag{23}$$

2.3.3. Ecologically Based Enterprises

In contrast to the construction method for energy-based firms, the first-order conditions for ecological firms are as follows:

$$w_t^g = (1-\alpha^g)\frac{p_t^g Y_t^g}{L_t^g} \tag{24}$$

$$R_{k,t}^g = \frac{\dfrac{\alpha_g p_t^g Y_t^g}{K_{t-1}^g} + (1-\delta^g)Q_t^g}{Q_{t-1}^g} \tag{25}$$

2.4. Capital Goods Manufacturers

Refer to Christiano, Eichenbaum, and Evans, Capital Goods Manufacturers purchase depreciated capital from two firms [7]. This capital is used to produce investment goods for both firms, denoted

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as I_t^i , $i = \{gb\}$. Conditional on the convexity of capital adjustment costs, the capital-producing firm produces ecological and energy-based investment goods. The optimization objective of the manufacturer is to choose the optimal quantity of investment goods to be produced to achieve the profit maximization objective, $ $Q_t^i I_t^i$ $ denotes the return on the investment, $ $[1+\frac{\phi^i}{2}(\frac{I_t^i}{I_{t-1}^i}-1)^2]I_t^i$ denotes the cost of producing the investment well, and the parameter $\phi^i \geq 0$ controls the size of the adjustment cost. Q_t^i denotes the price of the investment good. The utility maximization problem for the capital goods manufacturer transforms into:

$$\max E_0 \sum_{t=0}^{\infty} M_{0,t} \sum_{i=(g,b)} \{Q_t^i I_t^i - [1+\frac{\phi^i}{2}(\frac{I_t^i}{I_{t-1}^i}-1)^2] I_t^i\} \tag{26}$$

Its first-order condition is as follows.

$$Q_t^i = 1+\frac{\phi^i}{2}(\frac{I_t^i}{I_{t-1}^i}-1)^2 + \phi^i(\frac{I_t^i}{I_{t-1}^i}-1)\frac{I_t^i}{I_{t-1}^i} - E_t\ [M_{t,t+1}\phi^i(\frac{I_{t+1}^i}{I_t^i}-1\ \frac{I_{t+1}^t}{I_t^i}^2], i=\{g,p\} \tag{27}$$

2.5. The Government Sector

Government revenues include a carbon tax from energy companies and a tax on capital profits from energy-based and eco-businesses. Government expenditures include transfers to households and general government expenditures.

$$T_t + G_t = \tau_t^e e_t + \tau_t^p Q_t^p S_t^p + \tau_t^g Q_t^g S_t^g \tag{28}$$

$$\log\left(\tau_t^e / \tau^e\right) = \rho^{\tau^e} \log\left(\tau_{t-1}^e / \tau^e\right) + \varepsilon_{\tau^e,t} \tag{29}$$

$$\log\left(\tau_t^p / \tau^p\right) = \rho^{\tau^p} \log\left(\tau_{t-1}^p / \tau^p\right) + \varepsilon_{\tau^p,t} \tag{30}$$

$$\log\left(\tau_t^g / \tau^g\right) = \rho^{\tau^g} \log\left(\tau_{t-1}^g / \tau^g\right) + \varepsilon_{\tau^g,t} \tag{31}$$

$\rho^{\tau^e}, \rho^{\tau^p}, \rho^{\tau^g}$, denote the pulse duration parameters, respectively.

$\varepsilon_{\tau^e,t}, \varepsilon_{\tau^p,t}, \varepsilon_{\tau^g,t}$, denote exogenous shocks, respectively.

3. Parameter Calibration

The frequency of the steady state values of the parameters and variables of this model is quarterly. The calibration parameters include three categories: static parameters, environmental parameters, and policy-related parameters. The actual economic conditions, mainstream literature calibration, reference to other DSGE model calibration, and actual economic conditions calibration are used respectively. Data sources: People's Bank of China, Choice Financial Terminal Macroeconomic Database, National Bureau of Statistics, CEIC China Economic Database, International Energy Agency, etc.

3.1. Static Parameters

The calibration of the household sector parameters is performed first. The household intertemporal discount factor β is set to 0.995, corresponding to a quarterly interest rate of 1%, and the elasticity of substitution parameter ρ_L is set to 1. The inverse of the elasticity of supply of Frisch's labor ξ is calibrated 1 concerning the Ziguan Zhuang. Assuming that the value of the household's labor in the steady-state is 1/3, which corresponds to an 8-hour day of work, the weight parameter ϖ of negative utility of labor is calibrated to 8.3849. The relative risk aversion coefficient η is set to 2 concerning Li Kang.

The parameters are calibrated for the banking sector. The probability of bank survival per quarter γ is 0.972 concerning Chen Xiong. the parameter of bank transfers to households ζ is set to 0.0001 and the parameter of elasticity of substitution for the two intermediate goods ρY ρY is calibrated to 2 concerning Papageorgiou, C., Saam, M., and Schulte [8].

Parameter calibration for the final goods manufacturer sector. The parameter of the index function of production and carbon emissions, i.e., the output elasticity ε, is calibrated to 1. The weights of capital's share of output, α^p, and α^g, are often set to 0.35 and 0.33, respectively, in an RBC model. energy-based firms are slightly more likely than ecological firms to have a slightly higher, carbon-emission decay technique δ_X is calibrated to 0.9965. The energy-based and ecological investment adjustment cost parameters ϕ^p, ϕ^g are consistent with most E-DSGEs, and calibrated to 10 concerning Heutel [6]. Matching the value of the divertible funds ratio κ and the transfer parameter ζ to the banking sector's steady state leverage ratio of 4.5, calibrated concerning Gertler and Karadi κ= 0.3409 [2]. assets, the adjustment cost parameter ψ for banks is very small and calibrated to 0.0001. π^p is the proportion of energy-based goods in final goods, and to make the ratio of ecological capital stock to total stock $\overline{s_g}$ in steady state 0.60, it is calibrated to $\pi^p = 0.3326$.

3.2. Environmental Parameters

The loss function parameters d_0、d_1、d_2 refer to Gibson and Heutel while dividing by the corresponding power of the carbon emission stock, converted to dimensionless and set to -0.0076, 8.10*10^(-6),1.05*10^(-8) [9]. The abatement cost coefficient θ_1 is calibrated to $0.0015\frac{\overline{Y_{ss}}}{Y_{ss}^b}$ =0.00335 after adjusting for the ratio of energy-based sectoral output to total output in steady state [9]. According to Nordhaus, the exponential part of the abatement cost function θ_2 is calibrated to 2.6 [5]. The capital depreciation rate $\delta_p \delta_g$ for energy-based and eco-firms is calibrated to 0.025 concerning Qi Liang and Yi Hao. The calibration is based on the policy instrument being close to 0, so the steady state value of all tax rates τ is calibrated to 0.0001.The other national carbon emissions e^{row} are calibrated to 3.1499.

3.3. Dynamic Parameters

The pulse duration parameters ρ_A、ρ^{τ^e}、ρ^{τ^p}、ρ^{τ^g} are all taken to be 0.8.

The exogenous shock perturbation terms $\varepsilon_{A,t}, \varepsilon_{\tau^e,t}, \varepsilon_{\tau^p,t}, \varepsilon_{\tau^g,t}$ are all taken to be 0.0007.

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4. Analysis of Impact Effects

The economic significance of all the variables in the following charts is mentioned in the previous section, with the horizontal coordinates representing the unit period and the vertical coordinates representing the values of the variables.

4.1. One Unit of Positive Technological Shock

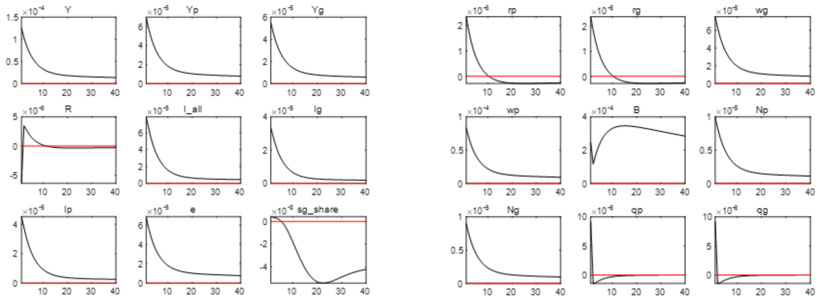

Figure 1: Macroeconomic impact of positive technology shocks

Under a one-unit positive technology shock, as shown in Figure 1, both eco-firms and energy firms increase their demand for labor supply, which leads to a rise in wages, labor use, capital compensation, and capital use in both eco-firms and energy firms. At the same time, asset prices rise, which leads to a rise in bank lending and a rise in the share of capital in total capital for eco-firms. In the end, both total output and energy or eco-firms grow, and since emissions are positively related to output, output growth also leads to growth in carbon emissions.

4.2. One-Unit Tax Shock on Interest Rates on Loans to Energy-Based Firms

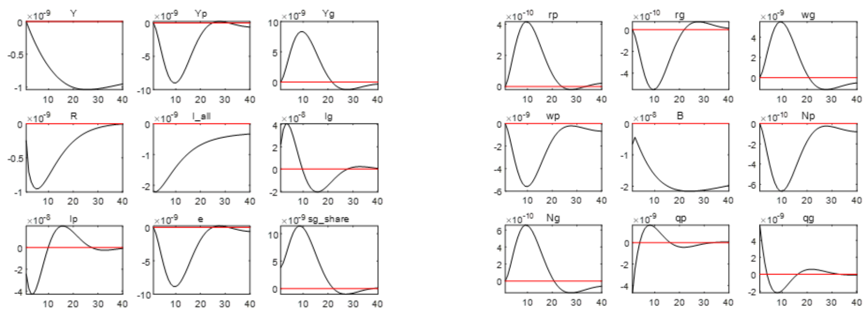

Figure 2: Macroeconomic impact of a tax shock on lending rates for energy-based firms (Original).

Figure 2 shows that total output rises when the government taxes the lending rate of energy-based firms, but because the government taxes the lending rate of energy-based firms, energy-based firms face higher lending costs, and energy-based firms' demand for both capital and labor declines, which results in a downward trend in the wages of the polluting firms but a rise in the compensation of capital. On the contrary, since the ecological firms have an interest rate advantage over the energy firms, the ecological firms can increase their demand for both labor and capital, and the share of capital in the total capital of the ecological firms increases. On the other hand, as the share of energy-based firms declines, the overall level of carbon emissions in the economy decreases, suggesting that the policy is effective in reducing carbon emissions.

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4.3. One Unit of Carbon Tax Shock

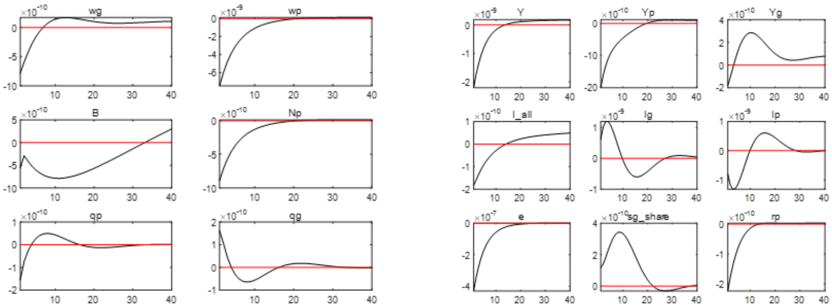

Figure 3: Macroeconomic impact of carbon tax shocks (Original).

As shown in Figure 3, under the one-unit carbon tax shock, which indicates that the government has increased the tax on carbon emissions, the demand for labor and capital of energy-based firms tends to decline under this policy, and thus wages and capital compensation decline to varying degrees, which leads to a decline in the output of energy-based firms. On the other hand, as the carbon tax has a stronger restrictive effect on energy-based enterprises, the proportion of eco-enterprise capital in the total social capital rises, which leads to a rise in the output of eco-enterprises around the third period, and as a result of the rise in the capital of eco-enterprises, the overall level of social emissions can be reduced, and the environment improves under this policy.

4.4. One-Unit Government Expenditure Shock

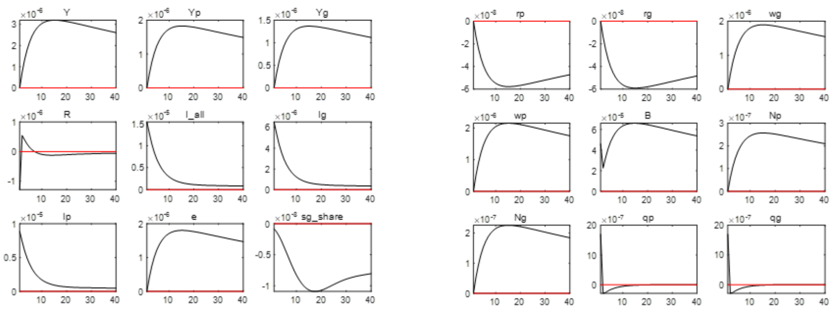

Figure 4:Macroeconomic impact of government spending shocks (Original).

Figure 4 illustrates that under a government spending shock, an increase in government spending causes the level of demand to rise across society, which leads to a rise in the demand for capital and labor by both ecological and energy-based firms, in which case the compensation of capital falls and labor grows, which leads to a rise in total output as well as in the level of output for both types of firms. However, an increase in the level of government spending will, in one respect, lead to a decrease in the ratio of ecological firms' capital to total capital; in short, an increase in the level of government spending is more likely to lead to the redevelopment of energy-based firms.

5. Conclusion

This study confirms that economic growth and environmental protection are not irreconcilable opposites. Appropriate policy tools, such as carbon tax, industry-specific fiscal policy adjustments, and an active role of the government in environmental protection, can effectively promote the transformation of the economy to a sustainable development model. At the same time, the positive effects of technological progress are not only reflected in economic growth but also in its potential to reduce environmental pollution and enhance resource use efficiency. Therefore, policymakers should emphasize the synergistic effect between scientific and technological innovation and environmental protection, and encourage the research, development, and application of clean technologies through the formulation of reasonable policies.

Future research could delve into the following areas:

Integration of technological innovation and environmental policies: further study the economic effects of different types of technological innovations under the framework of environmental policies, and innovate and refine the expression of different types of technological innovations and policy formulas, as well as how these technologies affect the restructuring and transformation of society as a whole and of the local economy.

Policy Refinement: Further modeling of macroeconomic policies to encompass most of the mainstream policies to study the changes in macroeconomic indicators and environmental quality under different policies.

Multi-dimensional assessment of social welfare: In addition to economic growth and environmental protection, future research should also focus on the impact of policies on various aspects of social welfare, including health, education, employment, etc., which can create a more refined household utility function and thus provide a more comprehensive policy assessment framework.

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Comparative Analysis of SVR and LSTM in Stock Price Forecasting Across Market Cycles

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Abstract: This study investigates the predictive capabilities of Support Vector Regression and Long Short-Term Memory networks on stock price trends across different market conditions—bear, bumpy, and bull markets. With the ongoing evolution of machine learning technologies, their application in financial forecasting has shown substantial potential for capturing complex patterns in vast datasets, which traditional models often fail to process efficiently. This study particularly focuses on the performance of these models in forecasting stock prices from the S&P 500 index, evaluated through the lens of Modern Portfolio Theory (MPT). The models are assessed based on their ability to forecast trends and their implications when applied to constructing investment portfolios, evaluating key financial metrics such as expected returns, standard deviation, Sharpe ratio, and maximum drawdown. The findings indicate that while both SVR and LSTM exhibit competence in trend prediction, especially in bull markets, their predictions diverge from actual market performance when applied to portfolio construction under MPT. This discrepancy underscores the need for further refinement in modeling approaches to enhance accuracy and reliability in real-world investment scenarios. This research contributes to the empirical literature by demonstrating the practical implications of deploying advanced machine learning and deep learning models in dynamic market environments and suggests directions for future enhancements.

Keywords: Stock price prediction, SVR, LSTM, MPT

1. Introduction

The prediction of stock market trends has been a prominent subject in the field of finance due to the strong interconnection between the stock market and the economy. This has significant consequences for individual investors, financial institutions, and policymakers involved in economic matters [1]. Accurate stock price forecasts can help investors make informed investment decisions, support financial institutions' asset management, and help policymakers understand and predict market trends. Extracting valuable information from the market and making accurate stock price forecasts is extremely challenging due to the market's complexity, the uncertainty of the external economic environment, and the volatility of investor behaviour [2].

Over the years, scholars have developed many forecasting models trying to reveal the underlying patterns of price movements from historical data. Due to the progress in machine learning and deep learning techniques, especially their extensive application in time series forecasting, the focus of

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research has gradually moved from traditional statistical models to these advanced forecasting methods [3].

In 1952, with the introduction of Markowitz's mean-variance theory, which provided the theoretical basis for a series of subsequent studies on quantitative investing [4], it followed that a series of predicted stock prices were applied to his theory in pursuit of ideal investment returns.

Extensive research has shown that machine learning has been successfully applied in financial forecasting. For example, Cortes and Vapnik made significant contributions to the theory of Support Vector Regression (SVR) in 1995, and subsequent studies have confirmed its effectiveness in predicting stock prices [5]. SVR utilises the principle of structural risk minimization and the kernel trick to enable the model to effectively perform nonlinear regression in high-dimensional spaces. This capability is especially valuable when dealing with non-stationary and highly noisy financial data. This is especially beneficial in financial data that is not stable and contains a high level of noise.

On the other hand, LSTM was proposed by Hochreiter and Schmidhuber and has rapidly become one of the mainstream techniques for processing sequence data in 1997, especially in forecasting complex financial time series. LSTM models, due to their unique gating mechanism, are able to efficiently capture long term dependencies in time series, which is often difficult to realize.

Existing literature also points out that although SVR and LSTM have improved in prediction accuracy compared to traditional models, there are still challenges. For example, the choice of hyperparameters for the models, the risk of overfitting, and their applicability in a variable market environment are all topical issues in current research. Moreover, the performance of these models is significantly affected by market efficiency and external economic factors, which are difficult to be fully accounted for in the models.

The aim of this study is to assess the predictive abilities of SVR and LSTM models in forecasting stock prices across various market cycles. Additionally, it seeks to evaluate the accuracy of these predictions using modern portfolio theory. The study aims to provide new empirical evidence in this field and test the practicality of modern investment theories in real-world market predictions. This study aims to determine the model that can accurately capture market trends in conditions of high market volatility and limited data. It will compare actual market data with forecast data and categorize the market's cycle into bear market, bumpy market, and bull market phases. By doing so, it will validate and assess which model can serve as a reliable reference for future stock price forecasting in various market environments.

2. Methodology

2.1. Segmentation of data sets and market cycles

Forecasting equity index prices is of utmost importance as it forms the foundation for making strategic decisions in the financial sector [6]. It improves risk management and helps in effectively diversifying investment portfolios. Precise predictions of indices offer crucial understanding of market patterns and economic prospects, which are vital for investors aiming to optimize their asset allocations. Investors can strategically mitigate their risk exposure, safeguard against potential downturns, and align their investment strategies with prevailing economic conditions by anticipating potential market movements. Moreover, regulators and financial institutions employ these predictions to oversee and uphold market stability, guaranteeing adherence to regulations and taking proactive steps to mitigate market fluctuations. Therefore, the capacity to forecast equity index prices not only aids in making individual investment choices but also strengthens the overall resilience and efficiency of the financial ecosystem. The dataset used in this study is historical price data for the S&P 500 index for the period January 1, 2021 to January 1, 2024 in Figure 1. The data is provided by Yahoo Finance and obtained

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through the yfinance interface program library. Daily closing prices are the main basis of the analysis and are used to identify market cycles and as base data for model training.

The identification of market cycles is achieved by visually analyzing the historical closing price trends of the S&P 500 index. This study employs a time-series decomposition methodology to classify price trends during the specified time period into three distinct market conditions: bear markets, bumpy markets, and bull markets, as shown in table 1. This categorization allows us to perform specialized analysis and model forecasts for different market conditions.

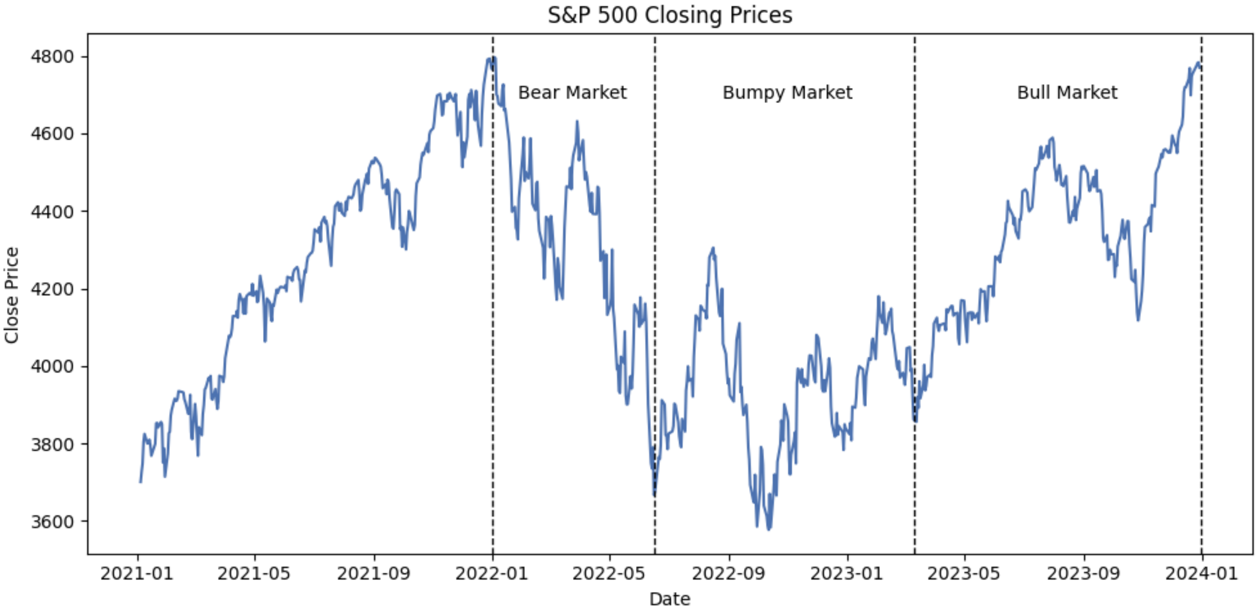

Figure 1: S&P 500 Closing Price Chart.

Table 1: Bear Market, Bumpy Market, Bull Market Divided in Time

Period	Time	Exponential change
Bear Market	2022.1.1-2022.6.16	-20.99%
Bumpy Market	2022.6.16-2023.3.11	5.31%
Bull Market	2023.3.11-2024.1.1	23.71%

Diversification is critical when selecting stocks in the S&P500 for forecasting and portfolio purposes. Diversification can help to diversify the unsystematic risk posed by a particular stock or sector [7]. A total of 25 stocks from various sectors including Energy, Materials, Industrials, Consumer Discretionary, Consumer Necessities, Healthcare, Financials, Information Technology, Communication Services, Utilities, Real Estate, and others were chosen for this study. The companies listed are Exxon Mobil (XOM), Chevron (CVX), Linde (LIN), Ecolab (ECL), Honeywell (HON), Boeing (BA), Amazon (AMZN), Tesla (TSLA), Procter & Gamble (PG), Coca-Cola (KO), Johnson & Johnson (JNJ), Pfizer (PFE), Merck (MRK), JPMorgan Chase (JPM), Bank of America (BAC), Goldman Sachs (GS), Apple (AAPL), Microsoft (MSFT), Nvidia (NVDA), AT&T (T), Verizon (VZ), NextEra Energy (NEE), Duke Energy (DUK), American Tower (AMT), and Prologis (PLD).

2.2. SVR

SVR is a regression technique that is derived from the principles of Support Vector Machines (SVMs), aiming to find an optimal regression function in a given dataset. SVR is well suited for analyzing data in high-dimensional spaces and has good robustness to points outside the data.

The fundamental concept behind Support Vector Regression (SVR) is to identify a function within the dataset that can accurately forecast the true target value, while adhering to a predetermined tolerance ε. This is achieved by minimising the complexity of the model to improve its ability to generalise. The core of this approach lies in the construction of a maximally spaced plane that is capable of handling not only linear problems but also nonlinear problems by introducing kernel tricks.

For a linear SVR, the model can be expressed as:

$$f(x) = w^T x + b \tag{1}$$

where w is the weight vector, x is the feature vector, and b is the deviation term.

The goal of the model is to minimize the following objective function:

$$min \frac{1}{2} \parallel w \parallel^2 + C \sum_{i=1}^{n} \xi_i \tag{2}$$

d the following conditions are met:

$$\begin{aligned} & y_i - w^T x_i - b \leq \epsilon + \xi_i \\ & w^T x_i + b - y_i \leq \epsilon + \xi_i \\ & \xi_i \geq 0 \end{aligned} \tag{3}$$

Here ξ_i is the slack variable to handle the case where the data points do not fall exactly within the ε tolerance band. The parameter C serves as a regularisation parameter, allowing for the adjustment of the balance between the error term and the complexity of the model.

2.3. LSTM

LSTM is a specialised variant of Recurrent Neural Network (RNN) that is specifically engineered to tackle the challenges faced by conventional RNNs when handling long-term dependencies. LSTM can efficiently capture dependencies over long time intervals in sequential data through its unique internal structure, which makes it very useful in financial time series analysis, language processing, and other applications that need to take temporal information into account.

The LSTM is primarily characterised by its cellular architecture, which consists of individual cells that incorporate three primary gating mechanisms: forgetting gates, input gates, and output gates.

Forget Gate - Determines which data to eliminate from the cellular state.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f \tag{4}$$

Input Gate - Determines which additional data to incorporate into the cell state.

$$\begin{aligned} i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\ \tilde{C}_t &= \tanh\,(W_C \cdot [h_{t-1}, x_t] + b_C) \end{aligned} \tag{5}$$

Module status updates - Updates the cell state by combining the old state and new information.

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$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{6}$$

Output Gate - Calculates the subsequent concealed state, which encompasses data derived from the revised cell state.

$$\begin{aligned} o_t &= \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \\ h_t &= o_t * \tanh\,(C_t) \end{aligned} \tag{7}$$

The output gate controls what information will be output as the activation value h_t for this cell, or the output of this step.

2.4. Ledoit-Wolf Shrinkage Estimation

Ledoit-Wolf shrinkage estimation is an improved covariance matrix estimation method proposed by Olivier Ledoit and Michael Wolf. This approach is particularly suitable for scenarios in which the sample size is relatively limited in comparison to the number of variables. It is commonly used in the examination of financial market data, specifically in predicting stock prices, especially when the time period of the data is short or there are only a few data points available [8]. The fundamental concept is to merge the empirical covariance matrix (a sample covariance matrix) with a more reliable target covariance matrix in a linear manner. The objective is to minimise the estimation error and enhance the accuracy of estimating the covariance matrix.

The formula can be expressed as:

$$\hat{\Sigma} = \rho \cdot F + (1 - \rho) \cdot S \tag{8}$$

The contracted covariance matrix, $\hat{\Sigma}$, is determined by optimising the intensity of contraction, ρ, which is a constant between 0 and 1. The optimisation aims to minimise the mean-square error between the estimated covariance matrix, S, and the target covariance matrix, F, in order to accurately estimate the true covariance matrix.

3. Empirical Analysis

3.1. Data Preprocessing

Prior to constructing the prediction model, data preprocessing was conducted. This study utilises the yfinance library to acquire the historical trading data of the chosen stocks within a defined timeframe. The data includes the opening price (Open), the highest price (High), the lowest price (Low), the trading volume (Volume), and the adjusted closing price (Adj Close) [9]. In order to optimise the efficiency of model training and testing, the dataset is divided into two segments. The training set, which accounts for 80% of the dataset, is utilised to facilitate the learning process of the model. The remaining 20% of the dataset is allocated as the test set, which is employed to assess the model's predictive capabilities. The target variable for analysis and prediction in this study is the adjusted closing price, which is a crucial indicator that represents the change in the market capitalization of a stock.

Normalizing the feature data is a critical step before making predictions. During this stage, the data features are adjusted to a standardised range, typically with an average of 0 and a standard deviation of 1. The purpose of the normalisation process is to mitigate the influence of variations in feature magnitudes, expedite the convergence rate of the algorithm, and augment the model's capacity to generalise to novel data [10]. The training set features were adjusted and converted using the

StandardScaler class. The same adjustment process was also applied to the test set to maintain data consistency.

3.2. Performance Indicator

The mean squared error (MSE) is a commonly employed measure in machine learning and statistical modelling for assessing the predictive accuracy of models [11]. It has undergone thorough validation and has been conclusively demonstrated to be highly effective. The Mean Squared Error (MSE) is a metric that quantifies the average of the squared differences between the predicted values of a model and the actual observed values. Specifically, for a given data point, MSE is calculated as follows:

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

n represents the total number of data points. y_i refers to the ith true observation, while $\hat{y}_i$ represents the ith predicted value.

In this study, MSE is used as an evaluation metric to measure the accuracy of SVR model and LSTM model on stock price prediction.

3.3. SVR

3.3.1. Model Building

When constructing SVR model, the choice of parameters has a decisive impact on the model performance. To systematically explore the parameter space and find the optimal parameter combinations, this study adopts a grid search (GridSearchCV) combined with five-fold cross-validation.

Grid search is a method of optimizing model parameters by traversing a given parameter grid. In this analysis, the parameter grid is set to contain multiple preset values of the regularization parameter C at different levels, the kernel function coefficient gamma, and the error term epsilon. The parameter C determines the model's sensitivity to errors; higher values of C can result in overfitting, while lower values can lead to underfitting. The parameter gamma determines the distribution of the data after the radial basis function (RBF) kernel transformation, which directly affects the model's capture of the data features. epsilon controls the width of the intervals in the SVR, which affects the model's fitting accuracy to the training data.

Cross-validation is a statistical technique employed to assess and enhance a model's capacity to generalise to independent data sets. Five-fold cross-validation involves partitioning the original data into subsets of equal size. During this procedure, four of these subsets are utilised as training data for each iteration, while the remaining subset is used to assess and validate the model's performance. This process is iterated 5 times, with a distinct validation set chosen for each iteration to ensure that each subset is given a single opportunity to be utilised as validation data. The result of cross-validation is usually the average of the five scores, which helps to minimize model performance bias on a particular sample set.

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3.3.2. Diversity Analysis of the Ledoit-Wolf Covariance Matrix

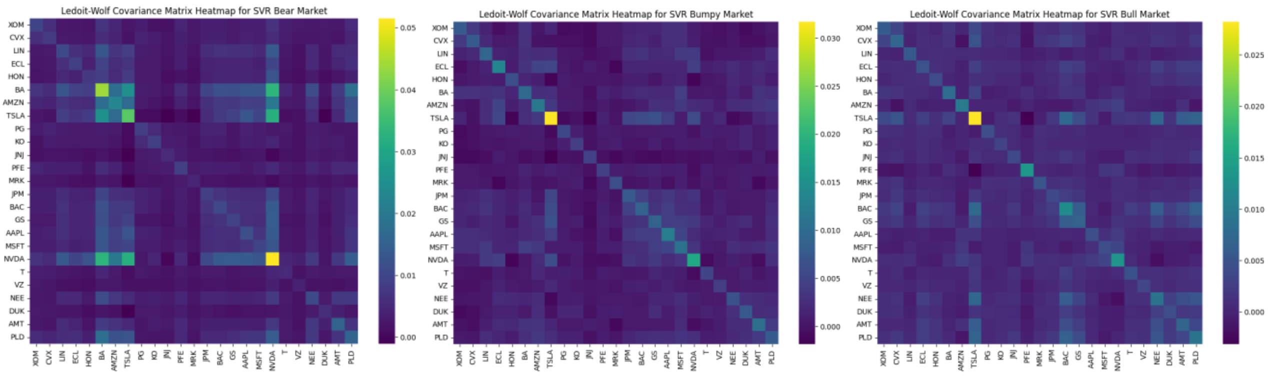

Figure 2: Heat map of Ledoit-Wolf covariance matrix for three periods of SVR.

In exploring the relationship between stock price movements in three different market cycles: bear market, bumpy market and bull market, the heat map visualization analysis (Figure 2) reveals the low covariance values properties. The generally low covariance values observed for most stock pairs in the covariance matrix are suggestive of a low degree of correlation between different stocks. This is consistently reflected even across market cycles. The stocks selected were from different sectors of the S&P 500 Index, and the prevalence of low covariance values is consistent with the desired effect of portfolio diversification. This cross-industry selection reduces the impact of a single market factor on the portfolio as a whole and helps to diversify the risk of specific industry or market events. And no significant increase in the covariance value is observed in the covariance matrix for all three market cycles, implying that the price volatility of the selected stocks remains independent even under drastic changes in market conditions. This phenomenon suggests that the distribution of assets within the portfolio is able to provide stable risk exposure under different market conditions.

3.3.3. Overview of projected effects

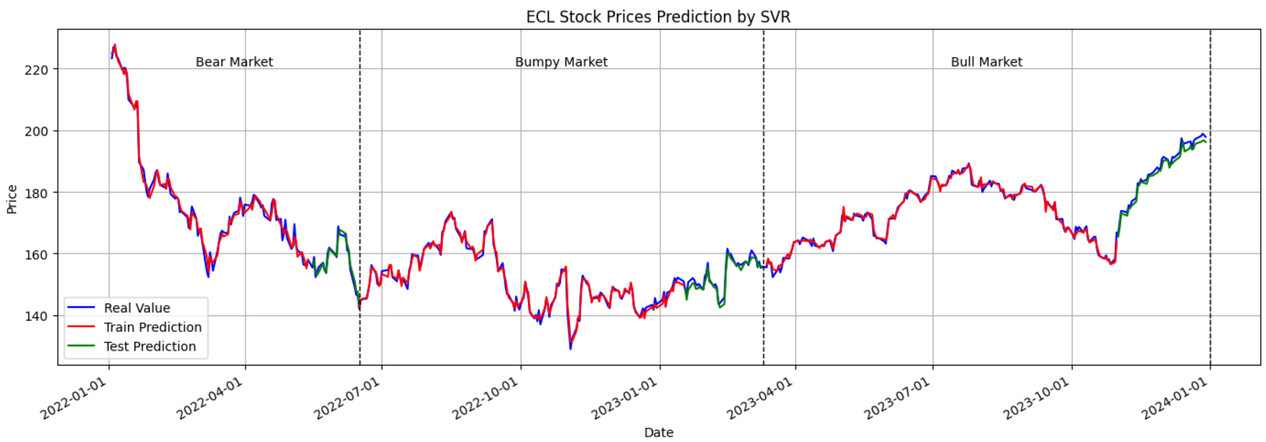

Figure 3: SVR's Stock Price Forecast Chart for Ecolab, Inc.

This study utilises the SVR model to predict stock prices during various market cycles and generates corresponding forecast charts. These charts show the model's predicted performance for each stock during three phases: bear market, oscillator market and bull market. The Figure 3 displays the prediction results of SVR for Ecolab over three time periods, including both the training and test sets.

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By synthesizing the forecast charts, the SVR model is able to accurately capture and follow the trend of actual stock prices in most cases. During both bear and bull markets, the model is able to demonstrate responsiveness to changes in market trends despite high market volatility. Irrespective of the data used for training or testing, the SVR model exhibits a high level of accuracy in predicting outcomes and maintains consistent performance across various time periods.

3.4. LSTM

3.4.1. Model Building

To train the LSTM model, a dataset containing a specific time window is first constructed. The time window is defined as a span of five consecutive days. This implies that the model will utilise data from the present day and the preceding four days to forecast the stock price for the subsequent day. The method is implemented through the function create_dataset, which accepts the original feature set with labels, and then outputs a new feature set, where each element contains five days of historical data, and the corresponding price of the next day as a label.

The chosen LSTM model contains two layers with 30 cells each and uses the ReLU activation function. In addition, two fully connected layers and a Dropout layer to prevent overfitting were included. The model is trained for 50 training cycles (epochs) and uses small batch gradient descent with a batch size of 32. The validation process involves reserving a fraction (10%) of the training data to monitor and prevent overfitting. During the training process, the training loss decreases as the number of iterations increases, indicating that the model is gaining knowledge about the characteristics and inherent relationships within the dataset.

3.4.2. Diversity Analysis of the Ledoit-Wolf Covariance Matrix

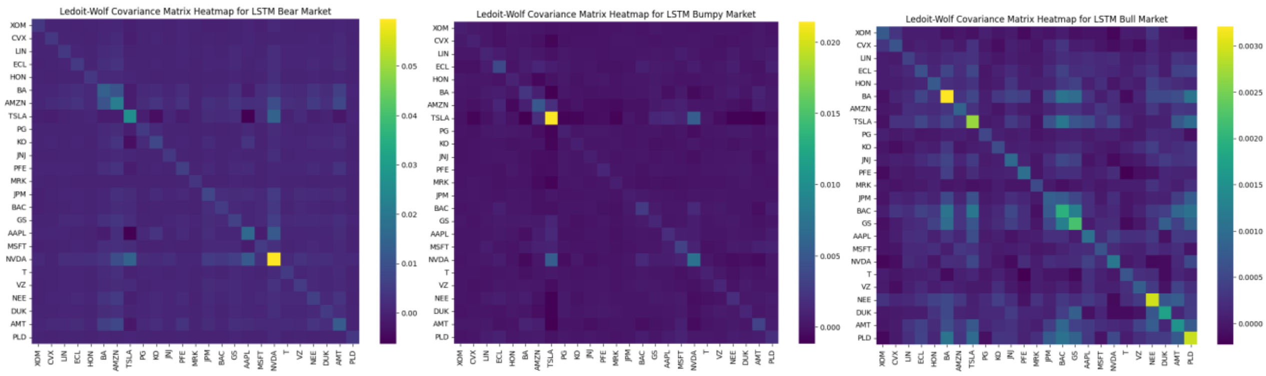

Figure 4: Heat map of Ledoit-Wolf covariance matrix for three periods of LSTM.

Similar to the SVR model, the LSTM model yields generally low covariance values throughout the analysis period (Figure 4), reflecting the low correlation of assets across sectors. This result supports the validity of the stock selection strategy, which is to reduce portfolio risk through diversification. The heat map of the covariance matrix over the periods shows relatively consistent low correlations among stocks, indicating that the selected stock portfolios maintain a robust diversification effect regardless of changes in market conditions. In addition, the covariance distribution pattern in the heat map further validates the stability of the predictive ability of the LSTM model across market environments.

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3.4.3. Overview of projected effects

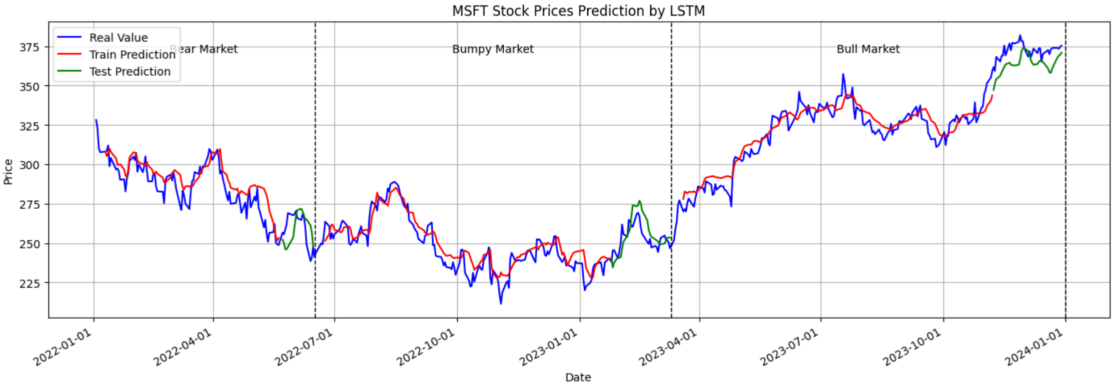

Figure 5: SVR's Stock Price Forecast Chart for Microsoft, Inc.

This study utilises the LSTM model to predict stock prices across various market cycles. This section aims to evaluate the overall predictive effectiveness of the LSTM model by comparing its generated predictions with the actual market prices. The Figure 5 depicts the graphs that demonstrate the forecast outcomes of LSTM for Microsoft across three distinct time intervals, encompassing both the training and test datasets. The LSTM model demonstrates a notable level of competence in monitoring and tracking stock price patterns. The model accurately captured the volatility patterns of stock prices and faithfully reflected the upward and downward trends of the market across different time periods. However, there is a gap in the numerical prediction accuracy compared to the SVR model. This may indicate that the LSTM model needs to be improved in handling absolute values of prices, especially during cycles of more intense market volatility. On the test set, the predictions of the LSTM deviate at some specific points, especially at market turning points or high volatility regions. This may be related to the model's limitations in learning about long-term dependencies.

4. Analysis of Result

When comparing and analyzing the prediction results of SVR and LSTM under different market cycles, we can comprehensively evaluate them in terms of four dimensions: expected return, standard deviation (risk), Sharpe ratio, and maximum drawdown [12].

Table 2: The performance of each model in different periods.

	S&P 500	Real Value	SVR	LSTM
Expected Return	-8.66%, -2.21%, 18.19%	-3.24%, -7.57%, 10.76%	8.74%, 7.51%, 20.77%	13.47%, 5.29%, 18.59%
Standard Deviation	11.03%, 7.64%, 5.11%	5.28%, 4.54%, 3.24%	9.95%, 7.50%, 3.39%	7.19%, 6.53%, 1.72%
Sharpe Ratio	-1.15, -0.81, 2.77	-1.37, -2.55, 2.08	0.48, 0.46, 4.94	1.32, 0.19, 8.48
Maximum Drawdown	-10.57%, -7.61%, -1.47%	-6.36%, -6.35%, -1.14%	-12.56%, -17.39%, -0.41%	-2.87%, -2.17%, -0.01%

In the Table 2, the "Real Value" represent the results fitted with Markowitz's Modern Investment Theory using the real values of the period of the test set, and the three numbers in each table represent the corresponding results for each of the three time periods.

The projected anticipated yields of both SVR and LSTM surpass the actual performance of the S&P 500 in bear and volatile market cycles, indicating that the models may exhibit excessive optimism regarding favourable shifts in market trends. In particular, during the bear market, the actual market showed negative growth, while the forecasts showed positive growth. The standard deviations of the SVR and LSTM forecasts, on the other hand, remain relatively consistent with the S&P 500 and the standard deviations of the true value fits over the three economic cycles. Compared to the actual market, SVR and LSTM show higher Sharpe ratios in all cycles, with LSTM in particular showing unusually high Sharpe ratios during the bull market. This indicates a significant difference in the risk-adjusted returns of the models compared to the actual market, possibly because the models did not accurately evaluate risk.

In terms of maximum drawdown, both SVR and LSTM show lower values than the actual market. SVR's maximum drawdown is particularly significant during bear markets, while LSTM maintains lower maximum drawdown values throughout all cycles, which may indicate that LSTM performs better in controlling market downside risk. Overall, SVR and LSTM perform best in predicting economic cycles in bull markets, with SVR being the best predictor of bull markets. In this study, SVR is relatively accurate in predicting the price trend of each stock in the market, which affirms to some extent the feasibility of SVR in stock price prediction.

However, both SVR and LSTM models fail to numerically match the actual market performance accurately, which is not uncommon when forecasting financial time series, as market prices are not only influenced by historical price data, but also by macroeconomics, market sentiment and external events. Both models tend to be optimistic in assessing positive market movements, while showing conservatism in risk estimation, resulting in high Sharpe ratio calculations. This suggests that the models need to be further adjusted and optimized to improve their ability to capture market volatility and reflect the risk-return relationship more accurately.

5. Conclusion

This study provides valuable insights into the accuracy of SVR and LSTM models in predicting stock price trends during bear markets, bumpy markets, and bull markets. Advanced machine learning and deep learning models can accurately detect and monitor market price trends in all types of market conditions. They exhibit the capacity to forecast future price trends by analysing past data.

However, while trend forecasts for a single stock are important from an investor's perspective, the actual investment decision usually involves constructing a diversified portfolio of stocks. In this regard, by evaluating these forecasting models using modern investment theory, there is a discrepancy between key investment metrics fitted based on the model's forecasting results (e.g., expected return, standard deviation, Sharpe ratio, and maximum drawdown) and metrics fitted based on actual market data. This disparity highlights the limitations of predictive models in modeling real market conditions and actual investor experience.

Therefore, although SVR and LSTM models have shown some effectiveness in predicting market trends, their model accuracy and parameters still need further refinement and adjustment when being used for actual portfolio management and optimization. Future research endeavours should prioritise model optimisation in order to enhance the precision of their predictions and ensure that the predictions more accurately capture the intricate dynamics of markets.

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Research on the Innovative Practices of Tourism Platform in Web3.0

- Taking Ctrip Trekki NFT Project as an Example

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Abstract: Against the background of the rapid evolution of the current Web3.0 technology paradigm, blockchain technology is gradually penetrating into the core of the tourism industry, heralding a disruptive industry transformation. This paper focuses on the Trekki NFT project launched by Ctrip as a reference to explore in depth the innovative application of Web3.0 technology in tourism service platforms and the deep-rooted value it implies. This paper firstly elaborates the core concept and key technical architecture of Web3.0, as well as the theoretical connotation and practical boundaries of non-homogenized tokens (NFT). Through a panoramic analysis of the Trekki NFT project, the paper reveals how Web 3.0 technology can stimulate the restructuring of business models of travel platforms, optimize the quality of user experience, and explore new opportunities for industry growth. In particular, the study demonstrates the strategic significance of Web 3.0 technologies in promoting the innovative development and industrial upgrading of the tourism industry. The discussion section of the study has refined a set of strategic frameworks and action recommendations for the deep integration of tourism platforms and Web 3.0 technologies, aiming at guiding and accelerating the technology adoption and progress of the tourism industry in the wave of the digital economy in the future.

Keywords: web 3.0, blockchain, NFT, Ctrip, digital transformation

1. Introduction

In the context of the current rapid changes in information technology, Web 3.0, a new era of Internet evolution, is gradually attracting widespread attention and penetrating into all levels of society.Web 3.0 is regarded as an important milestone in the development of the Internet, and it is expected to revolutionize many areas such as finance, governance, data security and privacy protection, and digital identity management [1], which is due to its deep integration of blockchain and other cutting-edge technologies to build a decentralized network ecosystem based on a token mechanism and advanced security capabilities. This change is due to its deep integration of blockchain, artificial

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intelligence and other cutting-edge technologies, and the construction of a decentralized network ecosystem based on the token mechanism with advanced security capabilities.

The rise of Web 3.0 has not only optimized the online experience for individual users, such as improving personalized browsing services, enhancing intelligent search functions and extending the performance of application programming interfaces. It has also spawned a range of key applications such as non-homogenized tokens (NFT), decentralized finance (Defi), cryptocurrencies and distributed applications (DApp) [2]. In view of this, this study will use the Trekki NFT project launched by Ctrip as a typical example to delve into the specific practices and innovative impacts of Web 3.0 technologies in the travel industry.

This study is dedicated to analyzing the profound transformation of the Trekki NFT project on the business model, user experience and industry development of tourism platforms, so as to enrich and deepen the industry's understanding of the digital transformation of the tourism industry. In terms of research methodology, literature review, case analysis, comparative study and other means will be comprehensively utilized. Combined with practical operational experience and detailed data support, the study will comprehensively examine the extensive and far-reaching impact of Web 3.0 technology on tourism platforms.

The core objective of the study is to identify the core features of Web 3.0 technologies and their potential application scenarios in the tourism sector, and to critically assess the innovative value and practical effectiveness of the Trekki NFT project. In addition, it will systematically investigate how Web 3.0 technologies can reshape the business model of travel platforms, improve user experience, and drive structural progress in the industry. Finally, based on the empirical analysis, the study will propose a series of forward-looking and feasible strategies to promote the effective integration and synergistic development of tourism platforms and Web 3.0 technologies.

2. Trekki NFT's Program Overview

Against the backdrop of the Web 3.0 technological revolution, Trip.com, the world's leading online travel service platform, has birthed a pioneering project in its overseas branches - the Trekki NFT program.The project follows the rise of blockchain technology and non-homogeneous tokens (NFT), and captures the vast potential that the Web 3.0 era has given to various industries. Trip.com seizes this technological trend in a timely manner and utilizes advanced NFT and blockchain technology to lead the travel industry to achieve in-depth innovation and provide personalized travel experiences like never before.

The Trekki NFT project has crafted an NFT collection of 10,000 hand-drawn travel-themed dolphin figures, each with a unique personality setting, a diverse background of travel scenarios, and varying rare attributes. The project design cleverly incorporates fun gaming elements, allowing holders to dynamically upgrade and develop their NFT holdings through exclusive platform commands, badge unlocking, or membership level advancement. In addition, Trekki NFT holders can enjoy a range of exclusive travel benefits ranging from discounted airfare and hotel bookings to attraction tickets. To ensure the fairness and transparency of the incentives, the program has integrated the industry-recognized Chainlink VRF technology, which ensures that the random number-based incentive distribution process is tamper-proof and auditable.

Trekki's NFT operating strategy is unique in that it creatively blends traditional memberships with the emerging world of digital assets. On the one hand, Trekki has successfully concluded a bridge between digital assets and physical travel experiences by introducing the concept of NFT, enabling users to manifest their personal travel history, achievement markers, and unique identities in the process of collecting and trading NFTs, and thus realizing the accumulation and appreciation of value in the market circulation. On the other hand, this operation model strongly promotes the digital transformation process of the tourism industry, fully utilizing the decentralized nature of blockchain technology, information transparency and security advantages, to build a more fair and transparent trading ecosystem with a higher degree of trust. This not only facilitates tourism platforms to digitize all kinds of tourism resources and services, and efficiently realize the digital transaction of tourism resources by issuing tourism-related tokens or NFTs, thus improving the utilization rate of resources, but also brings a refreshing tourism consumption experience to end users. Furthermore, the Trekki NFT operating model opens up new business opportunities in the travel industry. Through the issuance and transaction of NFT, the platform can attract and activate more user groups, and enhance user stickiness and activity; at the same time, the application of NFT also gives rise to a number of industry innovations, such as the development of customized tourism experience products and thematic activities relying on NFT, which further broadens the growth path of the industry, shapes the competitive advantage, and helps the tourism industry to achieve sustained progress and prosperous development in the Web 3.0 era. and prosperity of the tourism industry in the era of Web 3.0.

3. Theoretical Framework of the Trekki NFT Project

3.1. A framework for the Application of Blockchain Technology in the Tourism Industry

In the tourism industry, the use of blockchain technology can improve transparency, security and efficiency. The Ctrip Trekki NFT project can be seen as an example of this framework by using blockchain technology to ensure the verifiability and uniqueness of the travel experience while providing consumers with a new, digital asset related to the travel experience [3]. This innovative practice not only enhances consumer trust in travel platforms, but also pushes the tourism industry in the direction of being more environmentally friendly and efficient.

3.2. The Role and Impact of NFT in the Tourism Marketplace

NFTs (non-homogenized tokens), an emerging digital asset class, are changing the way the travel market works [4]. The Ctrip Trekki NFT program offers consumers a new way to collect and invest by creating unique, travel experience-related NFTs. These NFTs not only represent a digital proof of the travel experience, but also have the ability to act as a new type of commodity in the travel market, influencing consumers' purchasing decisions and the value proposition of travel brands.

3.3. Digital Transformation of Tourism Platforms

With the arrival of Web 3.0, travel platforms are facing the opportunities and challenges of digital transformation [5], and it is in this context that the Ctrip Trekki NFT project has realized the digitization and automation of travel services through the integration of blockchain technology, thus enhancing user experience and operational efficiency. This innovative practice not only helps travel platforms stay ahead of the curve in a competitive market, but also provides a viable path for the digital transformation of the entire tourism industry.

3.4. Consumer Behavior and Marketing Strategy

Consumer behavior is a key factor influencing tourism marketing strategies, and Ctrip's Trekki NFT program drives innovation in marketing strategies by meeting consumer demand for uniqueness and authenticity [6]. By offering NFTs related to the travel experience, Ctrip not only attracts technologically avant-garde consumers, but also enhances brand image through the scarcity and uniqueness of NFTs, which influences consumers' purchasing decisions.

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3.5. Technological Innovation and Sustainable Tourism Development

Technological innovation is an important driver of sustainable development in the tourism industry [7]. By adopting blockchain technology, the Ctrip Trekki NFT project not only improves the transparency and security of tourism services, but also promotes the sustainability of tourism products. In this way, Ctrip not only demonstrates its commitment to environmental protection, but also provides an innovative example of sustainability in the travel industry.

4. Trekki NFT Program Implementation Process and Impact Evaluation

The execution process of the Trekki NFT project encompassed a number of key aspects, including planning and design, technology development, system testing and marketing. In the early stages of the project planning, the team set clear strategic goals and ambitious visions, and carefully planned the morphological features and functional architecture of NFT. In the technology development phase, the team utilized Ethernet smart contract technology to build the underlying structure, effectively ensuring the security and transparency of the NFT issuance and transaction process. In the system testing phase, through rigorous internal validation and extensive user trials, the project team comprehensively examined the reliability of the system and the friendliness of the user interface, with a view to optimizing the overall user experience.

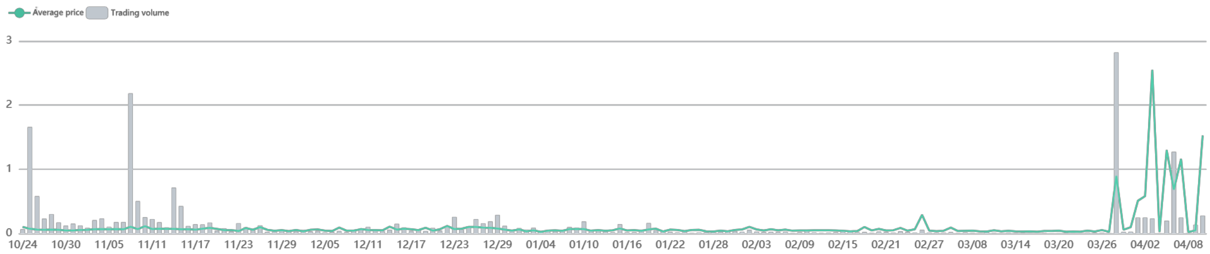

Figure 1: Trekki project NFT volume trend chart [8].

Based on the analysis of the economic performance data shown in Figure 1, Trekki NFT raised a total of 685.8432 ETH (approximately $2.124 million at the prevailing exchange rate) during the post-launch minting phase and exceeded its intended distribution target, achieving a subscription rate of over 110%.

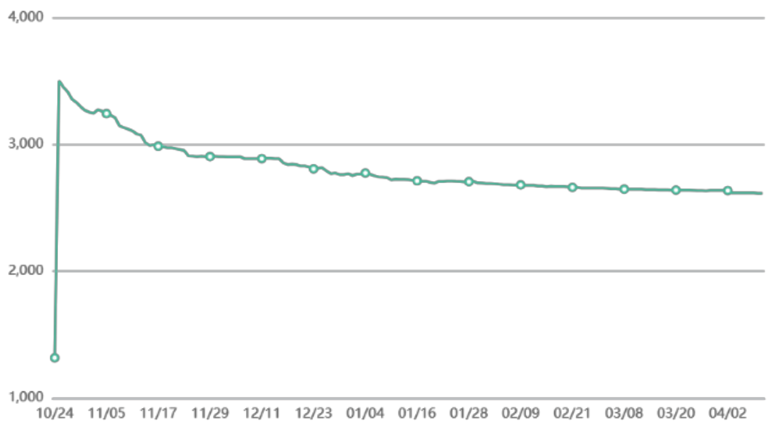

Figure 2: Trends in the number of Trekki program holders [8].

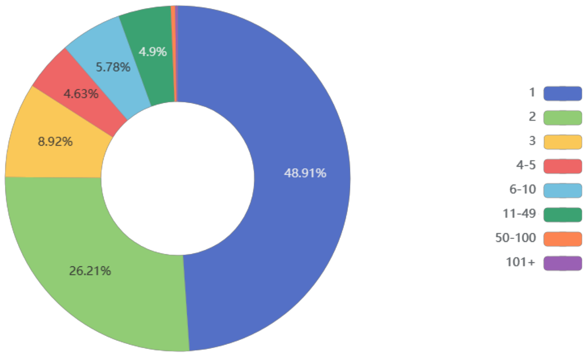

Figure 3: Map of Trekki project holders [8].

Referring to the user growth dynamics revealed in Figure 2, the highest number of holders of Trekki NFT climbed to 3,503 at one point after its debut. In the subsequent time period, although the number of holders experienced a rapid decline to around 2,700 or so between October and December 2023 due to market liquidity transactions, the total number of holders has stabilized since then and has remained above the 2,600 level.

Figure 3 shows that the proportion of users holding a single NFT is 48.91%, while more than half of the holders hold at least two or more NFTs, with those holding three or more NFTs accounting for about 25% of the total. It is worth noting that the minimum market price of Trekki NFT is set at 0.0199 ETH, while the proportion of pending orders is only 1.9%, which is a low rate of pending orders, indirectly confirming the market's high degree of acceptance and strong interest in this NFT product.

In terms of social impact, the Trekki NFT project, with its innovative NFT application scenarios, has driven the digital transformation of the travel industry and created a new form of travel experience for users. In addition to visual economic benefits, such as increased sales and profits, the Trekki NFT program has had a positive impact on soft indicators, such as brand value, user engagement and market influence. Specifically, as of today, Trekki NFT has attracted 42,820 members in the Discord community, with a daily active user ratio of 5%, while on the X social platform, it has accumulated 107.4K followers. These figures strongly prove that the Trekki NFT project has achieved substantial results in enhancing brand image power, expanding market share and strengthening user stickiness, and provides a valuable case of practical experience for digital transformation in the tourism sector.

5. Innovative Points of the Trekki NFT Program

In the Ctrip Trekki NFT program, its innovative practices are reflected in several dimensions. Firstly, at the artistic design level, the program follows the principle of "digital scarcity" to create each unique piece of artistic NFT work, which substantially grants holders real ownership rights and intrinsic scarcity economic value. Secondly, Trekki innovatively introduces the "eco-mining" mechanism, which subtly reduces the impact of carbon emissions and gives back to users through sustainable incentives, successfully optimizing both environmental protection and economic benefits.

From the perspective of technology integration, Trekki effectively integrates AR technology with NFT, providing users with an unprecedented immersive and interactive experience, which makes NFT go beyond the attribute of a mere digital asset and become a link between the real world and virtual space. In addition, the project adopts a "decentralized autonomous organization" (DAO) management model, which ensures the long-term sustainable operation and development of the project through a collective decision-making mechanism.

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It is worth noting that Trekki NFT has demonstrated excellent innovative practices in cross-chain interoperability. By adopting the "cross-chain bridge" technology, the project breaks through and realizes the seamless migration and circulation of NFTs between different blockchain networks, which greatly improves asset liquidity. Cross-chain bridge is a middleware that connects different blockchains, allowing assets to be efficiently transferred and exchanged across different chains. Based on this, Trekki NFT can be freely traded and used in diverse blockchain environments, effectively solving the problem of data isolation and greatly improving the level of interoperability of assets. Cross-chain interoperability allows users to freely choose and easily operate across different blockchain platforms for NFT transactions. This not only empowers users with increased flexibility, but also significantly boosts the project's scalability and compatibility with other systems. As a result, it attracts broader participation from diverse user groups and developers, collectively driving the expansion and development of the project's ecosystem.

6. Discussion and Reflection

In the context of the Web 3.0 era, travel platforms must adhere to the dual-wheel-drive strategy of technology adoption and regulatory compliance in the process of exploring and adopting emerging technologies [9]. This not only requires tourism enterprises to fully consider and comply with existing laws and regulations while promoting Web 3.0 technological innovations to ensure that all technological practices are carried out within a legally compliant framework, but also emphasizes the responsibility of the platform in enhancing the engagement, satisfaction, and trust of members of the virtual community [10]. In order to achieve this goal, travel platforms should take the initiative to establish a dialogue and cooperation mechanism with regulators, actively participate in the policy discussion and formulation process, and provide policy guidelines and legal advice for the healthy development of the travel industry, as well as ensure that challenges brought about by the convergence of technologies, such as data security and privacy protection, are adequately considered and appropriately dealt with in the strategic planning. By providing high-quality content and interactive experiences, tourism platforms can build and maintain users' trust, while developing effective risk mitigation measures to address challenges such as compliance with laws and regulations that may arise from the convergence of technologies, to ensure that the tourism business can be developed in a safe, compliant and sustainable manner in the Web3.0 era. Meanwhile, in the face of the complexity and sensitivity of blockchain technology, tourism platforms need to increase their investment in the research and development of blockchain security technology to ensure that the security and privacy of users are effectively safeguarded when they conduct transactions in the Web3.0 environment. This includes, but is not limited to, the construction of a solid security protection system and the establishment of a sound data protection mechanism, so as to continuously enhance users' trust and reliance on the platform.

In view of the fact that NFT and Web3.0 technologies are still in the initial stage of recognition among the majority of user groups, tourism platforms have the important responsibility of market enlightenment and user guidance. Platforms should systematically popularize the knowledge of Web 3.0 and NFT through diversified communication channels, and guide users to rationally perceive and appropriately use these cutting-edge technologies, so as to lay a solid user base for the wide application of the new technologies [11]. In addition, tourism platforms need to be enterprising in content innovation and service diversification, closely integrating the unique attributes of NFT, and actively exploring and developing innovative tourism products and experience modes. For example, NFT can be used to create unique tourism souvenirs, or through cross-border linkages with other fields such as culture and art, to enrich the connotation of tourism products and enhance their cultural added value [12].

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Finally, when tourism enterprises formulate development strategies, they must have a long-term vision, not only focusing on the specific applications of Web 3.0 technology and market hot topics, but also having a forward-looking insight and layout of the future development of the digital economy and trends. This is the only way to ensure that travel platforms can move forward steadily in the rapidly changing technological and market environments and continue to adapt to and lead the technological advances and market changes in the travel industry [13].

7. Conclusion

This paper discusses the significant impact of Web 3.0 technology on the innovation practice of tourism platforms through the in-depth analysis of Ctrip Trekki NFT project.Web 3.0 technology, especially blockchain technology and NFT application, has catalyzed innovative business models, improved the quality of user experience, and vigorously pushed forward the diversified development of the industry in the tourism industry.The Trekki NFT project, as a typical case, vividly demonstrates how digital assets can subvert the traditional tourism product and service model, improve user interaction and brand loyalty, and simultaneously enhance the brand influence and market competitive position of tourism platforms. A typical case, it vividly shows how digital assets can subvert the traditional tourism products and service model, improve user interaction and brand loyalty, and synchronize the brand influence and competitive position of tourism platform. However, it is worth noting that while the Trekki NFT program has demonstrated significant results in leading industry change and enhancing user engagement, there are still some limitations to the current study. This paper fails to conduct a comprehensive and in-depth investigation of the consumer adoption behavior of NFT tourism products and the motivation behind it, and further empirical research is urgently needed to accurately capture the characteristics of user behavior and formulate corresponding strategies accordingly, in order to achieve a seamless connection between technological progress and market demand.

Based on this study, we suggest to researchers and practitioners in the tourism sector that while embracing the vast opportunities presented by Web 3.0 technologies, it is important to consider the potential social issues and ensure that the development and application of the technology is fair and environmentally responsible. The advent of the Web 3.0 era has opened up a whole new chapter of discovery in the tourism industry, and the Trekki NFT project is just the beginning. The Trekki NFT project is just the beginning. Researchers and industry practitioners should remain humble, recognize the shortcomings of existing research, and continue to pay attention to and leverage the results of emerging technologies in order to promote more robust and sustainable innovation and development in the tourism industry.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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Whether Silver Serves as a 'Safe-Haven' for Crude Oil

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Abstract: In times of economic turbulence and geopolitical uncertainty, the fluctuations in crude oil prices can be particularly pronounced, posing significant challenges to investors by heightening market risks. This study sets out to explore the multifaceted landscape of risk associated with both crude oil and silver assets, with a specific focus on portfolio volatility. Through meticulous analysis guided by the Sharpe ratio, we aim to delineate an in-depth understanding of the efficient frontier, comparing portfolio performance against that of the S&P 500 index, especially during periods characterized by extreme market volatility. Our empirical investigations underscore that while silver displays certain tendencies towards risk aversion, it does not meet the criteria to be deemed a dependable "safe-haven" asset in the context of crude oil. These findings have significant implications, providing a catalyst for driving innovation and fortitude across interconnected domains. By enhancing our comprehension of portfolio dynamics in turbulent market environments, this research contributes to the advancement of strategies aimed at navigating risks effectively.

Keywords: Sharpe ratios, efficient frontier, crude oil, silver, save-haven.

1. Introduction

Crude oil is a significant energy commodity that is closely linked to other financial markets worldwide [1]. However, due to increased global uncertainty shocks and geopolitical risks, oil prices have experienced rapid declines and sharp rallies from time to time. Extreme market risks in the context of the crude oil market can be transmitted to other markets, triggering systemic risks. Identifying risks in the context of the crude oil market, is of great practical significance for investors and management organizations worldwide [2]. Precious metals, such as gold, are widely recognized as traditional hedge assets due to their ability to resist extreme market risks [3] as one of the most important precious metals, gold has been the subject of in-depth research by scholars.

Scholarly inquiry currently focuses on examining the relationship between crude oil and gold. One aspect under scrutiny is their interdependence. For example, the extraction of gold often requires the use of crude oil, leading to a noticeable positive correlation in their prices [4]. Additionally, gold plays a crucial role as a shock absorber in the crude oil market, providing a stabilizing effect during periods of volatility [5]. Gold's intrinsic properties make it a valuable tool for forecasting the repercussions of oil-related events [6].

The concept of 'safe-haven' attributes inherent in gold was first delineated by Baur and McDermott [7], and subsequent scholarship has delved into this phenomenon with vigor. The term 'safe-haven' refers to gold's capacity to retain or even appreciate. Empirical studies consistently

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demonstrate that during times of economic uncertainty or market turmoil, gold serves as a reliable refuge for crude oil investors. [8]. This underscores gold's importance as a risk mitigation tool in the volatile energy market.

Despite the extensive research on gold's ‘safe-haven’ properties, there is a noticeable gap in the literature regarding the exploration of similar attributes in other precious metal commodities. Therefore, this paper aims to address this gap by examining the potential of silver as a ‘safe-haven’ within the context of the crude oil market, leveraging insights from existing scholarship. To accomplish this goal, the study concentrates on a particular period of high market risk, specifically from January to March 2020, which coincided with the outbreak of the global epidemic and a significant decline in crude oil prices. The chosen timeframe offers an excellent opportunity to examine the response of silver to unfavorable market conditions. Methodologically, the study employs a rigorous approach, selecting ten companies whose primary business involves both crude oil and silver. Subsequently, the text conducts a meticulous analysis of the returns and volatilities of the asset portfolios, culminating in the calculation of their Sharpe ratios [9]. The pivotal comparison lies in juxtaposing these Sharpe ratios with those derived from the S&P 500 index during the same tumultuous period. A higher Sharpe ratio for the asset portfolio would indicate the potential for silver to function as a ‘safe-haven’ amidst the volatility of the crude oil market. This empirical analysis aims to determine the viability of silver as a risk-mitigating asset during periods of economic uncertainty and market turbulence.

2. Research Method

The investigation employs an asset portfolio optimization model to ascertain the optimal asset allocation ratio between silver and crude oil, intending to determine whether silver can serve as a ‘safe-haven’ for crude oil. To address this question, we will apply the efficient frontier construction methodology. The construction of the efficient frontier necessitates the determination of the expected returns, volatilities, and correlations of silver and crude oil. Subsequently, by adjusting the relative weights of the assets, multiple portfolios of silver and crude oil can be generated, and The anticipated returns and associated risks for each portfolio can be quantified. Ultimately, by plotting the effective boundaries of these portfolios, the relationship between silver and crude oil and their optimal allocation in the portfolio can be visualized. The benefit of utilizing this model is that it helps investors better understand the correlation and risk characteristics between silver and crude oil. Efficient boundaries are essential for investors to develop effective investment strategies that balance risk and return and maximize their investment objectives. Furthermore, the study of silver and crude oil as safe-haven assets is crucial for investors' risk management and asset allocation in the financial markets.

3. Application and Results

3.1. Data Collection and Selection

To assess whether silver can serve as a ‘safe-haven’ for crude oil, the survey selected a period when the crude oil market was at extreme risk. The study is analyzing data from January 1, 2020, to March 31, 2020, totaling three months. This time frame was selected to account for several significant events that occurred during this period. Firstly, it includes the outbreak of the epidemic in early 2020, namely the COVID-19 pandemic, which had a profound impact on global health systems, economies, and societies worldwide. Secondly, it encompasses the global economic downturn triggered by the pandemic, characterized by widespread business closures, supply chain disruptions, and heightened economic uncertainty. In addition, this period saw a significant decline in crude oil prices, influenced by a combination of reduced demand due to lockdown measures and geopolitical factors. By analyzing data from this specific time frame, the study aims to examine the interplay between these interconnected factors and their implications on various aspects of the economy and society. For the survey, we selected ten companies that mainly trade crude oil and silver: XOM, CVX, BP, TTE, COP, E, OXY, CNQ, NEM, and GOLD. Additionally, we included AG, PAAS, WPM, HL, SSRM, CDE, FSM, SVM, MUX, and EXK. We obtained the daily closing prices of these 20 companies from the yfinance database. We also screened the closing prices of the S&P 500 for the same period as a reference, following the same process.

3.2. Data Analysis

The survey employed the Sharpe ratio as a gauge of portfolio quality. The Sharpe ratio is a standardized risk-adjusted measure of portfolio returns, thereby allowing for comparisons across different portfolios. It is sensitive to risk due to its combination of returns with standard deviation. To calculate the Sharpe ratio, the daily closing prices of the 20 companies were used to determine their returns. The maximum Sharpe ratio of the 20 companies was then obtained through Monte Carlo simulation using Equation (1). The Sharpe ratio of the S&P 500 was also calculated for the same period. If the Sharpe ratios of the 20 companies are higher than that of the S&P 500 for the same period, it indicates that the asset portfolio obtained from the survey has been successful.

$$SharpeRatio = \frac{wTR\text{-}Rf}{\sqrt{\omega^T \sum \omega}} \tag{1}$$

In this equation, 'w' represents an n-dimensional weight vector that contains the weights of each asset, 'r' represents an n-dimensional vector of expected returns that contains the expected returns of each asset, 'rf' represents the risk-free rate, and 'Σ' represents the covariance matrix.

The survey analyzed the three-month stock movements of crude oil, silver, and the S&P 500, as shown in Figure 1,2. The results indicate that crude oil and the S&P 500 declined more sharply than silver, suggesting that silver may have a safe-haven value in extremely risky market environments. This finding is worth exploring further.

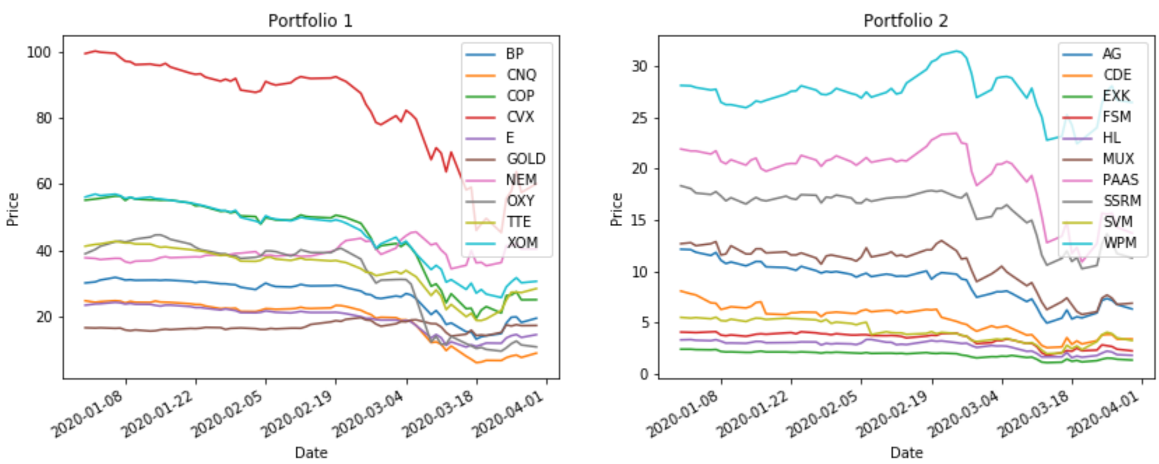

Figure 1: Crude Oil & Silver Company Stock Price Comparison

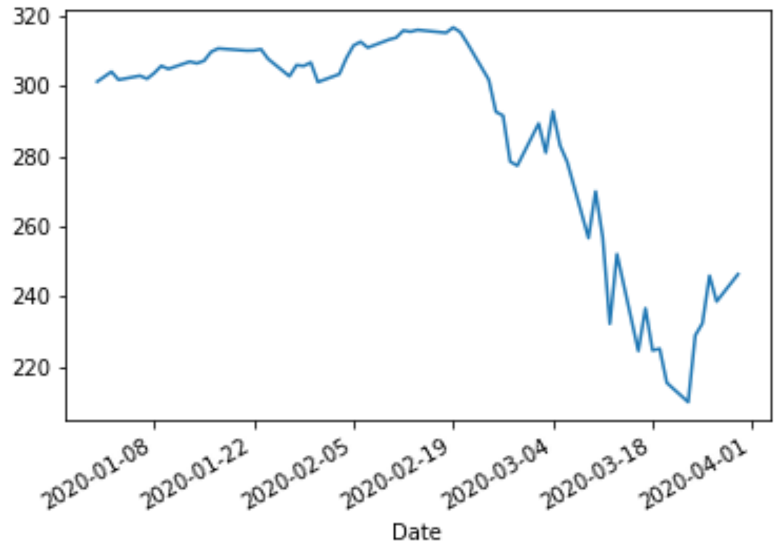

Figure 2: S&P 500 Stock Price

The investigation uses a special kind of simulation called Monte Carlo to figure out what to expect from each asset portfolio. Monte Carlo simulation entails the generation of multiple potential portfolios through the stochastic construction of different weights for the assets. For each generated portfolio, its expected return, volatility, and correlation are calculated, and the Sharpe ratio is computed. The portfolio with the optimal Sharpe ratio is then selected, which is the portfolio that provides the highest expected return for a given level of risk or the lowest risk for a given expected return. This step is designed to determine the best capital allocation strategy to optimize the portfolio. The efficient frontier is plotted, as shown in Figure 3, with the points of maximum Sharpe ratio and minimum volatility marked.

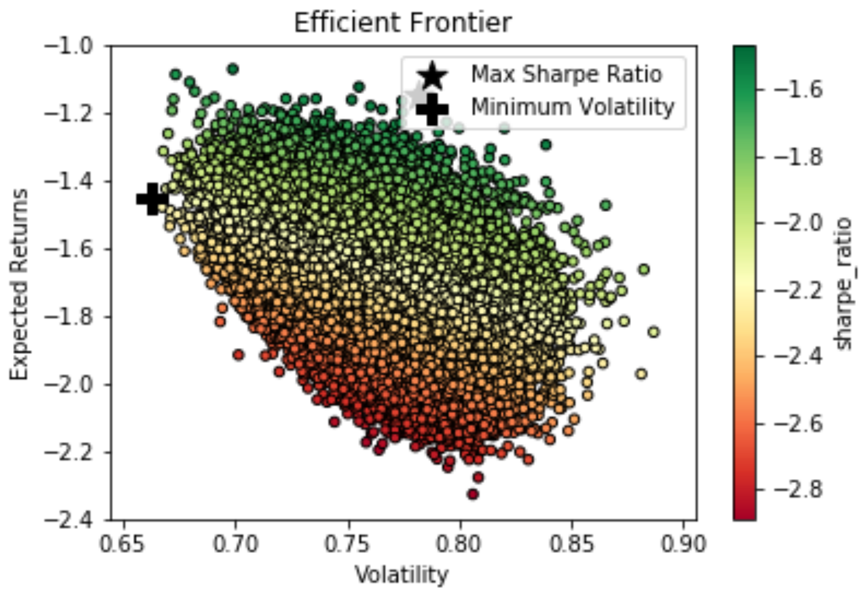

Figure 3: Effective frontier of the assets

The weights of each asset corresponding to the maximum Sharpe ratio are obtained and presented in Table 1.

Table 1: Weighting of assets

Assets	Weights
XOM	11.37%
CVX	6.87%
BP	1.86%
TTE	0.01%
COP	1.64%
E	0.47%
OXY	4.27%
CNQ	6.59%
NEM	7.31%
GOLD	6.56%
AG	0.82%
PAAS	0.39%
WPM	11.07%
HL	0.01%
SSRM	9.40%
CDE	2.90%
FSM	11.02%
SVM	6.98%
MUX	9.12%
EXK	1.35%

The study's empirical results provide valuable insights into silver's role as a ‘safe-haven’ asset in extreme market risk scenarios. The calculated Sharpe ratio of -1.4643 for the asset portfolio and -1.2033 for the S&P 500 indicates that the S&P 500 index outperforms the examined asset portfolio. The analysis shows that silver is a less effective risk-mitigating asset compared to the S&P 500.

Figure 4 visually represents the asset return curves for both the three-month asset portfolio and the S&P 500, confirming the quantitative findings. Figure 4 visually represents the asset return curves for both the three-month asset portfolio and the S&P 500, confirming the quantitative findings. The S&P 500 outperforms the asset portfolio.

Despite initial conjectures about silver's potential as a ‘safe-haven’, empirical evidence presents a nuanced perspective. While silver exhibits a gradual decline in its stock price during periods of extreme market risk, this behavior falls short of meeting the criteria expected of a dependable safe-haven asset. Therefore, it appears that silver may not have the strong risk-mitigating characteristics required to be a dependable ‘safe-haven’ in the volatile crude oil market.

These results emphasize the need for thorough analysis and careful consideration when assessing the safe-haven qualities of commodities other than gold. Moreover, this prompts further exploration into the underlying factors that influence silver's performance in adverse market conditions. This contributes to a deeper understanding of silver's role within investment portfolios and risk management strategies.

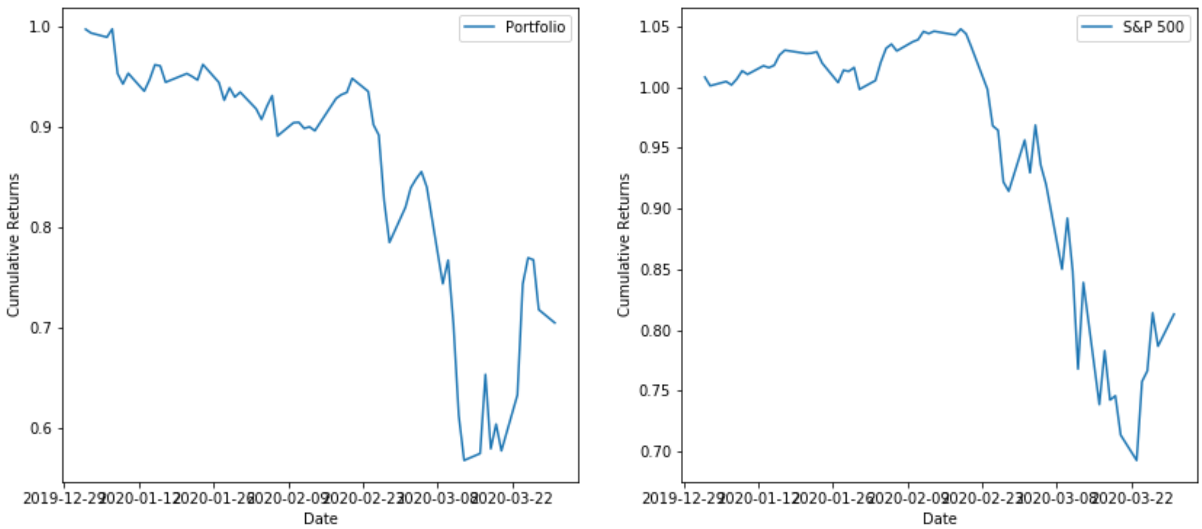

Figure 4: Cumulative rates of Comparative Portfolios and S&P 500

The survey concluded that the Sharpe ratio of the crude oil and silver portfolio was lower than that of the S&P 500 and could not achieve a hedging effect for several reasons. Firstly, the portfolio only considered two commodities, whereas the S&P 500 covers the stocks of companies in different industries, which could indeed have a higher Sharpe ratio. Secondly, as commodities, the price fluctuations of crude oil and silver demonstrate a strong correlation with the market. Studies have shown a strong correlation between the crude oil market and the precious metals market[10], limiting the effectiveness of diversification. Additionally, the correlation structure between assets in financial markets is often complex, and traditional methods may not capture features such as nonlinearities and tail correlations.

Based on the above reasons, the survey can be improved in the following ways: Diversification of research objects is proposed to mitigate risks. Incorporating additional commodities renowned for their hedging properties alongside silver can fortify the portfolio against market volatility. By broadening the scope to include such assets, the survey can offer a more comprehensive evaluation of safe-haven options within the crude oil market.

Additionally, the survey should recommend the use of advanced modeling techniques to explore the dynamic correlations present in asset portfolios. Utilizing emerging models such as DCC-GARCH [11] and SV allows for a more comprehensive understanding of the interactions between different assets, surpassing the constraints of static correlation analyses. These advanced methodologies enable the exploration of complex market dynamics, providing insights into how correlations evolve over time and under different market conditions.

4. Conclusion

This paper examines whether silver can be considered a 'safe-haven' for crude oil during the period of January to March 2020, when the outbreak of the epidemic first began and the price of crude oil fell.The empirical results indicate that silver cannot be considered a 'safe-haven' for crude oil. Although silver is less volatile than gold, a portfolio comprising silver and crude oil assets exhibits a smaller Sharpe ratio and return than the S&P 500. Therefore, it is recommended that investors choose the S&P 500 as a 'safe-haven' portfolio. Although the experiment had unsatisfactory outcomes, it is important to acknowledge that silver still possesses risk aversion properties. When used in conjunction with crude oil under specific market conditions, silver has the potential to serve as a hedge against risk. The results of the experiment suggest that silver may not be as effective as the

S&P 500 as a ‘safe-haven’ asset. However, it is important to consider the nuanced role that silver may play in risk mitigation strategies. These findings prompt a reevaluation of silver's utility within diversified portfolios, particularly during periods of heightened market risk.The research in this paper provides insight into the risk aversion properties of precious metals and their implications for asset portfolio construction. In today's unstable global environment, where geopolitics has become a major issue and the price of crude oil fluctuates drastically, it is urgent to find better ways to hedge market risk. This paper also compares the investment strategy with gold and explores their combined potential, guiding investors.

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Stock Prices Forecasting and Optimization Strategies Based on Support Vector Machines

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Abstract: With the global trend of digitization gaining prominence, the usage of machine learning methods such as Support Vector Machines and Reinforcement Learning for stock price prediction is becoming a hot topic. Over the past 40 years, China's economic market has undergone significant changes since the country's reform and opening up. In this study, the closing price and return of China's CSI 300 stock index are used as the database, and various data processing methods such as wavelet domain denoising, RSI screening and various SVM model optimization methods such as grid search and cross-validation are used to predict the upward or downward trend of stocks on the day after. The results of the study are presented by the model evaluation report and the heat map of the confusion matrix, which shows that the model prediction accuracy is 61% with the default parameters, and the accuracy improves to 67% after optimization. The results indicate that support vector machines are effective in stock price prediction, but there is still room for further improvement. This paper offers a potential approach that can increase return on investment and assist investors and financial institutions in making more informed investment decisions.

Keywords: SVM, Stock Prediction, Wavelet Domain Denoising, Parameter Optimization, Machine Learning

1. Introduction

Since China's reform and opening up, with the rapid development of the economy, the living standard of the Chinese people has improved significantly, and the investment field has been broadened. Stock investment has received widespread attention. Since the stock market was piloted in 1989, China's stock market has undergone radical changes after more than 30 years of development. As of September 2022, the number of listed companies in the A-share market reached 4, 911, with a total market capitalization of up to 82.58 trillion yuan and more than 200 million shareholders [1]. This indicates the strength of China's financial markets as well as the significance of the stock market to the country's economic structure. As markets continue to grow and investor structures become more sophisticated, the need for analyzing and forecasting the stock market grows.

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In the field of stock investment, investors rely on two traditional analytical methods: technical analysis and fundamental analysis. Technical analysis provides decision support based on market behavior, while fundamental analysis focuses on company fundamentals. However, these methods require investors to have high theoretical knowledge and rich practical experience, and their prediction results are often highly subjective. Therefore, how to enhance the science and precision of stock prediction has become an important topic for research.

In recent years, with the development of econometrics and statistics, the time series forecasting method has been extensively utilized in stock price forecasting., which focuses more on predicting the future trend of stock prices through historical data. However, traditional forecasting models such as ARMA and GARCH have limitations in dealing with the complex and variable nonlinear characteristics of the stock market [2]. The SVMs, as powerful machine learning tools, have been proven to have excellent performance in many fields, especially in binary classification problems. However, SVMs need to be further optimized and improved because of the complexity of stock market prediction [3].

The purpose of this study is to explore the SVM-based stock price trend prediction method and its optimization strategy. Taking the CSI 300 index as an example, an improved SVM model is proposed through literature research, text mining, data processing, and model optimization. The study uses RSI and wavelet domain denoising to preprocess the data, optimizes the SVM parameters through grid search and cross-validation methods, and finally verifies the validity of the model by comparing the prediction precision before and after the model optimization. The innovation of this study lies in the comprehensive application of multiple data processing and model optimization techniques to enhance the precision of stock market forecasting and offer more scientific and reliable decision support to investors, thereby reducing investment risks and enhancing economic benefits.

2. Research Status

Vapnik proposed support vector machines in the 1990s, which are outstanding in solving small-sample, nonlinear, and high-dimensional pattern recognition, and can be generalized to problems such as function fitting [4]. Support vector machines take various feature parameters as support vectors, map them into a high-dimensional space using a kernel function, and differentiate the data by finding a partition plane. In stock prediction research, forecasters use data from several technical indicators to make predictions. A Chinese scholar named Yuchuan, Z. used support vector machines to accomplish this model of stock judgment through technical indicators and has achieved an accuracy rate of about 65% through experiments [5]. However, it was found that support vector machines are more difficult to solve quadratic optimization problems when the training set is larger. Lifang, P. used the data of Shahe stock as a sample and experimented with neural networks and time series as a comparison, which showed that the support vector machine prediction model obtains smaller computational error and a better prediction curve. Nevertheless, the basis of parameter selection was not pointed out [6]. Zhiyuan, H. has proposed a GA-SVM algorithm based on the improvement of AUC values to test Shanghai Pudong Development Bank in different time windows using 30 independent variable features. It was determined that the method is effective in short-term investment, but the threshold is too absolute when transforming the rise and fall for positive and negative samples [7]. Yibing, C. used a regression model based on an improved SVM to forecast the Chinese stock market index. She found that the model gives better results when the stock market is on a steady rise or fall, but neither the neural network nor the support vector machine fits well under abrupt change conditions [8]. The parameter selection is especially critical in how to use support vector machines. All of the above use the radial basis function as the kernel function. Cheng, L. tried to use the support vector machine with a wavelet kernel for stock index futures price prediction and found that it performs better than the ordinary kernel function. It is considered that it can be used to predict the closing price of the main contract of stock index futures except for a special case of CSI 500 [9]. The study is mainly a comparison of kernel function selection and does not compare with other algorithms.

3. Support Vector Machine

3.1. Introduction of the SVM Concept

The SVM is a common machine learning algorithm, which is not only suitable for classification problems but also can be predicted. The algorithm converts the low-dimensional linear inseparable space into high-dimensional linear separable space, establishes an optimal decision hyperplane, divides the sample into two parts, and maximizes the distance between the two nearest samples of these two separation planes. Its advantage is that it is applicable regardless of whether the sample is linear separable, approximately linear separable, or nonlinear separable, and has a high accuracy [10].

3.2. Introduction of Common Kernel Functions of SVMs

(Xi and Xj in the following formula represent the feature vectors of two input samples).

Linear kernel functions: directly divide in the original feature space, do not make any transformation to the data, and the calculation formula is:

$$K(X_i, X_j) = X_i^T X_j \tag{1}$$

Polynomial kernel function: maps data to the upper air for classification, which is suitable for orthogonal normalized datasets, and is calculated as follows [10]:

$$K(X_i, X_j) = (\theta + \gamma X_i^T X_j)^d \ , d \geq 1 \tag{2}$$

Where θ is a constant term, γ scales the inner product, and d is the number of polynomials. Gaussian kernel function: It maps data into infinite dimensional space, classifies data points based on the distance between data points and support vector machine, and has good anti-interference ability in processing data noise [10]. The calculation formula is:

$$K(X_i, X_j) = \exp\left(-\frac{\|X_i - X_j\|^2}{2\sigma^2}\right) \ , \sigma > 0 \tag{3}$$

The σ is the bandwidth parameter, which controls the radial range of the function. Laplace kernel function: It is computationally simpler than the Gaussian function, and performs better than linear datasets in processing nonlinear datasets.

$$K(X_i, X_j) = \exp\left(-\frac{\|X_i - X_j\|}{\sigma}\right) \ , \sigma > 0 \tag{4}$$

Similar to the Gaussian function, σ is also a bandwidth parameter.

Sigmoid kernel function: The data is mapped into nonlinear feature space by hyperbolic tangent function, which is suitable for dealing with nonlinear separable cases. It is relatively rarely used in practical cases. The calculation formula is:

$$K(X_i, X_j) = \tanh(\beta X_i^T X_j + \theta) \ , \beta > 0 \, , \theta < 0 \tag{5}$$

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Where parameter β controls the slope of the kernel function and parameter θ controls the horizontal offset of the kernel function.

3.3. Introduction of SVM Parameters

SVM parameters and kernel function have an important impact on the final prediction accuracy of the model, and optimization of the parameters can enhance the prediction precision of the model. In general, the parameters to be optimized are penalty parameter C, and kernel function σ [10]. Common optimization methods are Grid Search, Random Search, and Bayesian optimization. In this paper, grid search is used to optimize the parameters.

3.4. Data Noise Reduction

Data noise reduction is a common technique in signal systems to improve the predictive ability and accuracy of models, and real signal information can be extracted from signals containing noise. In the financial domain, stock price data is usually affected by market fluctuations, trading volume changes, information dissemination delays, and other noises, so it is necessary to denoise stock price data. The traditional noise reduction methods include the moving average method, Fourier transform denoising method, Wiener filter method, and Kalman filter method. The moving average method is a simple and rough denoising method, which removes some useful information at the same time while removing noise; Fourier transform denoising is suitable for processing stable signals with strong change cycles and few spikes; Wiener filtering requires knowing the information of noise and useful signals in advance before use; Kalman filtering requires knowing the movement law of the system when used. Financial data time series is a kind of non-stationary, nonlinear, fluctuating data with unknown motion law, noise, and useful information that are not easy to distinguish, so the above methods are not applicable [11]. Wavelet denoising is a method that uses wavelet transform to decompose the signal into frequency domain components of different scales, filter the noise through threshold processing, and then reconstruct the filtered signal back to the time domain. Compared with the traditional filter denoising method, wavelet denoising can effectively retain the important characteristics of the signal and filter out noise. In wavelet denoising, the commonly used threshold processing methods are soft threshold and hard threshold: soft threshold sets the signal coefficient less than the threshold to zero, and linearly decays the signal coefficient greater than the threshold. The formula is as follows:

$$soft(x,T)=\begin{cases} x+T & x\le -T \\ 0 & |x|<T \\ x-T & x\ge T \end{cases} \tag{6}$$

The hard threshold values then directly set the signal coefficients smaller than the threshold to zero and remain unchanged for those larger than the threshold, as follows:

$$\eta_H(\omega,\lambda)=\{\begin{matrix} \omega & ,|\omega|>\lambda \\ 0 & ,|\omega|<\lambda \end{matrix}(7)$$

In this paper, wavelet denoising will be used to denoise the data by comparing the denoising effect of soft threshold and hard threshold to select the best method.

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4. Empirical Analysis

4.1. Data Selection

This paper selects the stock price index of CSI 300 for research, data processing, and data modeling process are completed with Python. Firstly, the API interface is obtained from the Alpha Vantage website, and the opening price, maximum price, minimum price, closing price, and trading volume of CSI 300 from 2003 to 2024 are obtained. The abnormal data with 0 index in 2003 and 2004 are deleted. The actual period is 4657 data from January 4, 2005, to March 8, 2024. The reason for selecting this data is described below from the perspective of relative strength index (RSI) [11]. The relative strength index shows the market according to the price rise and fall and divides a stock into two categories according to the price rise and price fall within n days, the higher RSI index is the price increase category, and the lower RSI index is the price decline category, and the specific calculation formula is [11]:

$$RSI = 100 - \frac{100}{1 + RS} \tag{8}$$

Where RS is the relative intensity and is calculated as:

$$RS = \frac{Average\ Gain}{Average\ Loss} \tag{9}$$

Taking the closing price (Close) of CSI 300 as an example, nearly 1,000 data are selected to establish a scatter plot of relative strength indicators and stock fluctuation as shown in Figure 1, in which the abscissa indicates the RSI size and the ordinate indicates the relative stock fluctuation:

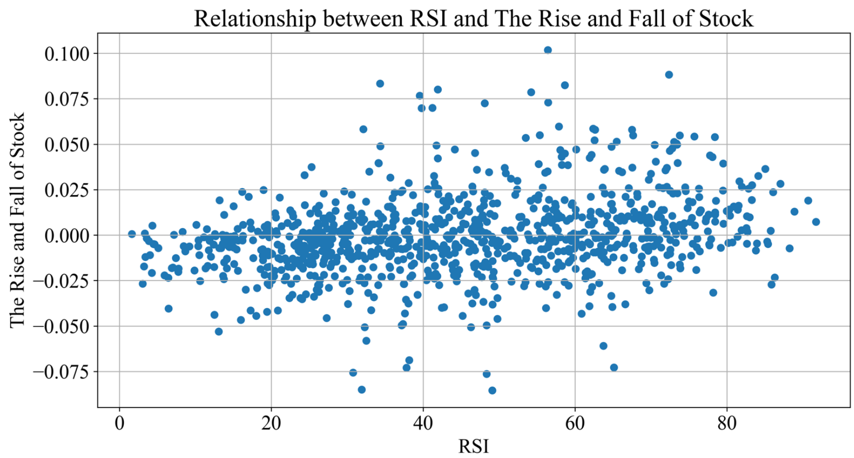

Figure 1: Relationship between RSI and The Rise and Fall of Stock (Photo/Picture credit: Original).

It can be seen from Figure 1 that at a lower level of RSI, the ordinate of the data is concentrated in the negative half-axis of the vertical axis, indicating that the stock has a downward trend; at a higher level of RSI, the ordinate of the data is concentrated in the positive half axis of the vertical axis, indicating that the stock has an upward trend, which is generally consistent with the above description of this index and can be used as an example to predict the stock price.

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4.2. Data Processing

4.2.1. Sample Division

This paper divides the data into a training set and test set according to the ratio of 8:2 from far to near according to time, and draws the closing price trend diagram of Shanghai and Shenzhen 300 from January 4, 2005, to March 8, 2024, by using Python's Pandas library and matplotlib library as shown in Figure 2:

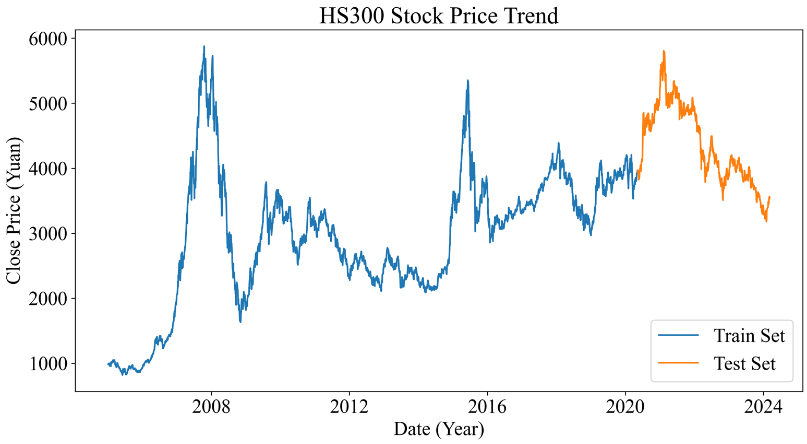

Figure 2: HS300 Stock Price Trend (Photo/Picture credit: Original).

In Figure 2, the blue part is the training set, and the orange part is the test set. It can be seen from the figure that the stock price of CSI 300 has fluctuated unevenly in the past 19 years, and the three-stock price plummeting occurred in 2008, 2015, and 2021, corresponding to the major historical events of the financial crisis in 08, the stock disaster in 15 years and the global epidemic in 21, respectively. After 21 years, the stock price showed a downward trend.

4.2.2. Feature Engineering

In empirical modeling of machine learning, feature engineering usually needs to extract the optimal data to predict to achieve the optimal effect of prediction, and feature engineering is to transform and process the original data to facilitate the machine learning model to better understand and use the process of data. In this paper, the feature engineering of the CSI 300 example includes the following aspects: in terms of feature enhancement, the data cleaning is carried out first, because the sample is large, and the direct deletion method is used for missing values and abnormal values; in terms of feature scaling, the data are normalized. In this paper, Z-score normalization is selected from Min-Max scaling, Z-score normalization method, and normalization method for normalization processing. The formula is as follows:

$$X_{norm} = \frac{X - \mu}{\sigma} \tag{10}$$

Where μ is the mean and σ is the standard deviation of the data.

4.2.3. Threshold Denoising

Financial time series data contains a lot of noise. In this paper, the wavelet denoising method is used to denoise the data of CSI 300 closing price after feature engineering with wavelet transform layers

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of 5, 6, 7, and 8 in turn. The results show that when the wavelet transform layers are 7, the denoising effect of the data is the best, and overfitting occurs when the layers are too high. Next, soft threshold and hard threshold methods are successively used for comparison: the comparison plot of the original data and denoised data under the soft threshold processing method is shown in Figure 3, and the data fit is too low:

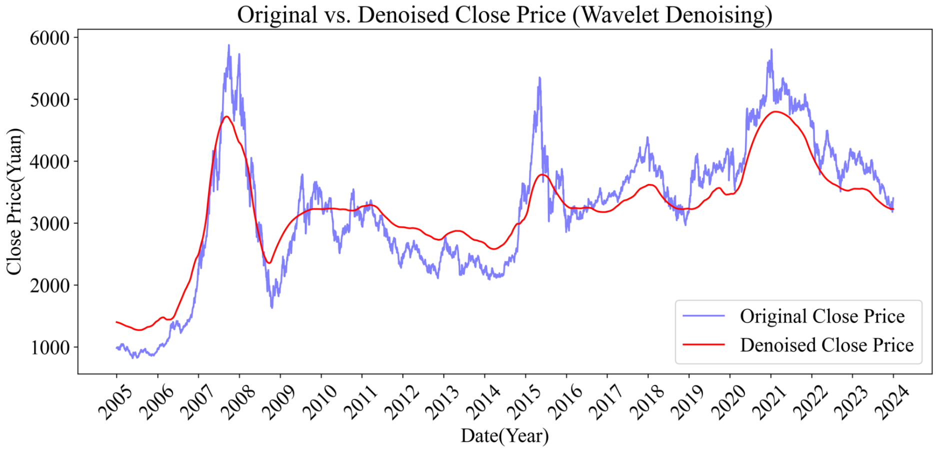

Figure 3: Original vs. Denoised Close Price (Wavelet Denoising)-Soft (Photo/Picture credit: Original).

The comparison between the original data and denoised data under the hard threshold processing method is shown in Figure 4, and it can be found that the data fitting degree is higher than that of the soft threshold processing method:

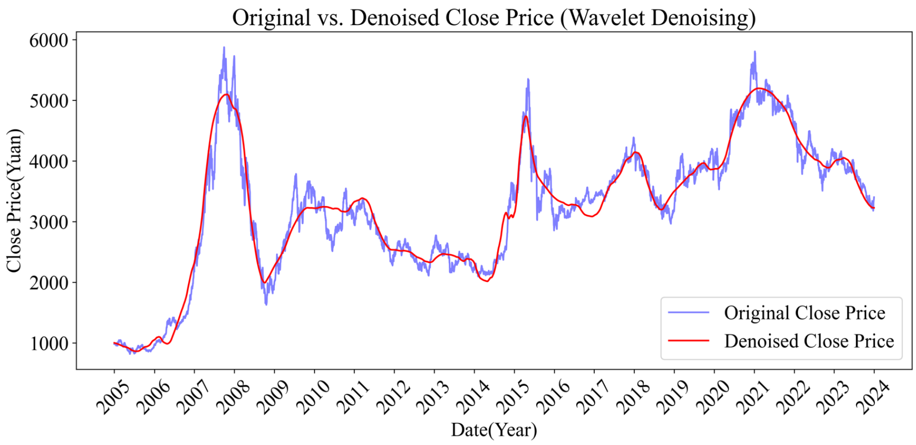

Figure 4: Original vs. Denoised Close Price (Wavelet Denoising)-Hard (Photo/Picture credit: Original).

In summary, the wavelet denoising hard threshold processing method is used to denoise the data.

4.3. Model Prediction

4.3.1. Model Parameter Setting

The penalty parameter C, referred to earlier, represents the tolerance for errors. In this paper, we use the model's default settings for the penalty parameter C, the kernel function, and the gamma parameter. The gamma parameter determines the distribution of data after mapping to the space; a larger value results in fewer support vectors.

Next, we will use the grid search method mentioned previously to optimize the model parameters:

- Define parameters: Set the range for the value of C.
- Choose scoring metrics: Select the metrics for assessing model performance, such as accuracy, recall, and F1 score.
- Set up cross-validation: Decide on the strategy for cross-validation.

Implement the grid search: Use the grid search functionality in the scikit-learn library in Python.

After aggregating the mean test scores and the variance of scores from the cross-validation, the results show that the optimal parameters for the model, after optimization, are C=10 and gamma=0.001.

4.3.2. Indicators for Model Evaluation

The penalty parameter C, or Error Tolerance, has implications for model bias and variance. A small value of C results in high bias and low variance, suggesting the model might be overly simple and unable to capture the complexities of the data, although it may perform consistently well on data outside the training set (low variance). Conversely, a large value of C leads to a complex model that fits the training data well but may lack generalizability.

Regularization: The parameter C is effectively the inverse of the regularization term. Regularization aims to limit model complexity to prevent overfitting. In SVM, a smaller C value is indicative of stronger regularization, whereas a larger C value is indicative of weaker regularization. Mathematically, the objective function of an SVM includes a regularization term, typically the L2 norm (sum of squares) of the model weights. C acts as a multiplier before this norm, controlling the strength of regularization. With a large C, the regularization is weaker, and the model prioritizes minimizing training error. With a small C, the regularization is stronger, and the model focuses on keeping the weights small to prevent overfitting.

In practice, cross-validation (such as k-fold cross-validation) is commonly used to determine the optimal C value. The process entails splitting the dataset into k subsets, using k-1 of these subsets to train the model, then verifying the remaining subset. To get the average performance of the model, this process is repeated k times, using a different validation subset each time. The results are then averaged.

Choosing the optimal C value is crucial to balance the model’s performance on training data and its ability to generalize to unseen data, ensuring the model neither overfits nor underfits. When evaluating the impact of parameter C on model performance, the following metrics are commonly used:

- Accuracy: The proportion of correctly classified samples in the dataset.
- Precision: The proportion of correct identifications.
- Recall: The proportion of actual positives that were correctly identified.
- F1 Score: The harmonic mean of precision and recall, providing a single metric that combines both.
- AUC-ROC: The area under the ROC curve, which describes the model’s ability to distinguish between classes. The ROC curve is a plot of the true positive rate (TPR) against the false positive rate (FPR), and the AUC measures the total area underneath this curve.

4.3.3. Evaluation of Model Prediction Results

Predictions were made based on the pre-optimisation model and the printed assessment is shown in Table 1:

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Table 1: Model Prediction Evaluation Report

	precision	recall	f1-score	support
-1	0.43	0.56	0.48	300
1	0.75	0.64	0.69	628
accuracy			0.61	928
macro avg	0.59	0.60	0.59	928
weighted avg	0.65	0.61	0.62	928

As can be seen in Table 1, the accuracy of the model prediction is 61%.

The model evaluation report resulting from the optimization of the parameters tuned by grid search is shown in Table 2:

Table 2: Model Prediction Evaluation Report (Optimized)

	precision	recall	f1-score	support
-1	0.74	0.55	0.63	481
1	0.62	0.80	0.70	451
accuracy			0.67	932
macro avg	0.68	0.67	0.66	932
weighted avg	0.68	0.67	0.66	932

It can be seen that after adjusting the parameters, the accuracy of the model prediction is increased to 67%, and the optimization effect is more obvious.

4.4. Model Prediction Results and Analysis

The new CSI 300 upward and downward trend prediction versus the actual price is drawn according to the optimized model parameters as in Figure 5:

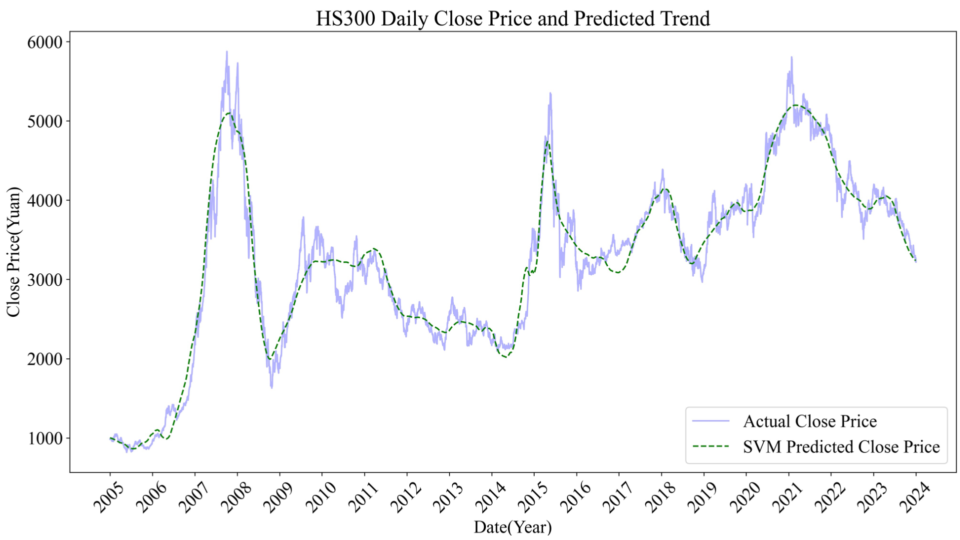

Figure 5: HS300 Daily Close Price and Predicted Trend (Photo/Picture credit: Original).

The blue solid line in Figure 5 shows the actual closing price of CSI 300 based on the time series, and the green dashed line indicates the stock's rise or fall on the following day as predicted using the SVM model.

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Looking first at the solid blue line section, the CSI 300 closing price saw a big rise in late 2007 to 2008, followed by a big fall due to the economic crisis after the big rise, and then a stock market rebound in 2009 with a closing price of around 3700. This was followed by a constant fluctuation of closing prices in the range of 2000-3500 from 2009 to mid-2014. Short-term fluctuations can be driven by short-term influences such as market sentiment, news events, technical factors, etc., and these many, many short-term fluctuations shape the long-term trend. In context, the fluctuations of the CSI 300 Index, a composite index reflecting 300 larger and more liquid stocks in the two main stock exchanges of Shanghai and Shenzhen, are usually influenced by macroeconomic factors such as the rate of economic growth, the level of inflation, and monetary policy, in addition to the international financial markets, sectoral factors, technological factors, and market sentiments, etc. 2014 Between mid-year and mid-2015, it rose by 165.8 percent, from over 2,000 to over 5,000, reaching the highest closing value in the decade. After the subsequent decline, the stock index rose 33% between end-August and end-December 2015, a period of 3.9 months, bouncing from over 2,900 to over 3,900 as a result of the official bailout. After the 20s, in 2021, the CSI 300 index had a major bull market, surpassing the top of the 15-year bull market and catching up with the '07 peak at over 5,800, potentially a long-lasting "housing" and capital shifting into the stock market for profit, or it could be the contrast between the Chinese and foreign situation coming out of the new crown epidemic.

And then see the green dotted line part, the overall model predicts the general trend and the actual match, but in some extreme data such as the peak when the prediction of a large error, such as the peak in 07 the actual value is much higher than the predicted value. Secondly, although the general trend is accurate, zoomed into the details of each period there are large and small errors, but the error range is generally not more than plus or minus 100.

After using the optimized model to predict the data to get the results, the confusion matrix was calculated using the predicted results and the real labels, and the heat map of the confusion matrix was plotted as in Figure 6:

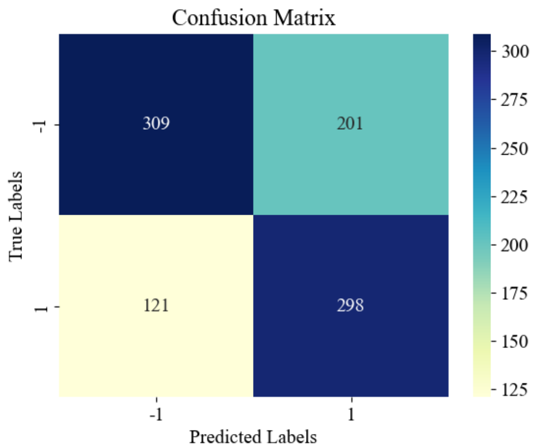

Figure 6: Confusion Matrix Heatmap (Photo/Picture credit: Original).

As can be seen from Figure 6, in 20% of the test sets of the CSI 300 time series, the model predicts the number of negative samples in negative categories as 263, the number of negative samples in positive categories as 218, the number of positive samples into negative categories as 92, and the number of positive samples into positive categories as 359. the model prediction accuracy, i.e., the ratio of the sum of the main diagonal elements to the total elements, is 67%, which is in line with the assessment report.

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5. Conclusion

The stock market is characterized by high risk and high return, and how to accurately predict the upward and downward trend of stocks has been a continuous concern for investors and research scholars. For a long time, Shanghai and Shenzhen 300 have maintained a high degree of heat in China. This study employs the widely-used support vector machine model to examine the upward and downward trends of the stocks in the CSI 300, using 4,657 trading days as the time series. The stock-related market indexes, such as the opening price, closing price, highest price, lowest price, and technical indexes of the RSI, are chosen, and the relevant feature engineering principles are applied to create forecasts. The accuracy of the results obtained from the forecasting process is 61%.

A grid search was used to find the parameter combination with the highest average test score, C=10, and gamma=0.001, to adjust the model parameters, and the new evaluation report obtained after the optimization showed that the accuracy rate was increased to 67%.

The shortcoming of this study is that even though a high accuracy rate was obtained, it is still unknown whether support vector machines are more suitable for stock prediction compared to other machine learning methods. In future research, a side-by-side comparison can be made between Support Vector Machines and other machine learning models such as Bayesian models, Gradient Boosting Trees, XGBoost, LightGBM, etc., to highlight the strengths or weaknesses of SVMs, and then analyze and optimise the strengths and propose improvements for the weaknesses.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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A Financial Analysis and Valuation on Disney

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Abstract: This paper focuses on a specific analysis of the corresponding situation of Disney. It introduces the development of Disney as a whole and lists three companies in different industries in the market that compete with Disney in different aspects, namely Netflix, Comcast and Mattel. By collecting and analyzing the corresponding data, the four companies are specifically compared in terms of liquidity, repayment ability and profitability respectively. The result is that Disney's profitability is slightly weaker than that of the other three companies, which may be due to the fact that Disney has a large investment in streaming media, but not resulting in a return that matches it. This paper also analyses Disney's stock market performance in relation to its competitors and shows that although Disney stock is overvalued at this stage, the NTM P/E ratios show that it will improve in the next period. This paper also analyses and summarizes Disney's strategy and risk profile and makes some predictions for the future. This paper believes that in the future Disney will have a better growth and also a better experience for the consumers.

Keywords: Valuation, Performance Evaluation, Entertainment Industry, Disney

1. Introduction

The Walt Disney Company (hereinafter referred to as Disney), founded in 1923, is a large multinational corporation headquartered in the United States of America, founded by Mr. Walt Disney together with his brother, Lloyd Disney, initially as Disney Brothers Studios, and later renamed as the Walt Disney Company. The company's main business at the beginning was the production and distribution of films, and in 1937 it succeeded in releasing its first animated film, Snow White, which became one of the most popular films of the time [1]. Subsequently, Disney made more and more progress in this field, releasing quality animated films such as Pinocchio, Fantasia, Dumbo, etc. [1]. In 1945, Disney hired live actors for the first time to play roles in the film ‘Song of the South’, and from then on, it also broadened the company's film genres and continued to release full-length live-action films. At the same time, the company also successfully built and opened the first Disneyland in California in 1955, which will make the name ‘Disney’ more and more familiar to more and more people. After that, Disney has been expanding its business market and successfully launched the Disney Channel on cable TV in the United States of America in 1983, on the other hand, it also endeavored to develop the Disneyland market in different regions such as Orlando Disneyland and Tokyo Disneyland, which enabled the company to achieve its major goals at the present stage. The establishment of Disneyland in different regions has not only brought lucrative benefits to Disney

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but is also slowly working towards making the company a leader amongst the entertainment companies in the global arena.

After entering the 21st century, Disney began to carry out a wide range of online media expansion, acquiring a number of companies such as Pixar, Fox, Marvel, etc., which has enabled Disney to achieve an important position in many fields and greatly expanded the company's business segments [2]. At the same time, Disney has also actively expanded other diversified businesses, such as gaming, consumer products, music, etc., which have brought Disney substantial revenues and increased its competitiveness in the global entertainment market [1]. In 2020, the company faced a major turning point during this period due to the outbreak of epidemic. As Disney's theme parks and cinema business are dependent on places where people congregate and thus operate, this has challenged Disney's traditional business model like never before. The Epidemic resulted in the limited or even forced closure of these venues, causing a significant drop in Disney's revenues, a financial shortfall that led directly to the official closure of Blue-Sky Studios. But as the epidemic gradually ended, Disney slowly got back on track. Last year was the 100th anniversary of Disney's founding, and in April the company released its 100th anniversary film, revisiting many of its classics with everyone. All in all, Disney has become a leading entertainment company in the world by virtue of its unique creativity, superior technology and excellent business strategy. It is believed that in the future, Disney will bring more excitement as well as unlimited possibilities to the audience.

2. Performance Evaluation

In the next part of this essay, three competing companies will be chosen to compare with Disney in three ways. As mentioned in the previous article, the scope of Disney's business has been expanding gradually. Therefore, the first competitor company, Netflix, has been selected from the film and television level. Netflix is a leading global streaming entertainment service company. As the main business of these two companies is inclined to film and television, there is competition in the target customers of film and television as well as the market flow of the corresponding placement. Secondly, the park aspect of Disney has been very popular in recent years, and if Disneyland is everyone's first choice, then the only one that can be mentioned alongside it is Universal Studios Park. Therefore, the second competing company is Comcast, which is the parent company of NBC Universal, the company that owns Universal Studios Park. It is an American multinational media and technology company, which is diversified due to its many different types of subsidiaries. One of these business areas is the park business, which has similarities with Disney in that they both build a different kind of fairytale park based on several animation or film IPs. Therefore, there is some competition between them in terms of attracting customers and growing revenues, as well as the right to develop certain areas is also an important factor in the competition between the two companies, which could affect the future growth of the company. The last competing company chosen was Mattel Inc. This is the world's largest toy company, which contains Barbie, Matchbox, American Girl and many other brands [3]. The two companies are in competition due to the fact that Disney, among others, is involved in the corresponding output of some toys or related items. These companies will be analyzed through the corresponding data (All data obtained from NASDAQ website on 2024/3/26).

2.1. Liquidity

Table 1: Liquidity ratios of Disney and its competitors.

Company	Current Ratio	Quick Ratio	Cash Ratio
Walt Disney	105.22%	98.91%	45.54%
Netflix	111.93%	111.93%	80.56%
Comcast Corporation	59.67%	59.67%	15.46%
Mattel	232.58%	190.00%	93.96%

Data source: Nasdaq

Firstly, the liquidity of the four companies will be analyzed, in terms of the current ratio, except Mattel, the remaining three companies show a ratio of less than 2, which will mean that the ability to realize the assets of the company is weaker than other companies of the same type. The lowest of these is Comcast's current ratio, which is only 59.67%, which would imply that the company's ability to repay debt in the short term is weak. In terms of quick ratio, Disney has a good performance. His quick ratio is 98.91%, which is the closest to 1. This would reflect that he would have a stronger ability to use its most liquid assets to service its debt than other competing companies without relying on inventory sales or other additional financing. Regarding the cash ratio, generally the cash ratio is 20% to 30%. Table 1 shows that Netflix and Mattel have cash ratios of more than 50%, which suggests that the liquid assets of these two companies are not being used properly, which may ultimately lead to an increase in the opportunity cost of the company. Comcast, on the other hand, presents a cash ratio of less than 20%, which indicates that the business does not have enough cash flow to pay its short-term debts or meet its daily operational needs. It may be caused by the business over-investing in long-term projects or insufficient sales revenue. Above all, this paper concludes that the four compared to the other three competing companies, Disney exhibits good corporate liquidity, while the others all have not so good performance in a certain ratio respectively.

2.2. Solvency

Table 2: Solvency ratios of Disney and its competitors.

Company	Total Debt Ratio	Long-Term Debt Ratio	Times-Interest-Earned
Walt Disney	47.30%	20.48%	4.9446
Netflix	57.75%	29.02%	9.8671
Comcast Corporation	68.68%	35.88%	6.0105
Mattel	66.61%	36.20%	4.7597

Data source: Nasdaq

Secondly, the repayment capacity of the four companies will be analyzed. In terms of long-term debt ratios, all four companies are at a similar level as shown in Table 2. The survey shows that the total gearing ratio of the company is generally in the range of 40%-60%. So Comcast and Mattel have higher ratios than the other two companies, which would not be good news for them. In terms of long-term debt, Disney shows a better value of 20.48%, while the other three companies have ratios of more than 25%. As long-term debt ratio mainly reflects the ability of a company to repay long-term debts, a high long-term debt ratio will increase the financial risk and financial cost of the whole company. In terms of earned interest multiples, both Disney and Mattel are close to 5, while both Netflix and Comcast show values over 5 or even close to 10. While the higher this indicator is, the better the company's ability to service its debt over the long term, internationally it is considered more appropriate when the indicator is 3. If it is too high, it will mean that the company needs more

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financing or investment to operate, which will increase the potential risk of the company. In conclusion, Disney also has a good performance in terms of repayment ability.

2.3. Profitability

Table 3: Profitability ratios of Disney and its competitors.

Company	Profit Margin	Operating Margin	Asset Turnover
Walt Disney	2.65%	5.74%	43.66%
Netflix	16.04%	20.62%	69.40%
Comcast Corporation	12.66%	19.18%	47.25%
Mattel	3.94%	10.32%	88.08%

Data source: Nasdaq

The last thing is to analyze the profitability of the four companies, as shown in Table 3. In terms of profitability, in general, the profit margins of the four companies are low when looking at the market as a whole, probably due to industry constraints. However, in comparison, two companies, Disney and Mattel, have very low profit margins of 2.65% and 3.94% respectively. This implies that the profitability of these two companies is weak, which may be due to the fierce competition in the current market or certain problems in the marketing strategy. Similarly, the values from the operating margins of the four companies show the same situation. Disney remains in the position of the lowest operating margin of the four companies, a phenomenon that may be due to the fact that its streaming service is in a loss-making position at the current stage, requiring a certain amount of capital investment, which leads to the low profitability of its company. In terms of asset turnover, all three companies except Mattel have an asset turnover of less than 80%. The company's asset turnover ratio is generally at the more appropriate level of 80%-100%. These three companies are characterized as capital-intensive industries, and due to the diversity of their business, they may require large-scale capital investment from the company, which leads to a lower asset turnover ratio, and may result in a lower evaluation of the quality of the business operations as well as the efficiency of utilization. Therefore, for the future development of the three companies may need to adjust the corresponding operation mode, and thus improve this ratio. In conclusion, in terms of profitability, Disney still has this big problem that needs to be improved continuously.

In terms of liquidity, repayment ability and profitability, the overall performance of Disney has performed better than the other three companies. However, this is only based on the situation reflected in the data at the current stage. In the future, Disney should summarize its own shortcomings and the successful experience of other companies in the same industry, and adjust the company's strategic approach and mode of deployment to make it more in line with the needs of the current market and customers, so as to make the company more successful.

3. Valuation

3.1. Forecast

Table 4: Valuation of Disney and its competitors.

2024/3/26	Walt Disney	Netflix	Comcast Corporation	Mattel
Stock code	DIS	NFLX	CMCSA	MAT
Stock price	119.93	629.24	42.48	19.4
TTM EPS	4	12.01	3.97	1.23

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Table 4: (continued).

NTM EPS	4.72	17.05	4.25	1.34
EPS growth rate %	18.00%	41.97%	7.05%	8.94%
Revenue growth rate	3.66%	14.24%	3.11%	2.92%
TTM P/E	29.98	52.39	10.70	15.77
NTM P/E	25.41	36.91	10.00	14.48
PEG	1.67	1.25	1.52	1.76
GP/A (Last Fiscal year)	14.45%	28.74%	32.03%	40.15%

The next step is to analyze and forecast the corresponding valuation of the shares of the four companies, and Table 4 is based on 26 March 2024 data as reported on the NASDAQ website. Firstly, regarding the EPS growth rate, Table 4 shows that NFLX has the best performance among the four companies with a value of 41.79%. This will mean that the company will earn higher earnings and also means that the company will have more profits that can be distributed to the respective shareholders. In contrast, CMCSA and MAT stocks have an EPS growth rate of no more than 10%, indicating that their companies are currently experiencing some difficulties and need to make some adjustments to their corporate strategies. Secondly, regarding the revenue growth rate, DIS, CMCSA, and MAT have similar values, but none of them exceed 5%. This indicates that all three companies are experiencing slow revenue growth, which could be due to a number of reasons, such as competitive pressure in the market or declining market share. Then there is about the P/E ratio, the TTM P/E ratio and NTM P/E ratio of each of the four companies are calculated in this paper, and NFLX reflects a very high result. This means that the companies are not only overvalued, but also may have a high degree of frothiness. The stock market may be inflated and exceeding its true value, which in turn poses some risk. CMCSA, on the other hand, reflects lower results and generally speaking, the appropriate range for P/E ratio is 14-20, which would imply that CMCSA may be undervalued. While DIS's TTM P/E ratio is also outside of a reasonable range, the NTM P/E ratio reflects a better result, and it is possible that the company may improve on this in the future, depending on the new quarterly data. In terms of PEG, all four companies have shown a similar picture. In terms of GP/A, DIS has the lowest value among the four companies with 14.45%. This corresponds to the profitability analyzed in the previous section, for which DIS has certain shortcomings, and which it is believed that DIS will be gradually resolved in the future as the various components are gradually improved and developed.

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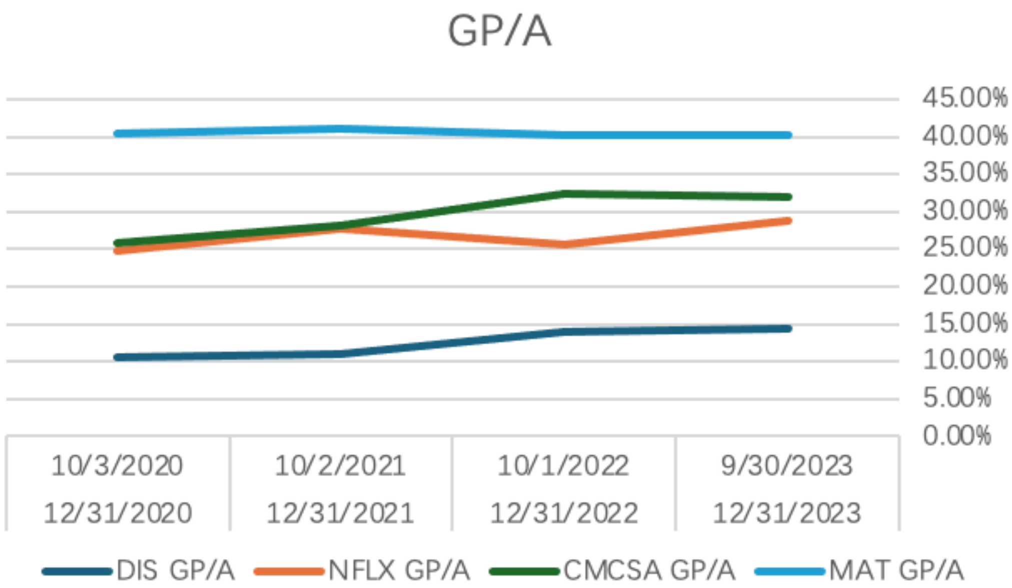

Figure 1: GP/A of Disney and its competitors (Photo/Picture credit: Original).

Figure 1 shows the GP/A combination of the four companies for different time periods. And since DIS has a different fiscal year than the other three stocks, two different sets of dates are shown in the horizontal coordinate. One of them, MAT, has remained the highest among these four companies and has been changing very steadily in recent years, staying around 40%. And both DIS and CMCSA stocks are gradually trending upwards, which means that both companies are actively making improvements in response to some of the problems that existed at various stages. NFLX, on the other hand, is on a downward trend in 2022, which according to the corresponding data of that year may be due to the fact that Netflix has invested more in original TV content production and the corresponding streaming services, which leads to its GP/A being in a lower position at that stage [4]. But in any case, judging from the situation in the last year, the situation of all four companies are slowly getting better, for some problems are also gradually resolved, which will be a good trend towards the future.

3.2. Strategy Management

Next is the aspect of having an excellent marketing strategy regarding the Disney Company, this paper analyzes the main aspects of its corporate strategy from three different perspectives.

3.2.1. Brand Acquisitions and Corresponding IP Rights

Disney has been a leader in several industries compared to other companies due to its ownership of many popular IPs and animated characters that customers have come to love. The acquisitions of Pixar Animation, Marvel Entertainment, Lucasfilm, and 21st Century Fox in the 21st century increased the number of IPs owned by Disney at the time [5]. The acquisition of Marvel alone brought Disney up to 5,000 IP characters such as Spider-Man, Iron Man, Thor, and Captain America. The acquisition of 21st Century Fox also brought the X-Men, Fantastic Four, Deadpool and other IPs into the Disney fold, putting it directly at the forefront of the industry [5]. In recent years, Disney launched the "Duffy family" is loved by everyone, and Disney also quickly seize this selling point, in the corresponding product output launched parks, festivals, series of many different limited series of peripheral, so as to expand the profitability. From the beginning of Mickey Mouse, Donald Duck,

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Snow White, and then to the current Star Dale, Ling Na Beier, Shirley Mae and so on multiple cartoon images, Disney has always been to "family entertainment" as the core of the brand concept, in the future, Disney will also promote more high-quality diversified IP, so as to better meet the customer's expectations [6].

3.2.2. Globalization of Regions

In 1955, the first Disneyland successfully opened in California, the United States, which is the first theme park in the modern sense of the word, once the launch of the park is greatly loved by the people, in just six-month time attracted more than 3 million visitors to play [7]. And in the coming period of time, the income and the number of visitors rose sharply, even just one day's income can be up to millions, and add the cost of facilities in the park and various other, its income is even more substantial. Therefore, Disney quickly seized this market and spent five years to build a more luxurious Disneyland, and successfully opened to the public in 1971, which is the Orlando Disneyland, is also the second theme park in the United States. With the completion of the most luxurious Disneyland at the time, the company's revenue increased, and it began to gradually expand its parks to other countries. 1982 Tokyo Disneyland in Japan, 1992 Paris Disneyland in France, 2005 Hong Kong Disneyland in China, and 2016 Shanghai Disneyland in China, the successful construction of these parks shows that Disney is gradually focusing its strategy on the whole country. strategy to gradually focus on the country. However, at this stage, there is no clear information on which region the company will build a new Disneyland, so the main focus is on expanding the scope of the existing parks. Moreover, Disney has indicated that it will establish Disneyland in each region according to the culture of different countries and regions, whether it is the expansion of the current region or the location of the new park in the future, which will be a good selling point for customers and attract tourists from all over the world [8].

3.2.3. Digitalization and Corresponding Technological Expansion of Streaming Media

In November 2019, the Disney Company, in order to adapt to the trend of digitization and meet the needs of consumers, therefore went live with its streaming service Disney + (D+ for short), and made it the focus of the company at that time, investing a large amount of money, focusing on the film and television content of Disney and enriching it continuously, optimizing the distance between the customers and the company, and thus attracting a certain amount of users. Coincidentally, the following year, the world suffered a serious epidemic crisis, which caused serious damage to the economy of Disney's real industry. Therefore, the existence of Disney+ played a major role in providing a wealth of entertainment for people living in isolation at home. And as of March 2021, Disney+ has surpassed 100 million subscribers worldwide, a number that far exceeded the company's initial expectations [9]. Disney is investing heavily in originality to keep its streaming platform on track, retaining as many of its current subscribers as possible while expanding its subscriber base in other regions [9]. Disney is also continuing to invest in technological innovation, for example, the current popularity of virtual reality technology, augmented reality sense of the new technology and so on have gained significant results [9]. Technological innovation not only makes Disney in the content greatly improved, but also makes the customer to get a better sense of experience, and then enhance the customer stickiness [9]. Therefore, in terms of the current development strategy of Disney, it is gradually transforming into a technology company rather than being limited to a traditional media company [9].

3.3. Risk Assessment

According to Disney's annual report for the year 2023, in terms of the economic market of the business, Disney believes that the downturn in the economic conditions in the global regions is now having a greater negative impact on the profitability of its business [10]. Due to the recession in certain regions of the market and a certain level of inflation, it may result in Disney being forced to increase its costs in certain areas, which in turn will generate a certain amount of revenue loss [10]. In terms of public taste preferences, Disney sees this as an unpredictable risk, as the company is unable to accurately predict public tastes, there is a risk that the images or IPs introduced may not be accepted by the market [10]. At the same time, a similar problem is reflected in Disney+, where fatigue is observed in the growth of streaming services, especially the existence of a constant decline in the number of payers, which may affect the company's revenues. In addition, due to the decline in traditional forms of distribution, this may thus lead to an increase in the cost of its corresponding content for the streaming service, which may have a negative impact on profitability [10]. Therefore, in the future it may be necessary to make certain adjustments to its content and corresponding targets.

4. Conclusion

To summarize, this paper believes that the future development prospect of Disney Company is more considerable, according to the recent social status, the public's expectation and love for Disney is getting higher and higher. Especially in the 100th anniversary of the founding of Disney last year, the broadcast of the movie "Star's Wish" makes more people revisit the classic Disney, which evokes a lot of memories. The recent opening of the "Zootopia" park in Shanghai Disneyland in China has also attracted a large number of tourists, allowing more people to understand Disney and love Disney. But for investors, need to consider a number of factors, and this article also mentioned that Disney in some aspects of the same type of other companies compared to the existence of a certain disadvantage, at the same time there may be in the current stage of the situation is slightly overestimated, so need to be integrated with a variety of factors to accurately judge whether to invest. In the future, Disney will develop steadily, with the situation gradually adjust the company's strategy and center of gravity, and then for the children of big friends to create a richer Disney ‘utopia paradise’.

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Research and Analysis of the Development of Live E-commerce on Xiaohongshu

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Abstract: This article analyzes the competitiveness and development prospects of the buyer e-commerce model on Xiaohongshu in the social e-commerce field. Firstly, by examining Xiaohongshu's community ecosystem, buyer resources, social shopping experience, and innovative brand partnerships, the unique advantages and business value of Xiaohongshu's buyer e-commerce model are revealed. Secondly, combining market demands and trends analysis with buyer resource and operational cost analysis, the feasibility and development prospects of Xiaohongshu's buyer e-commerce model are discussed. Lastly, from the perspective of competitor analysis and summarizing prospects, recommendations are provided to further optimize buyer resources, strengthen brand partnerships, control operational costs, enhance user experience, and improve community management. These suggestions aim to consolidate Xiaohongshu's leading position in the social e-commerce field, create better shopping experiences and marketing platforms for users and brand merchants, and achieve sustainable business growth.

Keywords: *Xiaohongshu*, Live E-commerce, Development Research, Buyer E-commerce

1. Introduction

Live e-commerce emerged in 2016, with MOGU introducing live streaming into e-commerce and Taobao launching live streaming functions, marking live e-commerce’s rapid development over just a few years. In 2019, Xiaohongshu introduced live streaming functions. In 2020, influenced by the pandemic, consumers stayed at home, causing significant disruptions to offline retail sales. Live e-commerce provided consumers with another way to shop, and consumer purchasing power was unleashed in live streaming rooms. Consequently, in 2020, live e-commerce entered a period of explosive growth [1]. However, with the rapid development of live streaming for product sales, some problems have gradually surfaced. Under the traditional live e-commerce model, brands prefer to work with popular, high-volume hosts. Metrics such as live streaming viewership, number of fans, comments, and sales figures have become the basic elements of industry competition. To maintain impressive statistics, some hosts resort to inflating data through methods such as fake orders, buying followers, and manipulating comments, gradually becoming industry norms [2]. Furthermore, many hosts lack relevant background knowledge, making it difficult to select truly high-quality products from a multitude of brands. This not only may Xiaohongshuuce consumer satisfaction after purchase but also can damage brand image and reputation [3]. In this context, Dong Jie's live streaming event

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provided Xiaohongshu with new commercial inspiration, prompting them to fully embrace live e-commerce. Differing from traditional "sales-oriented" live e-commerce, Xiaohongshu encourages the emergence of buyers with professional knowledge and unique live streaming styles, embarking on the path of differentiated live e-commerce.

Red's "Buyer E-commerce" model, as an emerging e-commerce model, holds significant research value and practical implications. This article aims to comprehensively analyze the model's differentiation strategies, competitive advantages, and development potential, revealing its differences from traditional e-commerce models and exploring innovations and competitive advantages in user experience, product selection, and marketing strategies. Additionally, through data analysis and feasibility studies, it assesses the model's development potential and the challenges it faces, providing theoretical support and practical guidance to relevant practitioners and decision-makers. This effort aims to promote the healthy development of emerging e-commerce models, foster industry innovation, and provide reference and assistance for the development of the e-commerce industry.

2. Overview of Xiaohongshu's E-commerce Development

Red was officially founded in Shanghai in June 2013 and launched its mobile application on the App Store in October of the same year. Initially, it served as a basic shopping guide primarily targeting entry-level users, covering popular tourist destinations such as the United States, Japan, and South Korea. However, this guide-style product, which was more static and focused on providing information, was insufficient for more time-sensitive shopping scenarios, such as seasonal discounts and store updates. The relatively static information flow made it challenging to establish real-time, interactive, and sticky engagement with users. Therefore, in December of the same year, the "Red Shopping Notes" app was launched. It was a vertical community primarily consisting of female users with overseas shopping habits. This community addressed the problem of users not knowing where to find good products but did not yet embark on its e-commerce journey.

It wasn't until December 2014 that Xiaohongshu officially launched its e-commerce platform called "Welfare Mart," marking the beginning of its e-commerce journey. It rapidly developed and achieved a series of milestones [4]. By July 2019, Xiaohongshu was asked to rectify its platform for the first time and, after 77 days of adjustments, resumed operation. Within a month of being back online, its monthly active users surpassed one hundred million, and it achieved profitability for that month—an impressive feat considering the context of many internet companies collapsing, especially those centered around content communities. However, by the end of the year, CCTV's criticism highlighted issues like stream padding and fake reviews, prompting Xiaohongshu to realize that content was the foundation of its existence. This realization made the platform more cautious in its commercialization efforts. In 2019, Xiaohongshu began internal testing for live streaming and officially launched it at the beginning of 2020, initiating its live e-commerce attempts [5].

In October 2023, Xiaohongshu officially closed its "Little Oasis" and "Welfare Mart" platforms and underwent internal restructuring. In March 2023, the live streaming business, originally under the e-commerce department, became an independent department on par with the e-commerce department. By mid-year, the e-commerce and live streaming businesses were integrated into the "Transaction Department," established as a primary department [6]. In August 2023, Xiaohongshu formally proposed a "buyer e-commerce" model as its core strategy to develop differentiated live e-commerce.

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3. Differentiation Strategy

3.1. Analysis of the Buyer E-commerce Model

The term "buyer" first appeared in Europe in the 20th century, where buyers needed to pay attention to trendy products and keenly predict fashion trends. In China, buyers were initially referred to as purchasers, merchandisers, or business department staff responsible for procurement. Over more than a decade of development, the buyer profession has received increasing attention, and related work has gradually become more specialized [7]. Generally, fashion buyers have their distinct fashion styles and accumulate a customer base that likes these styles. They purchase clothing brands that align with their style positioning and then sell them to customers who trust their taste. According to Ding Ling, the Chief Operating Officer of Xiaohongshu, buyers are both content creators and influencers, while principals have their own products and supply chains [8].

In Xiaohongshu's Creator Center, the key elements to becoming a buyer include account, product selection, notes/live streaming, and followers. The account and selection of products reflect personal style, notes/live streaming are monetization methods, and followers are sources of growth and feedback for buyers. Buyers need to manage private domain streams, build stronger follower stickiness, and trust.

In traditional live e-commerce, streamers focus on streaming. The larger their fan base, the stronger their bargaining power with brands. They attract orders through low prices, with the core being a large fan base and low-priced products. In buyer e-commerce, buyers focus more on product selection, rather than excessively pursuing a large fan base. They select and recommend products based on their own style and their followers' preferences. Followers place orders based on their recognition of the buyer's professionalism and trust in them, aligning with Xiaohongshu's community atmosphere.

3.2. Differentiation Strategy in Buyer E-commerce

3.2.1. Professionalism and Trust Building in Buyer E-commerce

Taobao operates as a traditional shelf-based e-commerce platform, employing a "people finding goods" model. By associating search keywords with products, Taobao maximizes the matching of products with consumers, completing the conversion from live streaming promotion to consumer behavior. TikTok and Kwai as leading short-video platforms emphasize interest-based content recommendation systems. TikTok and Kwai recommend products based on user interests, thereby transforming stream into live e-commerce based on user interests [9]. In further comparison, the core of Kwai's live e-commerce lies in attracting consumers with engaging content, converting them into private fans of streamers, establishing trust with these fans, and then converting this stream into actual purchases. In this model, consumers have a high level of trust in the streamers, leading to more repeat purchases. TikTok, on the other hand, uses content algorithms to profile users and accurately guide them to products that align with their interests. This method is more precise due to TikTok's advanced algorithms, which better match suitable products based on user interests. Xiaohongshu's buyer e-commerce model resembles Kwai's "trust-based e-commerce" but with differences. Xiaohongshu's buyers attract users and build private fan streams through high-quality product endorsement notes, based on users' trust in the buyers' expertise and credibility in specific fields. This trust relationship helps to foster higher repeat purchase rates and stable stream conversions.

3.2.2. Content Quality and Product Selection Strategy

Buyers on Xiaohongshu maintain a high level of consistency between their content quality, product selection, and their branding and expertise within specific tags and content domains. These buyers

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produce high-quality product endorsement notes focused on specific areas such as fashion, beauty, or home decor, ensuring that the quality and taste of the products align with the expectations of their followers. This consistency and professionalism increase consumer willingness to purchase and trust. In contrast, streamers on platforms like Taobao, TikTok, and Kwai often resemble professional salespersons who attract followers primarily through offering discounts and promotions during live broadcasts. Their product range is broad, and they often stream frequently, but they typically require a large following to succeed. As a result, the content they post on short video platforms may not always align with the products they promote during live streams.

3.2.3. User Stream Dispersion

The live streams on platforms like Taobao, TikTok, and Kwai often focus on attracting traffic through discounted offers. Therefore, live rooms that provide better discounts tend to attract more traffic. Brands also prefer to offer more discounts to streamers with larger fan bases. Unlike Taobao, TikTok, and Kwai, the buyer e-commerce model on Xiaohongshu naturally gathers user traffic around different professional buyers in various domains. This dispersion not only maintains traffic stability but also meets users' demands for diverse products and content. Based on trust in the buyers, this traffic is effectively converted into Gross Merchandise Volume. Analysis of consumer profiles and price acceptance indicates that among active users on Xiaohongshu, nearly 80% are women, primarily young women from first and second-tier cities. The overall consumption level of platform users is relatively high, and they also exhibit a relatively high acceptance of product prices.

4. Competitiveness Analysis

4.1. Community Ecology and User Base

As a social e-commerce platform, Xiaohongshu achieved a milestone of 300 million monthly active users in 2023. While TikTok reached this milestone as early as 2018, Xiaohongshu's unique platform style and community atmosphere provide significant advantages for buyer e-commerce. On Xiaohongshu, 90% of the content is user-generated content, and 70% of the posts include products, such as sharing purchasing experiences or reviews after using products for some time. Therefore, users on the platform are highly receptive to topics related to shopping and consumption. This user characteristic brings considerable commercial value to brands.

4.2. Buyer Resources and Content Quality

On Xiaohongshu platform, a group of outstanding buyers with strong sales capabilities has emerged, covering various fields such as fashion, beauty, home decor, food, and baby care. Among these top-tier star buyers are figures like Dong Jie and Zhang Xiaohui, achieving single-event Gross Merchandise Volume exceeding 100 million yuan, demonstrating their significant influence in the buyer e-commerce domain. Additionally, the platform boasts numerous buyers with tens of millions and millions of followers, spanning different domains and fan bases, providing users with rich shopping choices and experiences. These buyers establish distinct styles and personalities by setting clear niche tags such as "elegant and refined", "French chic", "Korean fashion", and others, creating differentiated styles. This diversity not only attracts different types of users but also enhances the quality and appeal of the content. Buyers share high-quality shopping experiences, product reviews, and styling recommendations, offering users diverse and personalized shopping references, thus strengthening user trust and loyalty to the platform.

4.3. Social Shopping Experience

Red emphasizes a social shopping experience where users can interact with buyers, ask questions, leave comments, and make purchases similar to platforms like TikTok. Additionally, users benefit from a stronger post-purchase experience. After making a purchase, users can share their experiences under "endorsement notes" or post notes detailing their purchase experiences. Xiaohongshu's unique recommendation algorithm disperses traffic, allowing users to often receive feedback. This interactive and social shopping experience makes it easier for users to engage and make purchases, ultimately enhancing the platform's transaction conversion rate and user loyalty.

4.4. Personalized Recommendation System

One of the major characteristics of Xiaohongshu is its unique information flow content presentation method, combined with a powerful recommendation system that achieves decentralized distribution, diverse interests, and breaking through user circles. A significant difference between Xiaohongshu and platforms like TikTok lies in their content distribution models. TikTok adopts a "centralized" traffic distribution model, whereas Xiaohongshu adopts a "decentralized" model, resulting in a lower proportion of top-rated content recommendations on Xiaohongshu [10]. In terms of creators, they desire quick exposure for their posts. Therefore, Xiaohongshu has optimized its recommendation algorithm to understand within minutes which audience should see these posts, how their quality ranks, and in what category they belong. This allows the system to quickly distribute new posts to the appropriate users and gather positive feedback in a shorter time frame, thereby encouraging the authors of these posts.

4.5. Industry Development Trends

The development of live-streaming e-commerce has transitioned from rapid growth to a phase of differentiated development, with platforms like TikTok, Taobao, and Kwai dominating the landscape. Xiaohongshu, leveraging its inherent content seeding genes and high user stickiness, has achieved differentiation in the field through the "buyer e-commerce" model. By attracting vertical fans through personalized tags, Xiaohongshu has established a highly trusted shopping experience. The collaboration between buyers and brands helps brands accurately target potential consumer groups, increase brand visibility, and promote growth in brand sales performance. In this model, Xiaohongshu injects new vitality and opportunities into the e-commerce industry, poised to further drive the development and prosperity of e-commerce businesses and bring about more innovation and possibilities for the industry.

5. Buyer E-commerce Feasibility Analysis and Recommendations

In the 2021 Spring Festival period, the live sales volume was only 190 million yuan, with the highest daily sales volume being less than 300 million yuan. However, by March 2023, Dong Jie's single live broadcast GMV exceeded 30 million yuan, with ballet shoes and cardigans priced at 5,000 yuan selling out completely. Users jokingly commented that "you can't leave Dong Jie's live broadcast without spending five figures" [11]. By the prelude to the 2023 Double Eleven, Dong Jie's single broadcast GMV reached 130 million yuan, and Zhang Xiaohui's single broadcast GMV also successfully exceeded 100 million yuan. There were also 21 buy influencers with sales exceeding tens of millions. Such achievements are closely related to Xiaohongshu's full-scale deployment of "buying agent e-commerce." In March 2023, after discovering Dong Jie's performance, Xiaohongshu decided to use Dong Jie as a benchmark and restart the influencer note-led sales to accelerate the creation of a commercial closed-loop within the platform. The organizational structure underwent two major reorganizations. In March 2023, the e-commerce department, as a secondary department, spun off its live streaming business to become a parallel secondary department responsible for live content and live-streaming e-commerce. By mid-year, the live streaming business and e-commerce business were moved out of the community department entirely and established as a new primary department called the Transaction Department, while other community business responsibilities remained with the Community Department. From this, it can be seen that Xiaohongshu is exploring the integration of community traffic resources and commercialization. Whether e-commerce business is an independent primary department or under the community department, it represents the platform's understanding and experimentation with native commercial systems. By August 2023, Xiaohongshu formally proposed a core e-commerce model centered around "buyers," reconstructing the platform's own e-commerce development focus.

5.1. Market Demand and Trend Analysis

Live e-commerce has evolved to a point where the sales model has become increasingly monotonous, and negative issues with top streamers are frequently exposed. Tax evasion scandals, such as Li Jiaqi and Viya, appearing frequently on hot searches. The trend of price competition in live streaming rooms has also deepened into intense "internal competition." In the first half of 2023, Xiaohongshu started gaining attention for its live broadcasts. Dong Jie's unique style, distinct from traditional hard-selling broadcasts, began to show results, prompting a reassessment of the current state of live e-commerce.

In the past, live streaming for sales mostly met consumers' immediate needs, with e-commerce platforms trading low prices for transaction volume. However, users still have a demand for higher-quality products. While there may not be much difference in the selection and pricing processes between Xiaohongshu's live streams and other platforms, and sometimes the prices are not lower than those on Taobao or TikTok, the main difference lies in the style of the streamer. Users and streamers alike have become tired of traditional live streaming formats. Moreover, brands need low-cost conversion channels. Xiaohongshu happens to meet the growth needs of some brands, with its unique "grass planting" gene and low investment becoming reasons for brands to choose it. In the past, there have been cases of Perfect Diary being promoted through planting, and now many designer brands are entering live streaming rooms. In May 2023, Grado began self-broadcasting on Xiaohongshu. By September, Xiaohongshu's channel sales accounted for 40% of Grado's online retail channels. In the future, more brands are expected to follow suit, with promising prospects.

The key to the success of Xiaohongshu's live streaming lies in the unique style of the streamers. It is recommended to continue cultivating and promoting streamers with personality and professionalism. By training and selecting, attract more high-quality streamers who fit the Xiaohongshu’s atmosphere and user demands, making live content more attractive and impactful. Secondly, strengthen cooperation with brands, matching them with suitable buyers based on brand characteristics and tonality, providing customized marketing solutions and services, understanding brand needs deeply, and promoting products with guaranteed quality. Additionally, by establishing a complete live streaming ecosystem, strengthen content review mechanisms and user feedback channels to ensure the quality and compliance of live broadcasts and guarantee user experience.

5.2. Buyer Resources and Operational Cost Analysis

As of April 2024, Xiaohongshu has cultivated a group of outstanding buyers with strong sales capabilities in fashion, beauty, home, and other fields. For instance, during the 2023 Double 11 pre-sale period, top buyers Dong Jie and Zhang Xiaohui each achieved a single-session Gross Merchandise Volume exceeding 100 million RMB, demonstrating the significant influence of buyers on the platform. Additionally, there are 21 buyers with tens of millions in GMV and 19 buyers with millions in GMV, achieving substantial sales in a short time frame. Particularly notable are the mid-tier buyers, who may have fewer followers but exhibit exceptional sales capabilities, bringing considerable commercial value to the platform. For example, home buyer ALLEN GY and fashion buyer Da Fei Da Fei have follower counts of only 80,000 and 70,000 respectively, yet achieved single-session live streaming GMVs of 17.81 million and 17 million RMB.

Red can further strengthen buyer recruitment and training to cultivate more influential and professional buyers. The platform should also focus on controlling buyer operational costs, providing more operational support and resources to help buyers maximize their sales capabilities. By efficiently utilizing buyer resources and controlling operational costs within the buyer e-commerce model, Xiaohongshu is poised to enhance its commercial value and development potential, aiding the platform in maintaining a leading position in the fiercely competitive market.

5.3. Brand Collaboration Analysis

The buyer e-commerce model has brought significant business opportunities and growth space for brand merchants. Through cooperation with buyers, brands can accurately target their desired audience that aligns with their brand characteristics, rapidly expanding brand awareness and influence. Some emerging and small to medium-sized brands have been incubated on the Xiaohongshu platform, achieving rapid brand growth through the buyer e-commerce model. According to data from the "rise100 Xiaohongshu E-commerce Digest," during the 2023 Double Eleven period, the number of Xiaohongshu e-commerce orders was 3.8 times that of the same period in 2022, with a number of transaction fields seeing a group of stores growing more than 10 times. For example, the original designer furniture brand Grado achieved nearly tens of millions in GMV during Double Eleven through cooperation with buyers. The overseas niche brand MY.ORGANICS achieved 10 million RMB in GMV through cooperation with Zhang Xiaohui. These cases demonstrate the significant effectiveness of the buyer e-commerce model in brand promotion and sales growth. The buyer e-commerce model fully leverages Xiaohongshu's grass-roots genes and high user stickiness advantages to achieve differentiated breakthroughs. Unlike traditional influencer-led sales models focused on traffic, Xiaohongshu's buyers each have specific labels that attract highly vertical fans, with fan demands prioritized and conversion effectiveness dependent on fans' trust in the buyers' professionalism.

5.4. Competitor Analysis

Compared to platforms like TikTok, Xiaohongshu gathers 70% female users, mainly concentrated in first and second-tier cities, possessing higher purchasing power, making it ideal for product endorsements. Although platforms like TikTok have broad coverage, there is a clear trend of user diversification, resulting in lower commercial value compared to Xiaohongshu, with average fan value not as high. Despite platforms like TikTok and Kwai having a massive user base, reaching 500-600 million Daily Active Users, they are fundamentally entertainment platforms. In contrast, Xiaohongshu's user scenario is more inclined towards searching for practical insights, ideal products, and lifestyles. Users here exhibit strong purchasing power and decision-making demands.

On Xiaohongshu, especially regarding product endorsements, content creation directly influences user purchasing decisions because user behavior on Xiaohongshu leans towards rational decision-making, following comprehensive research and comparisons before making purchases. Once a product is endorsed, it can lead to long-tail repurchases and spontaneous sharing, forming more enduring brand influence. In comparison, while TikTok can rapidly attract a large user base, due to its broad and generalized user demographic, cost-effectiveness of sales becomes more crucial, with relatively lower user retention rates. Brands aiming for scale may opt for extensive exposure and rapid growth on platforms like TikTok, whereas those seeking brand premiums and sustained influence are more suitable for marketing on high-quality platforms like Xiaohongshu, leveraging endorsements and precise marketing for greater commercial value.

In Xiaohongshu, product endorsements hold significant importance, suggesting the establishment of a more comprehensive endorsement ecosystem. Supporting users in generating more authentic and effective product endorsements and experience sharing, alongside collaborating with brands to launch targeted endorsement activities, enhances user trust and engagement with endorsement content. Continuously strengthening platform user experience design and community management is vital to ensuring content quality, user interaction, increased retention rates, and loyalty. Furthermore, considering Xiaohongshu users' preference for practical insights and products, reinforcing the platform's search functionality and endorsement experiences is essential. This ensures users can easily discover content and products of interest, enhancing search result accuracy and personalized recommendations, thereby optimizing user experience.

6. Conclusion

The development of live e-commerce has transitioned from a phase of rapid growth to one of differentiation. Platforms like TikTok, Taobao, and Kwai dominate the landscape of live e-commerce. Xiaohongshu has differentiated itself by leveraging its inherent characteristics of product endorsements and high user engagement to implement a "buyer e-commerce" model. By using personalized labels to attract niche fans, Xiaohongshu has established a highly trusted shopping experience. Collaboration between buyers and brands helps brands accurately target potential consumer groups, amplify brand awareness, and boost sales performance. In this mode, Xiaohongshu injects new vitality and opportunities into the e-commerce industry, poised to further drive the development and prosperity of e-commerce, bringing more innovation and development possibilities to the industry.

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A Study of the Capital Structure Characteristics Across Diverse Industries

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Abstract: The matter of how a company's capital is structured is frequently discussed in literature related to this topic since 1950s. Nevertheless, theories on optimal capital structure are categorized into different approaches, with their features often controversial and conflicting. The aim of this article is to provide a comprehensive review of the characteristics as well as determinants of the capital structure in capital-intensive, labor-intensive, and tech & healthcare industries in different countries, based on two main theories in capital structure-pecking order theory and static trade-off theory. The paper also highlights the important relationship between financial leverage and the company's performance and therefore tries to find the optimal capital structure. The study is composed of two main sections. The first part is to organize the previous study and various definitions of capital structure and some relevant theories. The second part shows how features of the leverage ratio vary across industries and how companies create value out of it. This paper proposes, after examining previous literature, that the factors influencing the optimal capital structure vary among companies depending on their characteristics. Companies in various sectors have their preferences to make the most use of debt and equity. It is hard to generalize a specific optimal ratio that suits every corporation.

Keywords: Capital Structure, Financial Performance, Diverse Industries.

1. Introduction

The majority of companies gather capital from two sources, which are internal financing and external one. As firms grow and they tend to need more funds to expand, that means the internal funds are insufficient to support the growth. Businesses must use external investment including debt and equity. The decision between debt and equity, known as the capital structure choice, and its impact on value generation, has been a prominent subject in finance ever since Modigliani and Miller introduced the concept of irrelevance [1]. Over the years, various theories such as the Pecking Order Theory and Trade-off Theory have emerged to elucidate a firm's capital structure. Even in today's highly dynamic and competitive market, decisions regarding capital structure remain critical for every company. Naturally, identifying optimal capital structure stands as a crucial responsibility for financial managers. Indeed, the quest for the most advantageous financial leverage has been central to capital structure theory. According to Myers' research, The Pecking Order Theory posits that companies will opt for borrowing rather than issuing equity when internal cash flow falls short of covering capital expenditures [2]. This means the company should always rely on debt to fill the gap. On the contrary,

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The Trade-off Theory appeals to reasonable debt levels by suggesting that companies will borrow until the point where the marginal tax benefits from debt are balanced by the financial distress costs. These two series both make sense but cannot be applicable to all scenarios. Meanwhile, based on the study, it suggests that even if there were a specific debt target to aim for, institutional and economic factors would present significant barriers to achieving the optimal ratio [3]. Likewise, the structural differences in various industries also matter. The study proves that discrepancies across segments exists and these rest with the company's asset structure, profitability, size, age etc. [4].

Although there are much research on the capital structure determinants on a particular firm or industry and on how they would impact firm's overall performances, there is a lack of comparative study that focus on summarizing the characteristic and determinants of financial leverage from all industry and then distinguish one another.

This paper will divide the economy into three segments, which are capital-intensive, labor-intensive and tech & healthcare sectors respectively, and review the findings targeting at multiple businesses, countries and regions, to get draw a comprehensive conclusion of capital structure in a particular industry.

2. Capital-Intensive Industries

The capital-intensive sector contains companies that need a large amount of capital to produce goods or services. It often includes automobile manufacturing, oil production and refining, steel production, telecommunications, and those who rely heavily on the funds to run their business. Therefore, the source and the amount of the fund play a crucial role in such an entity because the choice would finally impact the tax and net income. Constructing a reasonable capital structure could facilitate production and improve competitive advantages. In this part, the paper will analyze Japanese manufacturing companies, the Indian automobile industry, Indian property and real estate companies, and the U.S. hospitality industry respectively, to derive a comprehensive leverage pattern on such a sector.

Japan, as one of the most developed countries, has always been on the top list of research compared to other countries. Meanwhile, the importance of the Japanese manufacturing industry to the domestic and international economies is considerable. Thus, this study chooses Japanese manufacturing firms as an object. According to the Cortez & Susanto's research, it picks a sample of 21 Japanese manufacturing companies that are at the top list of the Tokyo Stock Exchange [5]. Meanwhile, the study hypothesizes five factors that may positively or negatively affect the enterprise's capital structure, which are asset tangibility, profitability, non-debt tax shield, company size, and growth rate. Besides, the research applies the quantitative approach by using the correlation coefficient model and panel data regression and tests the relationship between potential variables and the capital structure from the period 20000 to 2010. Moreover, in order to detect the effect of the effect of the 2008 economic recession, the regression is designed across two-time patterns, which are before the economic recession; namely between 2000 and 2007, and after the economic recession. The result shows that the amount of tangible assets is positively correlated with the leverage, which means a company is more likely to obtain debt when they have higher tangible assets. Whereas, the profitability and non-debt tax shield are negatively related to the leverage, representing that a highly profitable company with high depreciation expenses has less incentive to borrow from debt. Other variables indicate insignificant results. The experiment is in favor of both the pecking order and trade-off theory.

India, as one of the biggest emerging economies, plays a more and more pivotal role in the world's economy. The most momentous industry that drives the domestic economy is the automobile industry, with the highest contribution of 35% in GDP [6]. Thus, the paper puts emphasis on it and solves how the capital structure affects this industry.

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Based on the study by Tripathi, he selected a sample of 44 automobile companies listed on the Bombay Stock Exchange from 2001 to 2014, after excluding firms with missing values [7]. The research aims to explore the relationship between capital structure and ownership structure and finds a positive correlation between promoter shareholding (founders or controlling shareholders) and debt-equity ratio by controlling variables including asset turnover ratio, company size, and selling expense as a percentage of sales revenue using the panel regression model. The finding indicates that underscores the practice of using debt to reduce agency expenses within automobile companies. The study also reveals that asset turnover ratio and company size have a significantly adverse relationship with financial leverage, contending that adequately using the asset could increase profitability by reducing the need for debt. Meanwhile, such a result corresponds to the pecking order theory, showing companies' preference for debt due to the tax shield benefit and increase in profitability by showing positive expectation on the future cash flow.

Indonesia is one of the most populated countries, ranked fourth after the United States. Apparently, there is a huge demand for housing and the property sector is very competitive in this developing economy.

The research opted for property and real estate companies listed on the Indonesia Stock Exchange from 2013 to 2018 as the experiment sample [8]. The author wants to test the capital structure determinants in terms of the company's performance, risk, and size by postulating different performance matrices to measure it. Through coefficient regression test on the profitability ratios, the profitability and non-debt tax shield are significant to capital structure instead of growth rate and liquidity. Regarding the risk ratio, the collateral value of the asset has a positive relationship with capital structure. Besides, the size of a firm doesn't impact the leverage. The property company is reluctant to issue bonds when the company is in expansion. Meanwhile, the study also shows that a company with enormous fixed asset and non-debt tax shield depends more on debt financing, which is aligned with the pecking order theory.

Lastly, the paper focuses on the United States' hospitality industry. It is one of the most profitable industries that holds an extensive amount of land and equipment. It includes a series of spots including hotels, amusement parks etc.

Referring to the García-Gómez's research, the writer concluded that there is a negative relationship between leverage and a company's performance, typically for ROA and Tobin's Q, by conducting a Generalized Method of Moments analysis [9]. This study utilizes a sample of 313 hospitality companies based in the United States spanning eighteen years from 2001 to 2018. By controlling other factors that may influence capital structure like growth and sales, it's observed a noteworthy inverted U-shaped correlation between leverage and firm performance. For Return on Assets (ROA), the critical point is 0.150, while for Tobin's Q, it is 0.163, which indicates that leverage levels below 15% have a positive impact on ROA, whereas levels above 15% lower ROA (the same logic applies to Tobin's Q). The result coincides with the pecking order theory and implies that hospitality companies with high leverage ratios must find an alternative tactic to obtain external funds so that it would not harm the company's performance.

3. Labor-Intensive Industries

The labor-intensive industry is featured in a huge spending in labor rather than the capital. Companies in this sector usually own little fix-asset like equipment, but hold a huge amount of intangible asset that cannot be present on the balance sheet, like human capital because most jobs in this field are done by hand and cannot replaced by machines. Typical examples are agriculture, construction and some mining companies. Unlike asset, companies don't really possess labors. Workers can choose to quit a job if they want, but simultaneously they undergo unemployment risk. The labor market is dynamic, therefore factors that influence capital structure in such sectors are not only firm specific and macroeconomic, but more than that. In this part, the paper will talk about both in a boarder perspective, namely the whole economy and labor-intensive firms cases in Visegrad countries.

Generally speaking, Matsa did research on the relationship between workforce and capital structure among U.S firms and the result from regression model shows that lay-off rate, worker's bargaining power (indicated by worker union coverage), labor market regulation and retirement risk are significant to capital structure [10]. Lay-offs are directly connected to unemployment cost because firms have to cut jobs so that they can meet the budget during an economic downturn. Meanwhile, workers remained in position could sense the risk of unemployment and would ask for a higher wage to compensate the risk. The companies are forced to subtract leverage for lower cost needed to compensate for bankruptcy and unemployment risk. Besides, worker union coverage is positively related to leverage since firms with a strong union have higher bargaining power and therefore could improve the supply of debt and have proxy to make major decisions in a company. The labor market regulation is much more concise. With employment protection act, minimum wages and downward wage rigidity, firms are less likely to contract debts when the protection level increases. Furthermore, Pension plan is prevalent in most developed countries. As one of the financial strategies for companies, companies should pre-reserve the pension for the beneficiaries, which could be seen as a debt borrowed from the retiree. Thus, the firms must lower their debt ratio to reduce the risk of failure to pay back.

Visegard countries includes the Czech Republic, Hungary, Poland and Slovakia and occupy about 10% of EU's territory and devote to 6% of GDP [11]. Meanwhile, agriculture in this four country is a core industry in these country and therefore, analyzing the capital structure in this country could contribute to the growth of the whole Europe.

Based on the study of Fenyves et al., the authors employ panel regression model utilizing panel data from 2015 to 2017 to testify the influence of company cap, fixed asset ratio, ROA, and sales growth on the leverage ratio [12]. The findings display that company size and profitability are positively correlated with leverage ratio, indicating that larger profitable companies have easier access to external financing source, which follows pecking order theory. On the contrary, the companies' growth rate have a positive relationship with capital structure. This proves that fast-growing companies rely much on bond issuing as a source of fund.

4. Technology & Healthcare Industries

The technology and healthcare industry is a relatively emerging and burgeoning sector. It usually involves pharmaceutical, biotech, and technology companies. Unlike capital-intensive firms, tech companies do not need a huge amount of funds to finance fixed assets. Likewise, labor-intensive businesses usually require too little capital to operate, compared to tech companies. The tech industry often has a high expenditure on Research and Development account, which directly affects a company's efficiency and performance [13]. Therefore, this paper will clarify the capital structure features of such a sector and how exactly it changes enterprise performance. This part contains public Vietnamese pharmaceutical, Polish technology, and United States tech companies.

Vietnam is a rapidly growing developing country. The World Bank recorded a rise of 150.1% of GDP, from 77.41 in 2007 to 193.6 billion USD in 2015 [14]. Moreover, the Vietnamese government has drawn a greater concentration on domestic pharmaceutical companies, which makes it particular and representative.

The scholars tried to discover the relationship between capital structure and ROE (a typical performance indicator) from 30 pharmaceutical companies listed on the Vietnam Stock Market between 2015 and 2019 [15]. Hypotheses are made to test the influence of capital structure indicators, including leverage, long-term assets ratio, debt-to-asset ratio, and self-financing ratio, employing an Ordinary Least Square Regression model and the outcomes display that all ratios are correlated with

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enterprise performance. This means by appropriate asset apportion and bond issue, pharmaceutical enterprises can achieve an optimal ROE that boosts the whole businesses.

Poland has been listed as one of the most advanced countries since 2018, but the country still possesses some features that only appear in emerging economy, and it has one of the lowest R&D spending among EU countries. Thus, Poland is a unique case and worth talking about.

According to 31 Polish tech companies listed on the Warsaw Stock Exchange, the researchers found the potential factors that alter the firms' leverage ratio via regression analysis [16]. Empirical findings verified that internal and external investments, liquidity, and company age are significant to indebtedness in tech firms when profitability and growth opportunities are retained fixed. As internal investments increase, the leverage is prone to decrease in New Technology-Based Firms (NTBFs), whereas external investments in innovation have a positive impact on debt levels. These outcomes are likely due to greater information asymmetry and risk that may drive outsiders away from lending. The study also demonstrates an adverse correlation between a firm's liquidity and debt issuing, showing that a firm with excessive cash flow prefers to use its funds before debt financing. The age of the firm is proven to be a significant factor: NTBFs with a longer history have higher leverage. These two determinants are justified by the trade-off theory, in which companies are able to deduct bankruptcy risk. Apart from these, the result denies the effect of intangible assets and capitalization on the leverage.

The U.S. tech industry plays a dominant role in the world. There are a lot of world-famous companies like Apple, and Microsoft, and most people use their products enjoy their services. Also, according to Yahoo Finance, information technology companies monopolize the top 5 companies in market capitalization. Therefore, it's quite important to know how capital structure of this firm is characterized and affected.

The researchers constructed panel data and linear regression to analyze the determinants of capital structure on a sample of 51 tech companies listed on the New York Stock Exchange from 2005 to 2018 [17]. The variables for companies such as size, profitability, growth and inflation and macroeconomic factors like inflation and interest rate, are put into the experiment. The result manifests that debt ratio is adversely related to the size, liquidity, effective tax rate, financial return (ROE), inflation, GDP. The result from effective tax rate is debatable because theoretically, companies would prefer contracting debts when the tax rate is high so that they can benefit more from tax shield, however, the author reasoned that such outcome could due to a declining tax rate within firms holding long-term debt. The study also talks about the impact of corporate governance on the leverage, but this review paper would not consider that way due to difficulty to quantify the governance. The yield finally comes to pecking order theory on a whole, showing a favor to internal funds before external.

5. Conclusion

The paper aims to solve the problem of (i) What is the determinant of capital structure in different industries, (ii) How does capital structure differ across industries and (iii) Whether the result reflect pecking order theory or static trade-off theory. In order to solve these problems, the author gathers plenty of research on the internet and provide a comprehensive insight of the answer.

Not surprisingly, the factors that affect the indebtedness vary across industries and across regions. The differences not only lie in the type of determinants, but also in the relationship for the same factors. For capital-intensive industry, tangible asset, profitability, non-debt tax shield, promoter shareholding, asset turnover ratio, company size, firm size and collateral value of the asset can influence a company's capital structure, but they cannot be applied to all capital-intensive firms (At least no proof is made on such relationship). Moreover, the result can be opposite or inconsistent even in the same industry. For example, in Japanese manufacturing firms, non-debt tax shield is positively

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correlated with leverage. While the analysis on the property and real estate companies in Indonesia lead to a positive relationship between these two variables. In terms of labor-intensive industry, unlike asset, labors are more flexible and autonomous, and this means a much more diversified impacting factors. This paper separates the factor into two categories. One is on the basis of macroeconomy, which is made up of lay-off rate, worker's bargaining power, legal protection, and retirement issue, and another is based on corporate level indicated by the V-4 agricultural sector. This comprises company cap, fixed asset ratio, performance, and sales growth. For the tech & healthcare segment, the determinants of capital structure resemble to the combination of above two sectors, including ROE, liquidity, company age, fund source, company size, inflation, tax rate, GDP.

The outcomes for all cases partially explain the pecking order theory or the static trade-off theory, and might be a mix of them, however, they can neither be fully justified. Meanwhile, the finding also implies that the financial leverage determinant is firm-specific and country-specific. Therefore, it is not likely to generalize the factors and get an optical capital structure for the whole economy, even for the companies in the same industry and same country.

In-depth study of the specific firms needs to be done so that the outcome could help firms form more accurate strategies to pull through financial friction and develop competitive advantages.

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A Study of the Relationship Between Capital Structure and Corporate Performance

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Abstract: This study examines the impact of capital structure on the corporate performance. The findings on different industries like capital-intensive, labor-intensive, and technology and healthcare indicate that low leverage companies operate with greater capital flexibility and with reduced financial risk, but their ability to grow and expand will be constrained by a lack of sufficient funding. Highly leveraged businesses use money more efficiently, but they also carry a larger financial risk. The capital structures of the technological and medical sectors change at different phases. Typically, this innovative industry's substantial capital investment carries a considerable danger of financial strain in addition to the possibility for large reward. For different markets, developed countries' capital structures and impact are like those of low-leverage businesses, whereas developing countries' capital structures and impact are like those of highly leveraged sectors. Furthermore, it examines China and Vietnam among developing countries, considering their distinct features within the same market. China and emerging nations have comparable traits, but Vietnam depends more on retained earnings for development like developed countries, which reduces financial strain and risk but has an impact on the growth and development of businesses.

Keywords: Capital Structure, Firm Performance, Different Industries, Different Markets.

1. Introduction

In contemporary economy, the corporate sector plays a crucial role in particularly important role in economic growth through increased investment and transactions, innovative technology, and job creation. Thus, ensuring business performance is the key to economic growth. The corporate performance of is affected by its capital structure, which is an important variable, that is, the way in which its assets are financed by some combination of equity, debt, and mixed securities [1]. However, selecting an adequate capital structure to help the business achieve the intended performance is a challenging task, since the business must also determine if the capital can be used efficiently and identify the right source of funding. Due to insufficient capital structure, an excessive number of enterprises experience losses or bankruptcy. For instance, financial scandals and a highly leveraged capital structure caused the German industrial giant Siemens to incur large losses. This ultimately resulted in the arrest of some senior officials at the time, and the business was put under a great deal of financial and legal pressure. Whereas, a lot of businesses, like Amazon, have prospered with highly leveraged capital structures. Their combination of a highly leveraged capital structure and business strategy has allowed them to sustain steady, long-term growth in a fiercely competitive industry. In

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addition, there are also many companies with little or no equity financing, which can be understood as low-leverage companies, and have achieved considerable success, such as Huawei, which is a private company and its equity is mainly held by its founders and employees, rather than a publicly traded company. Although Huawei supported its development through a small amount of venture capital in the early days of its establishment, it did not undertake large-scale equity financing, but supported its business development through its own funds and sustained profits. This indicates that capital structure is like a puzzle, which is such complicated that different industries in which the company is located must be taken into consideration when analyzing the effect of capital structure on the performance of the enterprise [2]. It might be a labor-intensive sector with low leverage, a capital-intensive sector with high leverage, or the technology and healthcare sector through innovation to grow. Moreover, consideration should be given to various markets. Businesses that are situated in various countries may be found in developed countries that tend to be capital-intensive or in developing countries that are more likely to be debt intensive.

In summary, the capital structure of a corporate has an impact on its performance. But capital structure is a complicated variable that varies among industries and markets. This study specifically addresses this issue.

2. Capital Structure in Different Industries

2.1. Capital-Intensive Industries

As a capital-intensive industry, real estate industry is one of the most representative industries. Firstly, companies with high levels of leverage are more dependent on debt to fund their assets and activities, which puts them at more risk financially. Because businesses need greater returns and performance to offset the risks, managing these risks is essential to their success. According to Sarajoti and Sahin's analysis of leveraged portfolio performance, highest leveraged portfolio did not make up for the risks that investors assumed [3]. Hence, capital structure management and balancing the leverage-based portfolios are essential to corporate performance. A suitable debt ratio may lower financial risks and boost corporate performance. According to Ioana's paper, less than 66% is the ideal range for the total debt ratio [4]. The likelihood of bankruptcy and the company's financial autonomy are inversely correlated with the ratio. Secondly, the corporate performance in high leveraged industry is sensitive to market fluctuations, including macroeconomic factors, policies and regulations, market supply and demand. The operations and profitability of businesses can be significantly impacted by this uncertainty and volatility, particularly highly indebted businesses that must respond to market fluctuations with more caution. For example, according to Sarajoti & Sahin's study, highly leveraged real estate corporations would be disproportionately affected by the financial crisis-induced tightening of credit markets, which might result in financial difficulty or even insolvency [3]. Real estate industries are finding it more expensive to refinance or roll over their debt. During the crisis, investor attitude changed, leading to increased risk aversion and skepticism about highly leveraged investment vehicles. It may lead to financial difficulties and a decline in performance.

Furthermore, manufacturing industry is another one representative high leveraged industry. Corporate performance and the manufacturing industry's highly leveraged financial structure are strongly and positive associated. According to Stoiljković et al.'s paper, leverage functions as a disciplinary mechanism in minimizing the agency costs of outside equity, shareholders work in the owners' best interests to gain returns beyond the needed amount [5]. The existence of debt in the capital structure can serve as an incentive for management. Additionally, leverage function is reflected in capital investment efficiency, highly leveraged businesses typically rely more on outside funding for investment and expansion. More production capacity and market share can result in increased sales and profit margins for these businesses. When it comes to market competitiveness,

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borrowing to finance growth may help businesses introduce new goods and enter new markets more quickly. This can boost business competitiveness and ultimately lead to improved corporate performance. However, Stoiljković et al. constructed a nonlinear model specification and discovered that, at high leverage levels, the link between capital structure and company efficiency is non-monotonic, or it can turn negative [5]. Since businesses with high levels of leverage are subject to increased financial risk and interest costs. Their solvency may be impacted by market swings or economic recessions, which will have a detrimental effect on performance.

The correlation between high leverage and corporate performance is non-monotonic, which can be attributed to factors such as return on investment efficiency, debt risk, and market volatility. For highly leveraged companies, how to manage risks and control leverage ratio is the key to ensuring corporate performance.

2.2. Labor-Intensive Industries

In different industries, there are also low-leverage industries in addition to high-leverage industries. As a representative of the low leverage industry is the retail industry. As a low-leverage industry, retail industry's positive impact on corporate performance is usually reflected in financial stability. Low-leverage retail businesses often have lower debt levels, which might make them more resilient during unstable economic times. The ongoing operations and expansion of the business are facilitated by this type of financial stability, and the business's performance benefits from this as well. Csamspees, Gonzalez, and Molina have noted that since corporations raise equity funds without paying interest on those funds, a substantial portion of the equity in funds raised by the organization helps save money on interest payments [6]. Furthermore, low-risk external funding or debt financing is necessary to support the organization's financial health because equity stockholders are the company's owners and are exempt from repaying the cash. The flexibility of finances is another indicator of the low-leverage retail industry's beneficial performance on businesses. Retail businesses with low leverage typically have larger cash reserves and may find it simpler to get funding. Financial flexibility of this sort may enhance company performance and help businesses adapt more effectively to changes in the market and emergency scenarios. The perspective of Eshna’s paper, who underlined that paying dividends would result in a drop in retained earnings, which would impact liquidity [7]. Low-leverage sectors are more financially stable because they often have stronger credit records, require less capital to pay interest and principal on loans, and experience less financial stress. They are therefore more likely to receive favorable lending conditions. However, the retail industry, being low leverage, also has some detrimental implications on business performance, which are evident in investment limitations. Low leverage could make it more difficult for businesses to expand and make significant investments. Businesses may not be able to take full advantage of market possibilities owing to inadequate financial backing, which has an impact on the expansion and development of businesses. According to Muhammed Jadheer, the lack of activities and control between low-leverage enterprises and organizations leads to more opportunities and performance decline [6]. On the other hand, Karmazin and Bondar’s research also believed that when the market interest rate is low, the cost of equity is higher than that of debt, which reduces the actual profits of enterprises [6]. This suggests that low-leverage businesses may find it difficult to implement the essential product innovation or scale upgrade in the fiercely competitive retail market owing to a lack of funding, which would put them at a competitive disadvantage.

Low-leverage businesses thus impact corporate performance in both good and bad ways in the retail sector. From the standpoint of cash reserves, they provide the business with stability and financial flexibility, both of which can enhance corporate performance. Regarding investment limitations, the absence of substantial funding and the capacity to grow creates a competitive disadvantage that might lower performance.

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2.3. Technology & Healthcare

The technology and healthcare sectors are worth considering in relation to several industries. In general, the medical and technological sectors are known for their expensive research and development fee. Most high-tech businesses do not have very leveraged financial structures. According to Hogan and Hutson's survey, high-tech businesses are hesitant to forgo financial rewards to accomplish these objectives [8]. It shows why using debt rather than equity and internal funding instead of external funding is preferred. High-tech businesses often don't have very leveraged capital structures, but they nevertheless need a lot of money up front to fund their research. Hogan and Hutson pointed out that high-tech companies often demand more money and have longer product lead times compared to low-tech enterprises [8]. Consequently, to finance in the early stages, the high-tech business must expand leverage. Due to its ability to address these information asymmetries, venture capital and angel financing—forms of private equity—may be the most suited source of outside funding [8]. The capital structure features of the medical business are similar to those of the science and technology sectors in that they both have high market values, require substantial funding to continue research and development, initially finance through leverage, and have relatively low total leverage in later years. The Riyandi and Riyanto's findings indicate that the average percentage and makeup of the capital structure of healthcare issuers in the healthcare industry listed by IDX between 2017 and 2019 are mostly made up of their own capital [9]. The fact that R&D and innovation are typically funded by substantial sums of money indicates the beneficial effects of the capital structure of the research, technology, and medical industries on company performance. As a result, businesses may improve their capacity for innovation and foster the creation of new goods and technologies with the support of a modest capital structure, which will increase their performance in the market and competitiveness. Furthermore, there is a lot of room for growth in the technology and medical industries today, and both sectors might grow quickly because of the advancement of technology and the growing awareness of health issues.

According to Ravšelj and Aristovnik's descriptive statistics compiled by worldwide research organizations between 2015 and 2017, the profitability of these businesses is comparatively high when measured against their present operational performance [10]. This further demonstrates how businesses in the technology and medical sectors may increase the size of their investments, better grasp market possibilities, and achieve both company and profit development with the right capital structure and prudent use of leverage. Ravšelj and Aristovnik argued that investments in R&D have an adverse effect on operational performance in the now and an advantageous effect on operating performance in the future [10]. Because not enough profit is made to offset R&D investment, R&D spending initially has a negative effect on operating performance. This demonstrates the considerable risk and unpredictability that the technology and healthcare sectors usually encounter, as well as the possibility that they won't be able to make money until a product is released onto the market. Leverage may exacerbate financial strain, making it more difficult for businesses to pay off debt and continue operating daily. Overleveraging may make a company's risks worse and put it in danger of severe financial hardship if the market shifts or the project fails.

In summary, the technology and healthcare sectors have a capital structure that is generally positive about corporate performance, and if businesses are properly funded and leverage is utilized, they have enormous expansion potential. Otherwise, excessive leverage combined with a capital structure that demands a lot of financial support would hinder business performance.

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3. Capital Structure in Different Markets

3.1. Comparison Between Developed and Developing Countries

The effect of capital structure on the performance of a corporation may also be examined in terms of distinct markets, like developed and developing nations. As developing countries are more likely to use highly leveraged financial structures, or equity financing. Zeitun and Tian stated that given the undeveloped and stagnant bond and mutual fund markets in emerging nations like Jordan and others, commercial banks are crucial to the lending process [11]. Businesses' capital structures contain a greater amount of debt because of bankruptcy cost risk. This demonstrates that, businesses prefer debt financing in developing nations due to the generally less developed capital markets, restricted listing financing channels, relatively easy access to bank loans, and generally unstable financial and economic environments in developing nations when compared to developed nations. According to Zeitun and Tian's model, there is a negative relationship between growth and leverage, and a positive relationship between risk and leverage [11]. Therefore, debt financing typically has a lower cost, which has a positive impact on the performance of developing countries. However, debt financing can also put more pressure on businesses to repay their debts, especially in the event of rising interest rates or poor performance, which could jeopardize the businesses' ability to do so and negatively impact their financial stability and performance. Furthermore, debt financing raises an organization's financial risk. Businesses may have operational issues or even insolvency if the market climate shifts or there are financial challenges. Companies in developed countries tend to have more diversified capital structures, better capital markets and financial systems, and more flexibility to choose financing methods that suit their own development. Kijkasiwat et al. argued that financial leverage is found to have a strong negative correlation with ROA when leverage is employed as an independent variable in the context of developed economies [12]. The performance of the company will decline as financial leverage rises. Developed countries typically have little trouble securing enough capital through equity financing and other channels to support R&D, corporate expansion, innovation, and other endeavors that yield a larger return on investment and boost the company's profitability and competitiveness. But in advanced economies, the cost of debt and equity financing is typically higher, particularly when there are higher risks or interest rates. Businesses may also have to pay higher financing costs, and their profitability may be impacted by power imbalances and shareholder conflicts. Strong corporate management can lessen the likelihood that a business will encounter problems in the event of a financial crisis or conflict of interest [12].

In summary, among developed and developing countries, developing countries have the advantage of low financing costs while experiencing financial pressures. Developed countries have high flexibility but also need to be careful of risks and conflicts of interest, which can have different effects on company performance.

3.2. Comparison Among Developing Countries

Moreover, China and Vietnam are two examples of typical contrasts, which have particularities on capital structures as developing countries. China's capital structure is similar as a developing nation since many Chinese businesses often have a high-leverage capital structure, or one with a comparatively high percentage of debt. Due to the comparatively late emergence of China's financial system, enterprises' access to equity financing is somewhat restricted. Based on observations of Chinese listed companies, debt financing is less expensive than equity financing, and when financial leverage increases, ROE significantly improves [13]. This is due to the possibility that larger leverage would result in more money available for expansion and investment, which will foster the growth and development of the company. Furthermore, debt financing often has lower costs than equity financing, which can minimize an enterprise's capital costs and improve business performance overall. However, China's capital structure has the same detrimental effects on corporate performance as those of most developing countries. High leverage can also raise an enterprise's financial risk, particularly in the event of economic instability or intense industry competition. A high debt load can result in reduced solvency and even an increased risk of bankruptcy. Vietnam is a developing country whose capital structure is distinguished by a comparatively low leverage ratio, and it has recently been recognized as a market with strong development potential. Businesses in Vietnam often rely on retained earnings or their own cash and may choose to use a relatively low-leverage capital structure. According to Nguyen and Nguyen’s research, there is a favorable correlation between financial leverage and total company performance for businesses that operate in developed countries [14]. Companies with large debt ratios may turn out to be inefficient businesses, especially in developing nations like Vietnam where it is difficult to control the post-loan operations of commercial banks. Vietnam is a developing nation, therefore its capital structure benefits business performance. A lower leverage ratio can minimize an organization's financial risk, ease the burden of repaying debt, and support the long-term stability and sustainability of the business. Furthermore, decreased debt levels might cut an organization's cost of capital. On the other hand, an excessive dependence on internal funds or retained earnings may impede an organization's capacity to expand and make investments, leading to a deceleration in growth. Moreover, businesses could pass up some investment opportunities when the cost of financing is lower due to the comparatively low leverage ratio.

In summary, China and Vietnam are the two developing countries with distinctive capital structures. High leverage lowers financing costs but also carries risks, as seen in China and most other developing nations. Vietnam is a developing nation that depends increasingly on retained earnings for growth, which lowers risk but restricts businesses' capacity to grow and invest.

4. Conclusion

In conclusion, capital structure may be seen from the viewpoint of different markets and industries when analyzing impact of corporate performance. For highly leveraged businesses such as the real estate and manufacturing industry, developing countries, and China, often improve corporate performance in many industries by increasing capital usage and lower financing costs, but it may increase financial stress and risk. For low-leverage firms such as the retail industry, developed countries, and Vietnam, the positive impact on corporate performance is usually lower risk and high flexibility, while the negative impact is limited capital and limited scale expansion and business growth. For technology and healthcare industry, large investments in R&D and technological innovation typically have a positive effect on corporate performance by providing the necessary financial support for the business to foster growth and innovation. On the other hand, large capital investments can have a negative impact due to the pressure and risk they entail. The impact of capital is that structure on corporate performance is a complicated decision-making process. different markets and sectors must be considered while analyzing the impact since their financial structures differ. Additionally, various firms have distinct financial demands and are at different levels of leverage in the capital structure. Examples of these areas include technology and healthcare. Therefore, the impact of these distinctive capital structure on corporate performance will vary.

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An Empirical Study on the Impact of Investor Gambling Factors on Stock Cross-Sectional Returns

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Abstract: This study explores how investors' gambling preferences affect the cross-sectional returns of stocks in China's A-share market through behavioral finance factors. The portfolio ranking method and Fama-Macbeth regression analysis show how gambling behavior affects stock returns. On this basis, a multi-factor model (CHG model) incorporating gambling factor innovation was constructed to capture market dynamics more accurately. Research shows that going long on a low gaming index stock portfolio and short on a high gaming index stock portfolio can achieve significant average monthly returns. After adjustment by the Fama-French three-factor model, the returns of this long and short portfolio are significant at the 1% level. Significantly. In the CHG model, the coefficient of the gambling index Gamble is -0.0241, and the t-statistic is -6.1858, which is significant at the 1% level, further confirming the negative impact of gambling preferences on stock returns. In addition, the CHG model's ability to explain anomalies is also better than the CH-4 model. This study provides a new perspective on understanding behavioral finance factors in the Chinese stock market, and the results highlight the importance of considering behavioral finance factors in asset pricing and investment decisions in a highly irrational market environment. Future research can further explore the performance of behavioral financial factors in different market environments, as well as the differences and similarities of behavioral factors in different markets.

Keywords: Empirical asset pricing, cross-sectional stock returns, multi-factor model, gambling behavior.

1. Introduction

Since establishing Markowitz's modern portfolio theory, classical financial theory has been widely used in actual capital markets. However, with the development of the capital market, the market efficiency assumption and the rational person assumption are no longer fully applicable to the market. Shiller, Kahneman, and others relaxed the assumptions of rationality and efficient market, drew on psychology, sociology, and behavioral theories, starting from the psychological state and actual behavior of investors, and analyzed and established models to explain anomalies. Some scholars began to explore theories such as investor sentiment, herding effect, and anchoring effect, and constructed factors based on investor behavioral characteristics and incorporated them into factor investment models for application [1].

China's A-share market fluctuates frequently, and irrational trading behavior is obvious. Investors are often driven by news and policies and are easily affected by group behavior. This has prompted Chinese scholars to enter the field of behavioral finance and improve their explanation of China's capital market. Gambling factors are gradually receiving attention as an angle to study individual investor behavior. This natural preference for risk plays an important role in financial markets. Since individual investors lack professional investment knowledge, the information they obtain often lags, causing their investment behavior to deviate from rationality, and the market price of assets to deviate from the intrinsic value, which often creates an innate speculative atmosphere and affects market stability and efficiency to a certain extent.

On the other hand, since the CAPM model was proposed, empirical asset pricing has gradually formed a complete research system. In 1993, Fama and French added two factors, HML and SMB, which represent cheap stocks and small market capitalization effects, to the market factors of the CAPM model, and proposed the famous three-factor model, which became an empirical model in the stock markets of various countries around the world [2]. The first choice for asset pricing research. Based on the Fama-French three-factor model, academic circles have successively added momentum factors, profitability factors, investment factors, management and performance factors, etc., providing huge value in explaining cross-sectional return differences in stocks. Liu et al. added the abnormal turnover factor to the market, scale, and value factors, proving anomalies that cannot be explained by the Fama-French three-factor model.

From a behavioral finance perspective, an increasing number of studies focus on the relationship between these deviations and returns. However, in this research field, there are still gaps in theoretical and empirical research on the impact of investors' gambling behavior factors on stock cross-sectional returns. Therefore, this article introduces factors about investors' gambling behavior to explore how the behavior driven by investors' gambling psychology will affect the cross-sectional returns of stocks and compares it with the Chinese version of the four-factor model proposed by Liu et [3]. The purpose is to demonstrate the explanatory power and predictive ability of the model, further illustrate the prevalence of gambling behavior in China's A-share market, and have practical guiding significance for constructing investment strategies for excess returns and improving the performance of investment portfolios.

2. Overview of Research Status

2.1. Existence of Investor Irrational Factors and Empirical Asset Pricing

Tversky proposed that people's perception of potential losses is greater than their perception of potential gains of the same size when making decisions, which is due to people's instinctive aversion to losses [3]. Shefrin and Odean discovered the disposition effect, in which individual investors tend to sell stocks whose value increases prematurely and hold on to stocks that lose money [4, 5]. Fama believes that individual investors, especially when facing market uncertainty or pressure, may show more risk-averse behavior [2]. This behavior may not be entirely based on actual changes in market fundamentals, but rather on the impact of perceived risk and other psychological factors. Wurgle proposed that investor sentiment significantly affects the cross-section of stock returns [6]. They argue that sentiment can lead to stock mispricing, particularly affecting younger, less profitable, and more volatile stocks. Wu analyzed the investment portfolio data of China's open-end funds and verified that China's open-end funds have significant herding behavior in the stock market [7].

Jegadeesh proposed the cross-sectional momentum anomaly, which was the most significant of many anomalies at the time [8]. Carhart therefore added the constructed cross-sectional momentum factor MOM to the Fama-French three-factor model and proposed the Carhart four-factor model [9]. Novy-Marx pointed out that profitability and expected return rate are closely related, and thus proposed a four-factor model including market factor, size factor, momentum factor, and profitability factor PMU [10]. Based on its three-factor model, Fama added profit and investment factors, improved the construction method of the scale factor, and proposed a new five-factor model [11]. Stambaugh-Yuan introduced management factors and performance factors based on market factors and scale factors, which was the first multi-factor model from behavioral finance [12]. Daniel et al. proposed two behavioral financial factors on both long and short-term scales, aiming to capture mispricing caused by overconfidence and limited attention [13]. Liu et al. specially designed a multi-factor model for China's A-share market. The model believes that individual investors dominate the Chinese stock market, holding 88% of the market's free-floating shares [3]. This heavy presence of individual investors makes Chinese stocks particularly vulnerable to investor sentiment. To capture this emotional effect, Liu added a fourth factor based on turnover rate to the model to evaluate changes in investor sentiment based on the overall market and the trading volume of individual stocks [3]. Research has proven that individual investor behavior and market sentiment play a very important role in the Chinese market.

2.2. Investor Gambling Behavior Literature

In 1988, Thale conducted a study on horse racing and lottery tickets and found that investors would still place bets and buy lottery tickets to obtain high returns when the expected return rate is known to be negative, that is, investors are willing to Choose to risk losing a small amount of money to obtain high returns [14]. This goes against the assumption of rational people because the expected rates of return on horse racing and lottery tickets are negative. Tverks explained investment gambling preferences based on cumulative prospect theory and confirmed a unique four-point model of risk attitude: risk aversion for high-probability gains and risk-seeking for high-probability losses; risk-seeking for low-probability gains and risk-seeking for low-probability gains. Risk aversion to low-probability losses means that investors are risk-averse on the one hand and seek risks in high-probability losses on the other [15].

Kummar conducted the first systematic empirical analysis of individual investors' gambling preferences and their preference for so-called "lottery stocks" (i.e., stocks with high potential returns but low probability, high risk, and high skewness) [16]. These stocks usually have low prices, high idiosyncratic volatility, and high idiosyncratic skewness, which is similar to the nature of buying lottery tickets in reality, that is, speculating on small gains and big gains. Kummar's research found that individual investors do tend to buy such lottery-type stocks, thus confirming the existence of significant gambling preferences in the market [16]. Furthermore, Kummar not only successfully identified lottery-type stocks by constructing a "stock betting index" that includes stock prices, idiosyncratic skewness, and characteristic volatility, but also revealed the correlation between the betting characteristics of these stocks and their returns [17]. Research shows that during bull markets, investors have stronger betting preferences for lottery stocks, further verifying the dynamic changes in betting preferences under different market environments. Kummar’s research deepens the understanding of the motivations of gambling behavior in the stock market and provides empirical support for how investors pursue high-risk, high-return investment opportunities in the market [17]. Research by Chen and others put forward the view that investors’ gambling behavior is significantly affected by profit and loss status and emotions [18]. By analyzing China's stock market data, it is found that when profits are in a state, investors are risk-averse and tend to avoid "gambling" stocks; while when investor sentiment is high, they prefer such stocks. This research not only reveals the existence of gambling behavior in the stock market but also points out the psychological motivations and market impacts behind it, providing a new perspective for understanding market anomalies.

3. 3. Methodology

3.1. Portfolio Ranking Method

The purpose of the portfolio ranking test is to test the factor's expected return. Let $\{\lambda_t\}(t = 1,2,\dots,T)$ represent the factor return time series, then the estimate, standard error and t value of the factor expected return are:

$$\hat{\lambda} = \frac{1}{T}\sum_{t=1}^{T}\lambda_t \tag{1}$$

$$\mathrm{s.e.}\left(\hat{\lambda}\right) = \frac{\mathrm{std}(\lambda_t)}{\sqrt{T}} \tag{2}$$

$$\mathrm{t-statistic} = \frac{\hat{\lambda}}{\mathrm{s.e.}\left(\hat{\lambda}\right)} \tag{3}$$

Among them, the estimate of factor expected return $\hat{\lambda}$ is the average return λ_t in period T. The standard error of expected return $\mathrm{s.e.}\left(\hat{\lambda}\right)$ is the standard deviation of λ_t divided by $\sqrt{T}$. The t value is the ratio of the estimate of the factor's expected return to its standard error.

Double sorting is to sort by two variables and build a factor simulation portfolio. Consider two sorting variables X_1 and X_2, divide the stocks into L_1 and L_2 groups from small to large according to these two variables, and obtain a total of $L_1 \times L_2$ combinations P_{ij}. Drawing on Fama's processing, two variables are often divided into quintiles [2]. If you go long on stocks that rank high on this variable and short on stocks that rank low on this variable, and meet fund neutrality, then the rate of return of factor X_1 in period t is:

$$\lambda_{X_1 t} = \frac{1}{L_2}\sum_{i=1}^{L_2} R_{L_1 i,t} - \frac{1}{L_2}\sum_{i=1}^{L_2} R_{1i,t} \tag{4}$$

Among them, $R_{L_1 i}$ and R_{1i} respectively represent the return rate of the group with the largest and smallest sorting variable X_1.

In the same way, the return rate of factor X_2 in period t is:

$$\lambda_{X_2 t} = \frac{1}{L_1}\sum_{i=1}^{L_1} R_{iL_2,t} - \frac{1}{L_1}\sum_{i=1}^{L_1} R_{i1,t} \tag{5}$$

Among them, R_{iL_2} and R_{i1} respectively represent the return rate of the group with the largest and smallest ranking variable X_2.

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3.2. Fama-MacBeth Returns

Fama-MacBeth regression is a cross-sectional regression. Assuming there are N assets, it first obtains the exposure $\hat{\beta}_i$ of the asset to all factors through time series regression N times, and then performs OLS estimation on R and $\hat{\beta}_i$ respectively in each t period of each asset i (total T periods), and we get The estimate $\hat{\lambda}$ of the factor return in period t and the estimate $\hat{\alpha}_i$ of the residual. Finally, averaging them in time series is the factor expected return $\hat{\lambda}$ and the residual mean $\hat{\alpha}_i$. Its advantage is that it can eliminate the influence of the cross-sectional correlation of $\hat{\alpha}_{it}$ on the standard error.

3.3. α Test

The α test treats the residual α_i of each asset i independently and tests whether it is zero. After obtaining the test results of all α_i, they are averaged and used to evaluate the multi-factor model. For each asset used to test the multi-factor model, use its excess return as the explained variable, use the multi-factor model to be tested as the explanatory variable, perform time series regression, and estimate the standard error of its pricing error (usually when calculating the standard error using Newey–West adjustment). With $\hat{\alpha}_i$ and its standard error, calculate the t value. Under the null hypothesis, the multi-factor model can explain these assets, so $\alpha_i = 0$. The two evaluation indicators that the α test focuses on are $\hat{\alpha}_i$ and the mean of the absolute value of the t value. The lower these two indicators are, the better a multi-factor model can explain these assets and is therefore a "better" model.

3.4. Calculation of Gambling Index

To better reflect the irrational psychological behavior of investors when investing, especially those who are greedy for high risks and like to "take small to gain big", this article draws on Kumar's definition of gambling stocks and the proposed calculation method to construct the gambling index Gamble [14, 16].

First, do a Fama-French three-factor regression on the daily data of individual stocks in period t:

$$r_{i,d} - r_{f,d} = \alpha_{i,d} + \beta_{MKT,d}MKT_d + \beta_{SMB,d}SMB_d + \beta_{HML,d}HML_d + \varepsilon_{i,d} \tag{6}$$

The left side of equation (6) represents the expected excess return of individual stock i. $\mathrm{MKT_d}$,$\mathrm{SMB_d}$ and $\mathrm{HML_d}$ are daily market factors, size factors and value factors respectively.$\varepsilon_{\mathrm{i,d}}$ is the daily regression residual of stock i.

Then based on $\varepsilon_{\mathrm{i,d}}$, calculate the idiosyncratic volatility and idiosyncratic skewness of individual stocks in period t:

$$IVol_{i,t} = \left(\frac{1}{N_i(t)} \sum_{d \in S_i(t)} \varepsilon_{i,d}^2 \right)^{\frac{1}{2}} \tag{7}$$

$$\mathrm{ISKew_{i,t}} = \frac{1}{\mathrm{N_i(t)}} \cdot \frac{\sum_{\mathrm{d} \in \mathrm{S_i(t)}} \varepsilon_{\mathrm{i,d}}^3}{\mathrm{IVol_{i,t}^3}} \tag{8}$$

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Among them, $S_i(t)$ represents the set of trading days for individual stock i in period t, and $N_i(t)$ represents the number of trading days for individual stock i in period t.

Finally, construct the gambling index Gamble:

$$Gamble_{i,t} = \left(\frac{IVol\_Rank_{i.t}}{N} + \frac{ISkew\_Rank_{i.t}}{N} + \frac{Price\_Rank_{i.t}}{N}\right)/3 \tag{9}$$

Among them, $IVol\_Rank_{i,t}$ is the ranking of stock i's idiosyncratic volatility in period t from small to large. $ISkew\_Rank_{i,t}$ is the ranking of the idiosyncratic skewness of stock i in month t from small to large. $Price\_Rank_{i,t}$ is the ranking of the average price of stock i in month t from large to small. This indicator ranges between 0 and 1. The closer it is to 1, the stronger the impact of investors' gambling behavior.

4. Empirical Results

This paper uses the data of China's A-share market from 2010 to 2022 as samples, and the sources are Guotai's database and the Reisi database. According to Liu's method of data processing, stocks with a market value of less than 30% and those with ST and PT were excluded in this paper, and necessary tailing processing was carried out after data consolidation [3].

4.1. Sorting Results

Table 1: Descriptive statistics

	(1)	(2)	(3)	(4)	(5)	(6)
	Num	Mean	Sd	Min	Median	Max
Ret	1900	0.0076	0.0970	-0.1987	-0.0055	0.3660
Gamble	1900	0.5202	0.1616	0.1791	0.5137	0.8885
Beta	1900	1.0589	0.3157	0.3307	1.0406	2.0066
MV	1900	4.0122	0.8858	2.5074	3.8555	6.9351
BM	1900	0.5059	0.3353	0.0420	0.4299	1.8804
Moment	1900	0.0933	0.3440	-0.4427	0.0200	1.4908

Table 1 shows descriptive statistics of yield, betting index, Beta, market cap, book-to-market ratio, and momentum. The maximum value of the Gamble index is 0.8885, indicating that there are a large number of betting stocks in the sample range.

Table 2: Average monthly return rate of univariate ranking

Panel A: Equal weight					
Low	2	3	4	High	Low-High
Ret1	Ret2	Ret3	Ret4	Ret5	Ret(1-5)
0.0109*	0.0095	0.0082	0.0068	0.0023	0.0086***
(1.8713)	(1.6513)	(1.3926)	(1.1284)	(0.3650)	(4.4120)
Panel B: Market capitalization weighting					
Low	2	3	4	High	Low-High
Ret1	Ret2	Ret3	Ret4	Ret5	Ret(1-5)
0.0078	0.0048	0.0035	0.0037	0.0001	0.0077**
(1.4769)	(0.9039)	(0.6276)	(0.6322)	(0.0215)	(2.1432)

The t values adjusted by Newey-West are shown in parentheses.

Table 2 shows the results of the ranking test with betting index as a variable. Regardless of equal weight or market value weighting, it is found that there is a "low gambling effect", and the return rate of the portfolio decreases with the increase of the gambling factor. The average monthly return of the long-short combination constructed by long low betting index and short high betting index is very significant.

Table 3: Risk-adjusted returns for univariate ranking

	Low	2	3	4	High	Low-High
FREE	0.0089	0.0075	0.0063	0.0049	0.0003	0.0067***
	(1.5353)	(1.3053)	(1.0701)	(0.8040)	(0.0533)	(3.4373)
CAPM	0.0036	0.0021	0.0008	-0.0007	-0.0054*	0.0070***
	(1.2408)	(0.7649)	(0.2859)	(-0.2542)	(-1.7895)	(3.7560)
FF-3	0.0016	-0.0006	-0.0022**	-0.0041***	-0.0093***	0.0089***
	(1.2578)	(-0.6130)	(-2.4963)	(-4.2134)	(-8.7673)	(5.7170)
FFC-4	0.0017	-0.0005	-0.0022**	-0.0041***	-0.0092***	0.0089***
	(1.4342)	(-0.5939)	(-2.5524)	(-4.2343)	(-8.9995)	(5.6367)

Adjustments are made in parentheses for Newey-West's (1987) four-stage hysteresis.

FF-3 is a Fama-French three-factor model, and FFC-4 is a Carhart four-factor model.

Table 3 reports α returns for each of the five asset portfolios and their portfolio differences. Taking the Fama-French three-factor adjustment as an example, after adjusting risk, almost all T-values are greater than 2 in absolute value, and the adjusted return of the long-short combination is significant in all cases. This indicates that the relationship between the Gamble index and the expected stock return is of great economic and statistical significance.

Table 4: Returns adjusted for the FFC model of control scale

	Low	2	3	4	High	Low-High
L-MV	0.0101***	0.0067***	0.0063***	0.0033**	-0.0031*	0.0112***
	(5.1023)	(4.6728)	(4.2918)	(2.1739)	(-1.7293)	(5.6094)
2	0.0026*	0.0004	-0.0017	-0.0043***	-0.0097***	0.0104***
	(1.7503)	(0.3663)	(-1.2723)	(-3.8807)	(-7.2805)	(6.1088)
3	0.0018	-0.0041***	-0.0043***	-0.0089***	-0.0127***	0.0126***
	(1.1011)	(-3.4328)	(-3.0704)	(-7.5655)	(-8.5865)	(5.1117)
4	-0.0020	-0.0042***	-0.0062***	-0.0066***	-0.0117***	0.0077***
	(-1.3872)	(-3.1938)	(-4.4304)	(-4.6448)	(-6.9348)	(3.2867)
H-MV	-0.0008	-0.0034***	-0.0054***	-0.0063***	-0.0075***	0.0048**
	(-0.5065)	(-2.9949)	(-3.9043)	(-4.9775)	(-4.5612)	(2.0328)

Adjustments are made in parentheses for Newey-West's (1987) four-stage hysteresis.

Table 4 shows that after controlling the scale, the stock portfolio with a lower gambling index has a higher average monthly return, while the stock portfolio with higher gambling index has a lower average monthly return. A significant gain at the significance level of 1% can be achieved when taking a portfolio of stocks with a low betting index and shorting a portfolio of stocks with a high betting index.

Table 5: Fama-MacBeth regression results

	(1)	(2)	(3)	(4)	(5)
	FRFet	FRFet	FRFet	FRFet	FRFet
Gamble	-0.0184***	-0.0180***	-0.0197***	-0.0242***	-0.0241***
	(-4.4148)	(-4.3445)	(-4.9864)	(-6.1316)	(-6.1858)
Beta		-0.0038	-0.0031	-0.0026	-0.0030
		(-1.5424)	(-1.2776)	(-1.1483)	(-1.3182)
BM			0.0075**	0.0059*	0.0057*
			(2.3123)	(1.8350)	(1.9191)
Size				-0.0056***	-0.0057***
				(-3.0052)	(-3.1818)
Moment					0.0000
					(0.0042)
_cons	0.0152***	0.0188***	0.0163***	0.0411***	0.0417***
	(2.6317)	(3.4510)	(2.7478)	(3.5265)	(3.5874)
r2	0.0097	0.0197	0.0342	0.0575	0.0688
N	291241	291241	291241	291241	291241

t statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

When no control variables are added, the betting index is negatively correlated with the expected return of stocks, with a coefficient of -0.0184, which is significant at 1% level. When the control variables are gradually added, the size and significance of the coefficients are almost unchanged. Column (5) of Table 5 shows that when all control variables are added, the coefficient of the betting index is -0.0241 and the T-value is -6.1858, which is significant at the 1% level. The results in Table 5 show that when we control other factors, the betting index is negatively correlated with the expected return of stocks.

4.2. CHG four-factor model

The Chinese version of the four-factor model (hereinafter referred to as CH-4 model) proposed by Liu is as follows:

$$R_t = \alpha + \beta_{MKT}MKT_t + \beta_{SMB}SMB_t + \beta_{VMG}VMG_t + \beta_{PMO}PMO_t + \varepsilon_t \tag{10}$$

According to the research on gambling index in section 3.4, this paper proposes a four-factor model based on gambling index (hereinafter referred to as CHG model) :

$$R_t = \alpha + \beta_{MKT}MKT_t + \beta_{SMB}SMB_t + \beta_{VMG}VMG_t + \beta_{RMW}RMW_t + \varepsilon_t \tag{11}$$

Among them, RMW represents the gambling factor, and its structure is as follows:

W: Solid, Gamble's top 30% stock.

R: It's a risky Gamble. It's a stock in the bottom 30%.

M: Gamble is in the middle 40%.

Distinguish 2 groups according to market value, and then distinguish W, R and M groups within each group, a total of 2*3=6 groups, gambling factor RMW calculation formula is as follows:

$$RMW = \frac{1}{2}(SR + BR) - \frac{1}{2}(SW + BW) \tag{12}$$

The correlation among the four factors of CHG model, namely R2, is statistically as follows:

Table 6: R-square-CHG model

Variable	Obs	Mean	Std. dev.	Min	Max
R2_MKT	294,344	.3852443	.2151377	2.64e-10	1
R2_MKT_SMB	290,144	.4946449	.2104541	8.98e-07	1
R2_MKT_VMG	290,144	.4876834	.2057607	.0000223	1
R2_MKT_RMW	290,144	.440165	.2089332	.0000165	1
R2_MKT_SMB_VMG	285,983	.539094	.1980376	.0013594	1
R2_MKT_SMB_VMG_RMW	281,884	.5656501	.1906807	.0060932	1

It can be seen from Table 6 that with the addition of factors, the mean value of $\boldsymbol{R^2}$ gradually increases, the minimum value gradually increases, and the standard deviation gradually decreases, indicating that the fitting effect is gradually getting better.

Table 7: Correlation among factors -CHG model

	MKT	SMB	VMG	RMW
MKT	1.0000			
SMB	0.1274	1.0000		
VMG	-0.2673	-0.5707	1.0000	
RMW	0.3795	0.2931	-0.5500	1.0000

As can be seen from Table 7, there is no significant correlation between the four factors, so the problem caused by factor collinearity can be ignored.

4.3. Comparison Between the CHG Model and the CH-4 Model

Table 8: Comparison of models for α test

	Alphas concerning	
Factors	CHG	CH-4
PMO	0.0008	-
	(0.4301)	-
RMW	-	0.0042***
	-	(-2.4627)

The t values adjusted by Newey-West are shown in parentheses.

As can be seen from Table 8, after α test, the T-value of CH-4 model explained by CHG model is not significant, and $\hat{\alpha}_i$is small. This means that we do not reject the null hypothesis, that is, we do not reject alpha =0. CHG can explain CH-4. On the contrary, when CH-4 is used to explain the factors in CHG, the T-value is significant at the 1% significance level, and the null hypothesis should be rejected, that is, α is significant not 0, that is, CH-4 is difficult to fully explain CHG.

In this paper, the anomaly constructed in Liu et al. 's original paper is selected and α test adjusted by White statistic is performed on the two models respectively, comparing the mean of the two models $\hat{\alpha}_i$, the results are as Table 9.

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Table 9: CHG's interpretation of the vision

Category	Anomaly	α	t(α)
Panel A: Unconditional sorts			
Size	Market cap	-0.0013	-1.22
Value	EP	-0.004	-0.51
Value	BM	0.0023	0.49
Value	CP	-0.0002	-0.09
Profitability	*[1] ROE*	-0.0085	-1.08
Volatility	1-Month vol.	-0.0072	-1.29
Volatility	MAX	0.0065	0.48
Reversal	1-Month return	0.0022	0.44
Turnover	12-Month turn.	-0.0115	-1.16
Turnover	1-Mo. abn. turn.	-0.0008	-0.24
Panel B: Size-neutral sorts			
Value	EP	0.0004	0.29
Value	BM	-0.0016	-0.47
Value	CP	-0.0015	-1.11
Profitability	ROE	-0.0024	-1.1
Volatility	1-Month vol.	-0.0028	-1.17
Volatility	MAX	-0.0033	-1.37
Reversal	1-Month return	0.0033	0.87
Turnover	12-Month turn.	0.0071	1.13
Turnover	1-Mo. abn. turn.	-0.0122	-0.24
Average absolute value of α and t(α)		0.004163	0.7763

Adjustments are made in parentheses for Newey-West's (1987) four-stage hysteresis.

Table 10: CH-4 Explanation of the vision

Category	Anomaly	α	t(α)
Panel A: Unconditional sorts			
Size	Market cap	-0.001	-0.91
Value	EP	-0.0041	-0.61
Value	BM	0.0036	0.74
Value	CP	-0.0014	-0.61
Profitability	ROE	-0.0098	-3.33
Volatility	1-Month vol.	-0.0057	-1.39
Volatility	MAX	0.0052	0.77
Reversal	1-Month return	-0.0016	-0.34
Turnover	12-Month turn.	-0.0129	-0.53
Turnover	1-Mo. abn. turn.	-0.0026	-1.35
Panel B: Size-neutral sorts			
Value	EP	0.0006	-0.48
Value	BM	-0.0026	-0.75
Value	CP	-0.0006	-0.47
Profitability	ROE	0.0033	-1.39
Volatility	1-Month vol.	-0.0038	-1.54

Table 10: (continued).

Volatility	MAX	-0.0041	-1.98
Reversal	1-Month return	0.0065	1.86
Turnover	12-Month turn.	-0.0077	-0.41
Turnover	1-Mo. abn. turn.	-0.0103	-0.74
The average absolute value of α and t(α)		0.0046	1.0631

Adjustments are made in parentheses for Newey-West's (1987) four-stage hysteresis.

Table 9 and Table 10 show the results of the interpretation ability of the CHG model and CH-4 model for all 19 anomalies, and the absolute average value of residual and mean residual respectively. It can be seen that the CHG model can explain all the anomalies that can be explained by CH-4, and the average value of the absolute residual error under the CHG model is about 0.0042, which is less than 0.0046 under the CH-4 model. The average value of the absolute T-value under the CHG model is about 0.78, which is smaller than 1.0631 under the CH-4 model. The explanatory power of the CHG model is higher than that of the Liu CH-4 model.

5. Conclusion

Through systematic discussion and empirical analysis, this paper deeply understands how investors' gambling psychology affects stock cross-sectional returns, especially the performance in China's A-share market. By constructing A four-factor model based on gambling behavior (CHG model), this study not only demonstrates the existence of speculative gambling behavior in China's A-stock market, but also reveals the significant role of gambling factors in asset pricing, and provides a new perspective to explain irrational behavior in the market and its impact on stock prices.

In comparison with the traditional CH-4 model, the CHG model in this paper shows higher explanatory power. This difference is mainly reflected in the fact that CHG model can more accurately capture those investment behaviors driven by gambling psychology, and effectively explain how these behaviors affect the cross-sectional returns of stocks through the market mechanism. This finding is of great significance to investors, which can help them understand the volatility of stock prices in highly irrational market environment, and serve as a reminder and warning to investors' irrational behavior.

In summary, the empirical research results of CHG model in China's A-share market emphasize the importance of considering behavioral finance factors in asset pricing and investment decisions. This provides important strategic and theoretical guidance for the future theory and practice of asset pricing, especially in the emerging market environment of developing countries. Future research could focus on the performance of behavioral finance factors in different market environments. For example, during periods of high market volatility or different types of market cycles, the behavior of investors may be significantly different, and the effects of the corresponding behavioral financial factors may also be different. This understanding of dynamic change helps to better leverage these behavioral factors when building more flexible and adaptable investment strategies. On the other hand, considering the connectivity of global financial markets, studying the differences and similarities of behavioral factors in markets in different countries and regions is also an area worth exploring. Comparing the effectiveness of behavioral finance factors across different markets can reveal how factors such as culture, market structure, and the regulatory environment affect investor behavior and asset pricing.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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A Financial Analysis and Valuation of Energy Transfer LP

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Abstract: This paper presents a thorough financial analysis of Energy Transfer LP aimed at enhancing investors' comprehension of the company's financial standing and stock potential. Additionally, it provides insights into the company's current market position and detailed corporate information, serving as a guide for investors unfamiliar with the natural gas market in making informed investment decisions. The article also examines potential risks impacting the company's stock and proposes actionable investment recommendations. While Energy Transfer LP exhibits promising stock potential and a notable rate of return, analysis reveals inherent risks within its operational structure. Mitigating these risks through strategic enhancements could amplify its attractiveness to financial investors. Furthermore, given the significant influence of external factors, particularly public sentiment towards energy companies, investors are advised to conduct thorough investigations into the stability of the natural gas market's development trajectory in the coming years before making investment decisions. This paper underscores the importance of strategic planning to mitigate operational risks and emphasizes the necessity of comprehensive market analysis for informed investment decisions in the energy sector.

Keywords: Energy Transfer LP, Financial Analysis, Valuation, Risk Assessment

1. Introduction

North America plays an important role in the global natural gas market. According to statistics, North America's natural gas supply accounts for 26.2% of the world's total natural gas supply, ranking first in the world, and its global share is increasing year by year [1]. North America is characterized by its extensive geographical scope and rich resources, which includes the United States, Canada and Mexico. Among these three countries, the proportion of natural gas supply in the United States is far greater than that in the other two countries, reaching 79.3% of the natural gas supply in North America, compared with 12.8% in Canada and 7.9% in Mexico. However, the close connection between these three countries makes the whole North American natural gas market highly integrated, and the establishment of pipelines and infrastructure of energy companies facilitates the movement of natural gas across borders [2].

Among the different energy companies, Energy Transfer LP has attracted wide attention because of its considerable scale and rich business. The midstream energy sector in which this company is located is very important for the whole energy value chain because it is the link between energy producers and consumers, and it ensures the efficiency and reliability of energy resources transportation in the whole country [3]. This company operates in all states of the United States. In

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addition to building a large number of natural gas transportation pipelines and natural gas storage facilities in Texas and Oklahoma, it sells natural gas to end users such as power companies and power plants. Besides, Energy Transfer LP has natural gas collection pipelines and processing plants in other states in the United States, and its products also include natural gas liquid (NGL), coal, crude oil and petroleum. The various products have prompted Energy Transfer to show strong financial performance in recent years, and reached the 53rd place in the top 500 financial companies in the United States. The company's revenue is primarily generated from transportation and storage expenses and sales of energy products.

In recent years, Energy Transfer LP has participated in several important development projects, one of which is the completion of the Dakota Access pipeline. This project was announced to the public in 2014 and completed in 2017, with a total cost of 3.78 billion US dollars. This project enhances the company's ability to transport crude oil from Bakken formation to major refining markets and provides a possible safer and more reliable choice for crude oil transportation. With the continuous development of energy industry, Energy Transfer LP has placed a strong emphasis on environmental protection and social responsibility. The company has implemented various measures to reduce its carbon footprint, including investing in renewable energy projects and adopting cleaner technologies in its operations. The survey shows that the company's stock has a high reputation in the financial market, and its share price also rises with the company's operation. Many investors are attracted and are evaluating the performance of Energy Transfer LP. The purpose of this article is to make a comprehensive financial analysis of the company and to help stock investors make better decisions.

2. Performance Evaluation

2.1. Liquidity

Table 1: The liquidity ratios of Energy Transfer LP and its competitors in 2023.

Company names	Current ratio	Quick ratio	Cash ratio
Energy Transfer LP	1.1025	0.8828	0.0143
Kinder Morgan Inc.	0.3520	0.2793	0.0133
Enbridge Inc.	0.8259	0.7410	0.3433
Williams Company Inc.	0.7741	0.7271	0.3688

Data Source: Nasdaq

Table 2: The liquidity ratios of Energy Transfer LP from 2021 to 2023.

Year	Current ratio	Quick ratio	Cash ratio
2021	0.9725	0.7866	0.0310
2022	1.1652	0.9278	0.0247
2023	1.1025	0.8828	0.0142

Data Source: Nasdaq

When considering investing in Energy Transfer stocks, it is essential to evaluate its liquidity performance, including Current ratio, Quick ratio, and Cash ratio, because those ratios reflect the company's ability to repay short-term debts and the proportion of current assets to all assets [4]. In addition to comparing the ratio of Energy Transfer LP with that of its competitors, it is necessary to analyze it with its own historical data to discover the development trend of the company.

As Table 1 shown, Energy Transfer LP’s current ratio ranked the highest among the four companies in 2023, which is 1.1025. According to market standards, if a company's current ratio is greater than one, it means that it is considered less risky, because the company can more easily liquidate its current assets to repay short-term debts. The asset liquidity of Energy Transfer LP is competitive, and it has the strongest ability to repay short-term debts. This can show that the financial risk faced by Energy Transfer LP is smaller than that of other companies, because the lack of debt repayment ability will lead to the bankruptcy of the company. However, only considering this ratio may result errors in the final analysis result, because a large part of the company's current assets are inventories and account receivables that cannot be quickly liquidated.

Quick ratio can make the evaluation of liquidity more complete because its calculation eliminates the inventory contained in current assets. Although the quick ratio of Energy Transfer LP is lower than the ideal value of 1, which is 0.8828, it is still far higher than its competitors, and its ability to repay short-term debts without relying on clearing inventory is still considerable. However, the cash ratio of Energy Transfer LP is greatly inferior to that of its competitors, which reflects that the company has less cash reserves for short-term liabilities. Investors should pay extra attention to this value when considering investment, because it means that Energy Transfer LP may need to liquidate other assets to obtain additional financing when repaying debts.

Compared with the three-year liquidity ratio of Energy Transfer LP, this company has the strongest asset liquidity in 2022 (see Table 2). And its cash ratio is decreasing year by year, which reflects the gradual decrease of the company's cash ratio to total assets. However, the reduction of this ratio should not be absolutely considered negative, because it is closely related to the company's business strategy. For example, the company may use lots of cash to expand its business. Although it will bring short-term liquidity risk, it may be beneficial to the long-term development of the company.

2.2. Solvency

Table 3: The Solvency ratios of Energy Transfer LP and its competitors in 2023.

Company names	Total Debt Ratio	Long-term Debt Ratio	Times-Interest-Earned ratio
Energy Transfer LP	0.6755	0.4519	3.1711
Kinder Morgan Inc.	0.5733	0.3952	0
Enbridge Inc.	0.6592	0.4144	3.0668
Williams Company Inc.	0.7643	0.4442	4.5639

Data Source: Nasdaq

Table 4: The Solvency ratios of Energy Transfer LP from 2021 to 2023.

Year	Total Debt Ratio	Long-term Debt Ratio	Times-Interest- Earned ratio
2021	0.6972	0.4626	4.0309
2022	0.6827	0.4568	3.6331
2023	0.6755	0.4519	3.1711

Data Source: Nasdaq

The company's ability to meet its long-term obligations has also been highly valued by investors and shareholders [5]. The ratios that can show the solvency of the company include Total Debt ratio, Long-term Debt Ratio and Times-interest-earned (TIE), which can help investors better understand the position of Energy Transfer LP in the market and its financial performance.

As Table 3 shown, the total debt ratio of Energy Transfer LP in 2023 is 0.6755, which means that 67.55% of its assets are financed by debt, and this ratio is close to that of its competitors. This shows that the debt ratio of Energy Transfer LP is in the middle range in the industry, and there is no outstanding performance for the amount of its total debt. Among the four companies, Energy Transfer LP has the second highest total liabilities, which may indicate that the company is highly dependent

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on debt and will face some debt risks. Similarly, the long-term debt ratio of Energy Transfer LP is close to that of other companies in the market, which is 0.4519, and this ratio means that the long-term debt of this company accounts for 45% of its total assets.

The value of Times-interest-earned ratio displayed by Energy Transfer LP is very healthy, which is 3.1711. The ratio means that the pre-tax income of the company is three times of its interest expense, which shows that the company's financial performance is gratifying, and it is not under great pressure to repay debts and interests. Except Kinder Morgan Inc, all competitors of Energy Transfer LP in the natural gas market have similar Times-interest-earned ratio, which also demonstrates that the natural gas market is currently in good financial health and the industry development is worth looking forward to.

In the past three years, the Solvency ratios of Energy Transfer LP have not changed much (see Table 4). Although there are some small fluctuations, all the ratios are in the middle range. The only thing worthy of attention is that the company's Times-interest-earned ratio is in a continuous downward trend, which may be caused by the company's reduced income. But overall, Energy Transfer LP has a balanced debt ratio, and the debt does not cause great pressure on it, so it can spend more time on improving its business strategy. From the perspective of the whole market, most energy companies have similar ratios, which may prove that most companies adopt similar strategies in debt management.

2.3. Profitability

Table 5: The Profitability ratios of Energy Transfer LP and its competitors in 2023.

Company names	Profit Margin	Operating Margin	Asset Turnover
Energy Transfer LP	0.0501	0.1056	0.7439
Kinder Morgan Inc.	0.1559	0.2780	0.2188
Enbridge Inc.	0.1418	0.1982	0.2497
Williams Company Inc.	0.2915	0.3953	0.2252

Data Source: Nasdaq

Table 6: The Profitability ratios of Energy Transfer LP from 2021 to 2023.

Year	Profit Margin	Operating Margin	Asset Turnover
2021	0.0811	0.1304	0.7086
2022	0.0529	0.0861	0.8402
2023	0.0501	0.1056	0.7439

Data Source: Nasdaq

When considering investing in a company's stock, it is essential to analyze its profitability, because it can understand the profitability performance of Energy Transfer LP and find its potential strategic improvement through its profit margin, operating margin, and asset turnover.

In 2023, the profit margin of Energy Transfer LP is the lowest among the four companies as shown in Table 5. Its profit margin is only 5.01%, which shows that only 5 cents of its income per dollar can be converted into net income. Its competitors have much higher profit margin than it, and the highest Williams Company Inc even reached 29.15%. The low profit margin of Energy Transfer LP indicates that it may have problems in cost management or pricing, and it has huge room for improvement. Similarly, the Operating margin of Energy Transfer LP is much lower than that of its peers, accounting for 10.56%. Williams Company Inc has the highest Operating Margin and its margin four times that of Energy Transfer LP. The relatively low operating margin reflects that Energy Transfer LP may have higher operating costs, or its competitors may have better operating efficiency.

However, the asset turnover rate of Energy Transfer LP is the highest among the four companies, reaching 74.39%. This value is in sharp contrast with its performance on profit margin and operating margin. This ratio shows the positive operational capability of Energy Transfer and proves that the company can effectively use assets to support its product sales and generate income from assets.

According to the data of the past three years, Energy Transfer LP has not made a big improvement in profitability (see Table 6). From its profitability ratios, the company can focus on enhancing cost control and the transformation of net income to increase revenue and show stronger profitability.

3. Valuation

3.1. Forecast

Table 7: Forecast of Energy Transfer LP and its competitors.

Company Name	ENB	KMI	ET	WMB
Share Price (21-Mar-24)	$35.79	$18.11	$15.59	$38.43
TTM EPS	2.07	1.07	1.09	1.91
NTM EPS	2.05	1.22	1.45	1.82
EPS growth rate	-0.97%	14.02%	33.03%	-4.71%
Revenue growth rate	-1.33%	15.03%	10.05%	1.05%
TTM P/E ratio	17.29	16.93	14.30	20.12
NTM P/E ratio	17.46	14.84	10.75	21.12
PEG	-17.90	1.21	0.43	-4.27
GP/A (based on the most fiscal year)	12.36%	10.69%	9.54%	13.09%
Profitability ratio (based on the most fiscal year)	0.24	0.22	0.69	0.21
Gross Margin ratio (based on the most fiscal year)	0.51	0.49	0.23	0.63

Data Source: Nasdaq & Estimize

Through price comparison, it is easy to find that the current share price of Energy Transfer LP is lower than its competitors, especially far lower than Enbridge Inc. and Williams Company, which is only half of their share price (see Table 7). The lower stock price can be considered that the investment barrier of this stock is not high, and it will not cause great economic pressure to investors who want to buy this stock in large quantities. The TTM EPS and NTM EPS exhibited by these four companies all show that there is little difference in stock returns in the natural gas market, which may be because the impact on the stock prices of energy companies is more from the external environment. An outstanding figure is the growth rate of earnings per share of Energy Transfer, which is 33.03%, and it is far greater than its competitors. The remarkable EPS growth rate of Energy Transfer stock may attract growth-oriented investors [6].

However, although the stock of Energy Transfer LP has its unique competitive date, investors still need to pay attention to all its ratios. It is worth mentioning that the Gross Margin of this stock is the lowest among the four companies and far below its competitors. Gross Margin represents the percentage of the company's net income in Revenue after deducting the Cost of Goods Sold. The Gross Margin ratio of Energy Transfer LP is 0.23, which means that the company can only keep 0.23 dollars in every dollar of its income. Low gross margin ratio often represents the company has problem in cost management. Investors should carefully consider the impact of this ratio before investing, because it may be a harbinger of potential problems, and low net income may affect the long-term development of the company, such as expansion. In contrast, the competitors of Energy Transfer LP can control the Gross Margin ratio at about 0.5, and the difference may indicate that the operation of Energy Transfer LP may be different from its peers in labor cost and raw material selection.

Regarding the estimation of future prices, the NTM P/E ratio exhibited by Energy Transfer shows a downward trend, and its P/E ratio is the lowest among the four companies. Low P/E ratio generally indicates that the company's share price is undervalued compared with its income, and investors' expectations for the future growth of the company's share price are relatively low. In addition, the low P/E ratio may also be closely related to the emergence of new energy sources. At present, many energy users prefer to use products driven by new energy, such as new energy vehicles that consume electricity, because it is cheaper and more environmentally friendly [7]. Therefore, investors' expectations for the natural gas market have decreased, and the P/E ratio of the whole industry is declining.

For investors who are considering buying shares of Energy Transfer LP, this stock has its investment advantages, but it also has certain risks. Before investing, investors must consider whether the return they can get is greater than these risks, and whether they are willing to bear the losses caused by risks. From an optimistic point of view, the high EPS growth rate of the shares of Energy Transfer LP means more potential returns, and investors can get huge benefits from this investment [8]. From a pessimistic point of view, the inferior ratio of Energy Transfer LP means that there are problems in the company's operational efficiency, which may lead to the company's future development becoming worrying.

3.2. Risks and Strategy

Environmental concern will be a risk for the natural gas industry. With the public paying more and more attention to the environment and reducing pollution, natural gas companies will face potential restrictions, increased costs, and damaged reputation. Because although natural gas is considered as a substitute for coal and oil, the production and use of natural gas will still lead to a large number of greenhouse gas emissions, and which will lead to more serious water pollution and habitat destruction. Therefore, in the future, consumers may object to the use of natural gas, or natural gas companies will invest money to reduce emissions.

Changing policies will also be a risk for the natural gas industry because it may lead to rising costs and fines. Policy restrictions will cause natural gas companies to spend extra money and energy on controlling emissions and complying with regulations, which will lead to a substantial increase in costs. Because if the company's current technology can't support its emissions to stay within the prescribed range, it will have to reduce production or buy and develop new technologies. In addition, the political situation and environmental problems will also affect the operation and consumption of natural gas. Natural gas companies need to continue to pay attention to the current economic and political situation and make corresponding adjustments, otherwise they may face losses and fines.

Technological change will also be a risk for the natural gas industry because consumers' demand for natural gas will be reduced with the emergence of renewable energy [9]. With the development of technology, the production cost of renewable energy such as solar energy and wind energy has been greatly reduced, and their production efficiency may also exceed that of natural gas in the future. Therefore, the long-term viability of natural gas companies may be at risk because of technological changes, and their profitability will also decline.

Strategically, Energy Transfer LP should focus on cost control and optimization because its GP/A ratio and Gross Margin ratio are the lowest among its competitors. The cost mainly comes from labor cost and production cost, so the optimization can be completed by adjusting the internal operation structure and products. For the internal structure, Energy Transfer LP should conduct a complete investigation on its expenditure on labor, then find out unnecessary projects and reduce the expenditure on investment. In addition, Energy Transfer LP can also find ways to understand the operation mode of peers, change part of its human structure, and make the company's operation more efficient. For products, the company can make additional investment in products with higher yield ratio, or withdraw funds from projects with poor performance, so that the profitability of products can be further increased [10].

4. Conclusion

Generally speaking, the stock of Energy Transfer LP has great potential, and it has a considerable rate of return. According to the data of the past few years, the performance of this stock is stable, and the operation of the company has not experienced great fluctuations. Through the analysis of stock data, it can still see that there are some risks in this stock, and these may come from the company's operation structure. If the company can make some strategies to improve this, this stock will be more attractive to financial investors. In addition, a large part of the stock risk of energy companies comes from the external environment, such as people's attitude towards energy companies. Therefore, before investing, investors need to make some investigations on the natural gas market to ensure whether the development trend of this industry is stable in the next few years.

Moreover, while Energy Transfer LP demonstrates stability and potential for favorable returns, the analysis also highlights underlying risks stemming from its operational framework. Addressing these risks through strategic initiatives could enhance the stock's appeal to financial investors. Additionally, it's crucial to acknowledge the significant influence of external factors, particularly public perception towards energy companies, which can significantly impact stock performance. Therefore, prospective investors are advised to conduct thorough assessments of the natural gas market to ascertain the industry's developmental trajectory in the forthcoming years. By integrating these insights into their investment strategies, investors can better position themselves to capitalize on the opportunities presented by Energy Transfer LP and navigate the potential challenges inherent in the energy sector.

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The Impact of Industrial Clusters on Supply Chain Resilience: The Moderating Role of Supply Chain Concentration

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Abstract: This study aims to explore the relationship between industrial agglomeration and supply chain resilience. This study is built upon a theoretical framework grounded in the effects of industrial agglomeration, including the scale effect, industry correlation effect, and spillover effect. Through analyzing industrial agglomeration phenomena, the study posits that the clustering of numerous related enterprises within specific geographical areas may lead to increased supply chain resilience. The significance of supply chain concentration is essential as it acts as a moderating factor in this association, potentially enhancing the resilience of the supply chain. This research hypothesizes that such clustering incentivizes enterprises to establish collaborative relationships with nearby suppliers to reduce transportation costs and streamline supply chain complexity, enhancing theoretical research on the influence of industrial agglomeration on supply chain dynamics constitutes a significant aspect of this study. Therefore, this study will provide new theoretical perspectives in related fields and important references for firms to improve supply chain resilience.

Keywords: Industrial agglomeration, Agglomeration theory, Supply chain concentration.

1. Introduction

In the contemporary landscape of global trade and commerce, the resilience of supply chains has emerged as a critical determinant of organizational success and economic stability. Supply chain resilience refers to the ability of supply chains to endure and bounce back from disruptions, ranging from natural disasters to geopolitical tensions and unforeseen market shifts [1, 2]. As researchers and professionals explore the intricacies of supply chain management, there is a growing focus on understanding the influence of different elements on supply chain resilience.

One such factor that has attracted considerable interest is the phenomenon of industrial agglomeration. Industrial agglomeration, characterized by geographic concentrations of interconnected firms and supporting institutions within a particular industry, has long been recognized for its potential to stimulate innovation, enhance productivity, and foster economic growth [3]. However, their influence on supply chain resilience remains a subject of ongoing inquiry and debate.

This study aims to examine how industrial agglomerations impact the resilience of supply networks in the face of disruptions, specifically focusing on the moderating role of supply chain concentration. Existing literature has offered useful insights into the separate impacts of industrial agglomeration and supply chain concentration on resilience, more attention needs to be devoted to examining how these factors interact and potentially shape the resilience outcomes of supply chains. Moreover, the conditions that cause changes in this spatial impact still need to be comprehensively comprehended. However, it primarily emphasised the significance of the size and status of a business inside the supply chain. [4].

Several key questions are addressed in this study: First, what is the relationship between industrial agglomeration and supply chain resilience? Are these two phenomena interconnected, and if so, in what ways? Second, what is the specific impact of supply chain concentration when acting as a moderating variable? What is the impact of industrial clusters on the robustness of supply chains?

Thus, this research puts forward two hypotheses. The first group presents contrasting views on the impact of industrial clusters on supply chain resilience. While proponents argue that clustering fosters collaboration, knowledge exchange, and resource pooling, skeptics point to potential risks associated with dependency and vulnerability within concentrated industrial ecosystems. The second group extends the analysis to consider how the concentration of supply chain activities may interact with industrial clusters to shape their impact on supply chain resilience. The interplay between clustering effects and supply chain concentration levels presents an intriguing avenue for exploration, offering insights into the nuanced mechanisms underlying supply chain dynamics.

Through in-depth exploration in this field, it can better comprehend the intricate relationship between industrial agglomeration and supply chain resilience, offering comprehensive strategic guidance to business decision-makers. Furthermore, this study offers a new theoretical insights for academia to investigate the intricate correlation between industrial agglomeration and supply chain resilience, offering important insights for future research endeavors.

2. Literature Review

The notion of agglomeration was initially developed by, highlighting the advantages of industrial agglomeration in fostering knowledge spillovers, information sharing, and optimizing infrastructure and production factors, such as labor [5, 6]. Within these industry agglomerations, associated service enterprises converge, establishing a specialized and substantial labor market and codifying various knowledge and information within the agglomeration. The productivity of labor, capital, energy, and other resources factor alignments is consequently enhanced when the reciprocal sharing of information lowers the cost of information seeking and factor matching [7]. These positive externalities improve production efficiency, consolidate knowledge and technology, stimulate innovation and accelerating technological progression. Which, in turn, strengthens the competitiveness of the entire supply chain, enabling rapid adaptation to market fluctuations and evolving demands. For instance, it explored the positive correlation between industrial agglomeration and technological innovation using per capita GDP as an intermediate variable [8]. Similarly, the influence of foreign trade factors on industrial agglomeration and economic growth was investigated, and a nonlinear relationship model was constructed based on threshold effects [9].

Supply chain resilience refers to the innate capacity of agents within a supply chain network to effectively react to unforeseen circumstances and restore regular operations. It involves addressing malfunctions, maintaining satisfactory service throughout the repair process, and actively diagnosing and preventing potential risks and errors [1, 10]. The current research primarily focuses on the enterprise's operational and financial performance [11]. However, the significance of industrial agglomeration on the resilience of supply chains has been greatly overlooked.

Supply chain concentration refers to the level of focus a company place on its suppliers and customers, particularly in terms of the importance of key suppliers and customers [12, 13]. Supply chain concentration enhances a company's competitive edge from its synchronized processes with suppliers [14]. The trust and behavioral norms that result from interdependent actions should protect collaborative companies from opportunistic behavior, ensure fair distribution of benefits even without comparative market contracts, and decrease the risk of disruptions in the supply chain [15]. High levels of supply chain concentration suggest that a company relies heavily on a small number of key suppliers for a significant portion of its purchases, or that it sells a large proportion of its products to a small number of main customers [16].

3. Hypothesis Development and Model Design

3.1. Hypothesis Development

In microeconomic terms, the scale effect epitomizes the concept of economies of scale, fundamentally characterized by the cost benefits accrued by enterprises due to the magnitude of their operations [17]. This advantage stems from a comprehensive resource pool encompassing financial, human, and technological assets, which collectively empower companies to adeptly navigate and recover from disruptions in the supply chain [18]. According to Chen et al., the scale effect can be classified into two categories: the human resources scale effect and the land resources scale effect [18]. The former underscores the value of a large and diverse workforce, enabling robust problem-solving and innovation. The latter pertains to the advantages of extensive land holdings, which can facilitate operational diversification and resilience against localized disruptions. However, an over-dependence on specific processes or technologies, a byproduct of the scale effect, can inadvertently lead to rigidity within the system. This inflexibility potentially heightens the vulnerability of supply chains to certain types of disruptions, underscoring the need for a balanced approach in leveraging the scale effect to enhance supply chain resilience [10, 19]. According to the analysis provided, this research proposes two hypotheses.

Hypothesis 1: Industrial agglomeration has beneficial direct impacts on supply chain resilience.

The literature highlights that the spillover effect often shifts demand from platforms to direct channels [20]. As noted by Hsu et al., spillover effects intensify with higher industry concentration [21]. On the other hand, the literature also suggests that the spillover effect could reduce demand for sales platforms, indicating a potential shift in the balance of power within supply chains [20]. Additionally, Yu et al. find that the operational values of Blockchain Technology regarding supply chain enterprises and its spillover effects on the workforce vary with customer demand correlation [22]. While industrial clusters foster interconnectedness and knowledge sharing [23], they also create an environment of interdependence [24, 25]. This interdependence, at higher levels of supply chain concentration, might introduce vulnerabilities or dependencies that attenuate the positive influence of industrial agglomeration on resilience. Based on the above analysis, the study provides two hypotheses.

Hypothesis 2: Supply chain concentration acts as a moderator in the relationship between industrial agglomeration and supply chain resilience. A higher level of supply chain concentration enhances the favorable effect of industrial agglomeration on resilience.

3.2. Model Design

Based on the theoretical analyses and research hypotheses, this study devised a testing model to explore the process by which agglomeration's effect on resilience.

$$Resilience_{it} = \alpha_0 + \alpha_1 agglomeration_{ij} + \alpha_2 Controls_{it} + \upsilon_{it} \tag{1}$$

$$Resilience_{it} = \beta_0 + \beta_1 agglomeration_{ij} + \beta_2 Controls_{it} + \beta_3 SCC + \beta_4 agglomeration_{ij} \times SCC + \varepsilon_{it} \tag{2}$$

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3.3. Variable Construction

3.3.1. The Location Quotient

Referring to existing research, seven effective methods for measuring the industrial agglomeration level have been summarized. These include location quotient, industrial agglomeration index, industry concentration, Herfindahl index, spatial Gini coefficient, and E-G index. After repeated comparisons, it was found that the industrial agglomeration index requires not only a large number of calculations but also overlooks the impact caused by business size, industry concentration is easily affected by seasons; the Herfindahl index has a weaker measure of spatial association; the spatial Gini coefficient ignores the difference in business size; the E-G index, which is based on the spatial Gini coefficient, has a problem of incomplete statistics. Therefore, this paper will employ the location quotient as a metric to quantify industrial agglomeration [26]. The formula for calculating the location quotient is as follows.

$$agglomeration_{ij} = \frac{q_{ij}/\sum_i q_{ij}}{\sum_j q_{ij}/\sum_i \sum_j q_{ij}} \tag{3}$$

The i represents industry, j represents region, and q_{ij} represents output indicators. As the value of industrial agglomeration increases, so does the level of agglomeration.

3.3.2. Supply Chain Resilience

References Dormady et al., and Jiang et al., were consulted [27, 28]. The study examines the application of production functions for assessing the level of supply chain resilience. This is because they analyse the distribution of resources and the corresponding degrees of efficiency, elucidating how the relationships between inputs and outputs change based on scale. The degree of change in current productivity relative to previous productivity can effectively measure resilience [10].

$$Resilience_{it} = TFP_{it} - TFP_{it-1} \tag{4}$$

The variable i represents the firm, the variable t indicates the period, and TFP stands for the total factor productivity of firm i in period t , and TFP_{it} serves as the residual for firm-level regression.

3.3.3. Supply Chain Concentration

Customer and supplier concentration are both components of supply chain concentration. In accordance with the findings of the previous investigation [29-31], the mean is determined through the aggregation of the proportions of sales revenue generated from the top five consumers and purchases made from the top five suppliers.

$$SCC = \frac{\sum_{j=1}^{5}(\frac{Purchase_{ij}}{Purchase_i}) + \sum_{j=1}^{5}(\frac{Sales_{ij}}{Sales_i})}{2} \tag{5}$$

While $Sales_{ij}$ and $Purchase_{ij}$ represent the total sales and purchases, $Sales_{ij}$ and $Purchase_{ij}$ indicate the sales made by enterprise i to major customer j and purchases from major supplier j, respectively. Lower values indicate a lower degree of concentration, whereas higher values indicate higher concentration.

3.3.4. Control Variables

As in the prior literature [12, 32, 33], to enhance comparability with previous literature and control for uncertainties caused by external factors, this paper employs several variables: company age (Age), measured as the natural logarithm base of the number of years since initial public offering plus one; cash flow operations (Cfo); the proportion of independent directors (IND); CEO-chairman duality (Dual), coded as 1 if the same person holds both positions and 0 otherwise; board size (Boa), treated by taking the logarithm of the quantity representing the number of board members; enterprises growth ability (Growth); company(Size); total debt ratio (TDR); ownership concentration, represented by the largest shareholder's stake (OC_1) and the top ten shareholders' combined stake (OC_10); fixed assets (PPE); return on assets (ROA); net working capital (NWC); and the annual growth rate of primary business income (ROI).

4. Conclusion

The forthcoming phase of this research involves gathering data and performing empirical tests. Our approach includes compiling data from various dimensions, primarily focusing on Chinese A-share listed companies, spanning 2010 to 2022. The China Stock Market & Accounting Research Database (CSMAR) will be used for data collecting. Specifically, this study aims to integrate industry agglomeration, supply chain resilience, and supply chain concentration data, aligning them with the stock codes of these A-share listed entities. The sample refinement process will exclude firms lacking vital data, those within the financial sector, and companies classified as ST, ST*, or PT. For a robust analysis, this study will consider only those samples that maintain a consistent data record for at least three consecutive years. A winsorizing technique will be applied to all continuous variables at the 1% extremities to control for statistical outliers.

The empirical analysis represents a crucial direction for future research. Consequently, this research intends to enhance empirical studies, providing ample and rigorous data support to substantiate the findings.

This study could enrich knowledge on industrial agglomeration and its impact on supply chain resilience. It introduces new perspectives, including the scale effect, industry correlation effect, and spillover effect as crucial factors in understanding industrial agglomeration. Furthermore, it underscores the moderating influence of supply chain concentration within this particular framework, thereby potentially expanding the scope of theoretical constructs in the discipline.

From practical sights, the research findings could provide valuable insights for both enterprises and policymakers. Companies may better comprehend how their geographical location and relationships with local suppliers influence their supply chain resilience. Meanwhile, policymakers can use these findings to create conducive environments for industrial agglomeration, improving overall supply chain resilience in an area or industry.

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The Impact of COVID-19 Pandemic on the Private Equity Valuation

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Abstract: As the downward pressure on the world economy increases, the financial industry continues to suffer, especially private equity funds. In recent years, the frequent occurrence of major special events and hot news around the world cannot help but make people doubt whether these special events will have an impact on the valuation of private funds. This paper takes COVID-19, the most typical and influential special event in recent years, as an example, combined with various data during COVID-19, to discuss the impact of the epidemic on private equity valuation models and the private equity market. This paper finds that the COVID-19 pandemic has severely affected the valuation accuracy of discounted cash flow method and made the valuation of the market method lower than the true value of the company. While sectors such as real estate, tourism and hospitality and logistics have been severely negatively impacted by COVID-19, the pandemic has boosted sectors such as fintech, healthcare, pharmaceuticals and biotechnology. After the test of this epidemic, investors and management teams need to make timely adjustments to valuation models, while taking into account long-term market trends and industry changes, more prudently evaluate investment opportunities, and make sound investment decisions.

Keywords: Private Equity, COVID-19 Pandemic, Discounted Cash Flow

1. Introduction

In the 1980s, the concept of venture capital entered China, and now private equity investment has a history of 40 years in China, during which it has experienced many upsurges. In recent years, China's private equity investment fund industry has developed rapidly, and the scale of funds under management has continued to grow, from 1.73 trillion yuan in 2015 to more than 10 trillion yuan in 2021 [1].

As an important investment tool, private equity investment fund plays a very significant role in the capital market. With the continuous development and improvement of the theory and method of financial instrument valuation, valuation becomes more and more important in the whole process management of private equity investment funds. As the scale of private funds increases, investors are increasing, and the money-making effect is gradually decreasing, when the accuracy of valuation plays a crucial role. China's domestic private equity investment valuation methods generally use cash flow method, relative ratio method and other traditional valuation methods, which may have problems in the accuracy of private equity valuation [2]. In 2020, the novel coronavirus epidemic swept the world, dealing a major blow to the world economy, and the global financial market shook sharply. Personnel flow control will seriously affect the fund raising, fund registration and project investment of early investment funds, and have a bad impact on the private equity industry [3]. As the world's first currency, the US dollar has naturally become an important tool for international financial intermediaries to deal with redemptions, and the US dollar liquidity has been run. The Federal Reserve kept cutting interest rates, but it did not change the fact that interest rates continued to rise, and private valuations fell sharply. The existing literature only studies the impact of the epidemic on the financial sector unilaterally, and does not start with private valuation. Therefore, this paper will start with private equity valuation and analyze some typical private equity valuation during the epidemic to find out the impact of special events on private equity valuation.

2. Research Background and Literature Review

2.1. Private Equity Development Background

Private equity investment first originated in the United States in the 1940s and was a "tool" for the wealthy at that time. In 1984, the concept of venture capital was introduced to China, and private equity investment was only known to the Chinese market. In the 1990s, after the reform and opening up, many foreign private equity investment funds chose to enter China, which produced a wave of private equity investment in this emerging economy at that time. In the late 1990s, the Chinese government issued a series of policies to encourage the development of private equity investment, such as the Decision of the Central Committee of the Communist Party of China on Strengthening Technological Innovation, Developing High Technology, and Realizing Industrialization, and Several Opinions on Establishing China's Venture Capital Mechanism. China has also set up a number of government-led venture capital institutions, such as Shanghai Chuanglian and Zhongke Merchants, which have also set off a second wave of private equity investment. The development of private equity investment in China has begun to take shape, and China has gradually become one of the most dynamic markets for private equity investment [4]. The COVID-19 pandemic that swept the world in 2019 and 2020 has severely affected financial markets around the world. Previous research has suggested that more closed private equity investments are less affected by market fluctuations than other public market investments. Private equity valuation methods in China are relatively simple, and most private equity management institutions adopt traditional valuation methods such as cash flow method and relative ratio method [2]. When it comes to major special events such as the COVID-19 pandemic, traditional valuation methods affect the valuation of the company, which in turn affects the investment decisions of investors.

2.2. COVID-19 Pandemic Background

The impact of the COVID-19 epidemic on the financial market has been so great that many investors have to re-evaluate the value of their investment projects. In past studies, global markets have been affected to varying degrees. In a sample of mainly North American and Western European companies, the epidemic has caused about 40% of invested companies to be moderately negatively affected, 10% to be severely negatively affected, and 50% of companies have not been significantly affected [5]. Faced with the impact, private equity investors are still looking for new investment opportunities and pay more attention to creating value through revenue growth [5]. Looking at fund manager expectations, private equity firms generally expect the performance of existing funds to decline. In the long term, the epidemic has also accelerated the adjustment of private equity companies' operating models and crisis management capabilities, demonstrating the adaptability and resilience of the private equity industry in adversity [5].

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In another study focusing on the European market, after the outbreak (taking March 1, 2020 as the split time), the proportion of PE MM fund managers who expected their portfolios to deteriorate sharply increased from 8% to 40%. However, when considering long-term growth prospects, private equity fund managers are generally optimistic [6].

From a Chinese perspective, China was the first country to be hit by the COVID-19 pandemic. However, thanks to its early control of the epidemic and the lifting of internal travel restrictions, China became the only major economy in the world to achieve positive GDP growth in 2020. The increase in the number of investors and their purchasing power makes mainland China continue to be regarded as one of the best investment locations by emerging market investors [7]. In view of the recovery of China's consumer market and the improvement of economic conditions, it is believed that although China's private equity market has suffered a certain impact in the short term, the market has a strong ability to recover and develop in the long term. Figure 1 below shows the process of China's economic recovery after the impact of the epidemic in 2020. Although China's economy suffered negative growth in the early stages of the epidemic, the growth rate quickly returned to normal levels after rapid control.

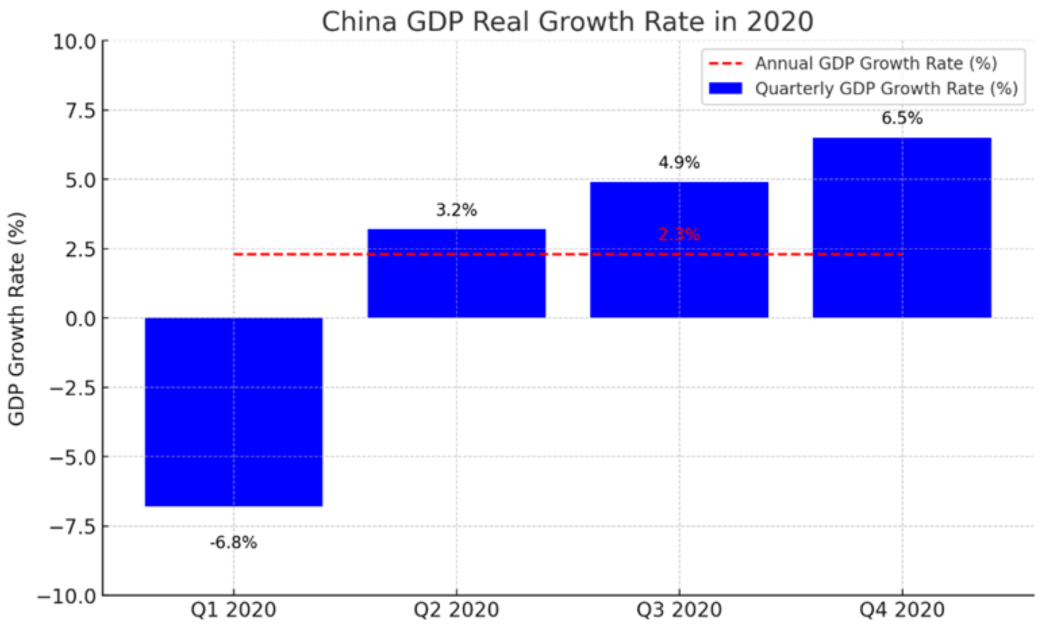

Figure 1: China GDP real growth rate in 2020 (Photo/Picture credit: Original).

Generally speaking, based on previous research, various markets around the world were severely hit in the early stages of the epidemic. However, as the means to deal with the epidemic have increased, production has recovered, and the financial confidence market has improved, people's overall long-term expectations for private equity valuations are still optimistic.

2.3. Private Equity Valuation Model

Private equity investment valuation refers to the reasonable valuation of various asset portfolios in private equity investment to determine the net present value of the asset portfolio, so that private investors and private investment institutions can make relevant choices. At present, the mainstream valuation methods in the world can be roughly divided into three categories: income method, market method and cost method. The income method is the most common, and the most widely used is DCF (Discounted Cash Flow), and DCF can be subdivided into FCFF (Free Cash Flow to Firm). FCFE (Free Cash Flow to Equity) and DDM (Dividend Discount Model) [8]. Market method includes

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Comparable Company Analysis and Precedent Transactions Analysis. Comparable Company Analysis is to evaluate the target company by comparing similar companies with the target company in terms of industry, customers, products, terminals, etc., and referring to their main financial ratios. Precedent Transactions Analysis is based on the same industry as the target company, and in the recent investment or merger of the company, based on its financing amount or merger pricing as a reference, to value the target company. Private investment companies usually adopt more than two valuation methods to evaluate, and the various methods confirm each other, and the conclusion is often not a definite value, but a valuation range.

3. The Impact of COVID-19 on Private Equity Valuation Models

This paper believes that the impact of COVID-19 on private valuation models lies in the discounted cash flow method on the one hand. Although DCF is widely used, it also has its drawbacks. The input in the DCF model is the prediction of the target company's future, and the accuracy of this prediction is highly dependent on the investment company's understanding of the target company's industry, as well as the in-depth investigation and research of the target company. Due to the impact of the epidemic, the Chinese government has taken a series of measures to prevent and control the epidemic out of concern for people's lives. One is restricted mobility, which makes it impossible for investors to conduct site visits and assess target companies. In order to stimulate the economy, China will adopt a certain interest rate reduction policy, which may lower the discount rate. Coupled with the impact of the epidemic on global financial markets, the future is full of instability, and investment institutions have to act prudently. The above is not conducive to DCF's data collection, but also affects the accuracy of its evaluation results. However, most investment institutions still choose to use DCF for valuation because there is no better method.

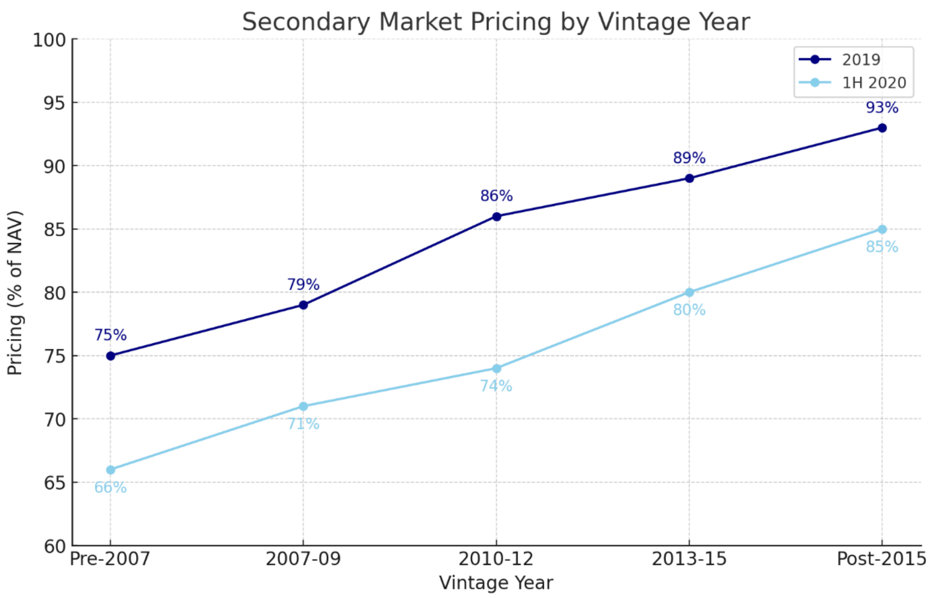

Figure 2: Secondary market pricing by vintage year (Photo/Picture credit: Original).

On the other hand, the COVID-19 pandemic has also affected market-based valuation models. Market methods rely primarily on market data, some of which are updated daily, such as market capitalization. However, most of the required forecast data and the historical financial data of the target company will be affected by the release mechanism, and the update will be delayed, which leads to the failure of the valuation model using market method to evaluate the target company in time. Timeliness is particularly important in private equity, where many investment opportunities are fleeting. Using pre-COVID-19 historical data for valuation results in an undervaluation of market multiples (Since the numerator in the formula is updated in time, such as market capitalization, but the denominator may not be updated after the pandemic, such as net profit), in turn, the fair value is undervalued. For example, during the epidemic, many private investment management institutions thought it was a good opportunity for bargain-hunting, similar to the SARS period before, many companies have a low valuation, undervaluing the value of about 8% to 12%, as Figure 2 shown.

4. The Impact of COVID-19 on Private Equity Market

In addition to valuation models, the impact of the COVID-19 epidemic on private equity valuations is also reflected in its direct impact on the private equity market itself. From an investor's perspective, due to the economic uncertainty and market volatility caused by the epidemic, investors tend to be less tolerant of risks, which will lead to more conservative valuations of investment projects in the short term, as mentioned above.

From the perspective of companies receiving investment, the impact or opportunities brought by the epidemic on various industries are different. This extremely important and rare "black swan" event will cause huge changes in the value of different industries themselves, thus triggering valuation changes. value changes. The impact on different industries in the private equity market shows significant differences. Some industries have been severely impacted by the epidemic and need to reconsider and adjust their business models, while other industries have shown strong resistance to risks and have been less affected.

Industries such as real estate, hotel tourism and logistics have been severely affected by the COVID-19 epidemic. The epidemic has restricted travel, leading to a rebound in demand in the tourism and hospitality industries. Likewise, the housing market has been rocked by economic uncertainty causing people to delay purchase decisions. Although the logistics industry has temporarily survived the epidemic due to increased demand for essential goods, it is also facing challenges due to disruptions in global supply chains and transportation restrictions.

On the contrary, industries such as fintech, healthcare, pharmaceuticals and biotechnology have shown their resilience during the epidemic. The demand for services and products in these industries has not decreased but increased during the epidemic. For example, fintech companies benefit from the potential to facilitate risk-free contact payments and online financial services; the healthcare and biotech industries are growing rapidly due to pandemic needs and the urgency of vaccination.

This industry heterogeneity requires private equity firms to re-evaluate their investment portfolios during the epidemic, optimize resource allocation, and increase their focus on potential growth industries. At the same time, for those industries that have been impacted and expanded, private equity companies need public attention on how to help these industries adapt to the new normal, accelerate digital transformation, and optimize operational efficiency.

The publicity of private equity valuation data is often low, and changes in valuations of listed companies in the industry can also reflect changes in private equity valuation prices to a certain extent. It has displayed two groups of representative companies to demonstrate the impact of the epidemic on different industries in the private equity market. Impact:

As shown in Figure 3, the market value of Pfizer Pharmaceuticals in the biological field rose rapidly during the epidemic, because the epidemic led to a surge in demand for Pfizer vaccines or other corresponding medical products; and in Figure 4, the market value of Hilton Group in the Chinese tourism and hotel industry increased significantly in the early stages of the epidemic. The decline may be due to the impact of the epidemic on the tourism industry. People tend to reduce travel and stay in hotels. After the epidemic stabilizes, the market value rebounds. These changes reflect the impact of COVID-19 on consumer and investor confidence in the industry. That is, there is an overall impact on the market. Some industries have suffered a greater negative impact due to restrictions,

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while a small number of related industries have developed due to the increased demand caused by the epidemic.

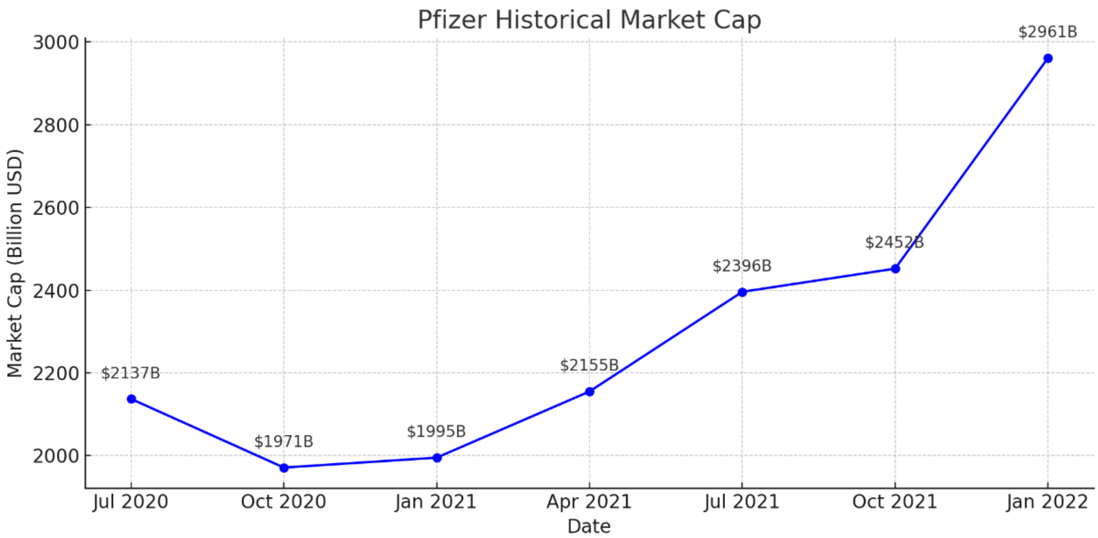

Figure 3: Pfizer historical market capitalization (Photo/Picture credit: Original).

Figure 4: Hilton historical market capitalization (Photo/Picture credit: Original).

During the epidemic, the valuation of the private equity market was affected by many aspects such as market environment and confidence. Investors need to evaluate investment opportunities more prudently and pay more attention to long-term market trends and industry changes.

5. Case Analysis and Suggestions

5.1. Suggestions for Improving Valuation Methods

Regarding the future uncertainty caused by the COVID-19 epidemic, investment companies should increase the frequency of valuations and use updated data to determine whether the impact of the epidemic on the target company is permanent, and if not, how long it will take for the target company

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to recover. At the same time, investment companies should add sensitivity analysis and correlation analysis to determine the impact of the epidemic on relevant data. The company's life cycle theory should also be taken into consideration, and corresponding valuation methods should be used according to the different stages of the target company to improve the accuracy of the valuation.

5.2. Case Analysis: Spring Airlines

During the COVID-19 epidemic, the regulations imposed by various governments and the decline in people's willingness to travel have had a huge impact on airlines, and the overall operation of the aviation industry has been difficult [9]. Many airlines need to significantly reduce or cancel flights to cope with the problem of reduced passengers and cost control. A large number of aircraft are idle on the ground, with excess capacity, and flight operations are severely restricted. From a financial perspective, the sharp drop in passenger numbers has directly led to a significant drop in revenue, while airlines still have to bear high fixed costs. These have put great pressure on airlines, and when it is unknown whether the epidemic situation will improve, these negative blows may seriously affect the valuation of airlines. Investors, combined with risks, may generally significantly reduce airline valuation expectations.

Spring Airlines is one of China's largest airlines and China's first low-cost airline. Since its establishment, the company has provided cost-effective services through strict cost control and efficient operating models, becoming a competitive domestic airline. Company [9]. During the epidemic, the aviation industry as a whole has been hit, and even low-cost airlines that are more attractive to consumers are facing losses. After the outbreak, Spring Airlines flexibly adjusted its route network and launched the "Fly as You Want" campaign, covering all domestic and Hong Kong, Macao and Taiwan routes, stimulating customers' consumption desire. With its low-cost model and flexible operation strategy, in the third quarter of 2021 Becoming the only profitable airline, its passenger load factor is much higher than other airlines [9]. On the other hand, the epidemic has led to lower expected incomes and lower spending levels for some people. These new price-sensitive groups are also more likely to become Spring Airlines' target customers [10]. In the subsequent development, Spring Airlines has also demonstrated better development space and investment value.

As shown in Figure 5, due to the widespread impact of the epidemic, Spring Airlines' market value also declined in early 2020. However, due to its excellent operating strategies, the development of the low-cost airline market after the epidemic and other factors, Spring Airlines has escaped the atmosphere of decline in the domestic aviation market. The market value is rising rapidly. According to the traditional market law model, since Spring Airlines and other airline companies have suffered similar impacts in terms of turnover, passenger flow, etc. During the epidemic, the degree of decline in their valuations according to the model will be similar; and free cash In the discounted flow method, since it is difficult to consider when the epidemic will end and to predict the fixed expenses of airlines to maintain idling daily operations. It is also difficult to accurately estimate the impact on the company's future free cash flow when the epidemic ends, which will cause problems such as Spring Airlines and other companies. Companies with excellent strategies and development prospects are undervalued.

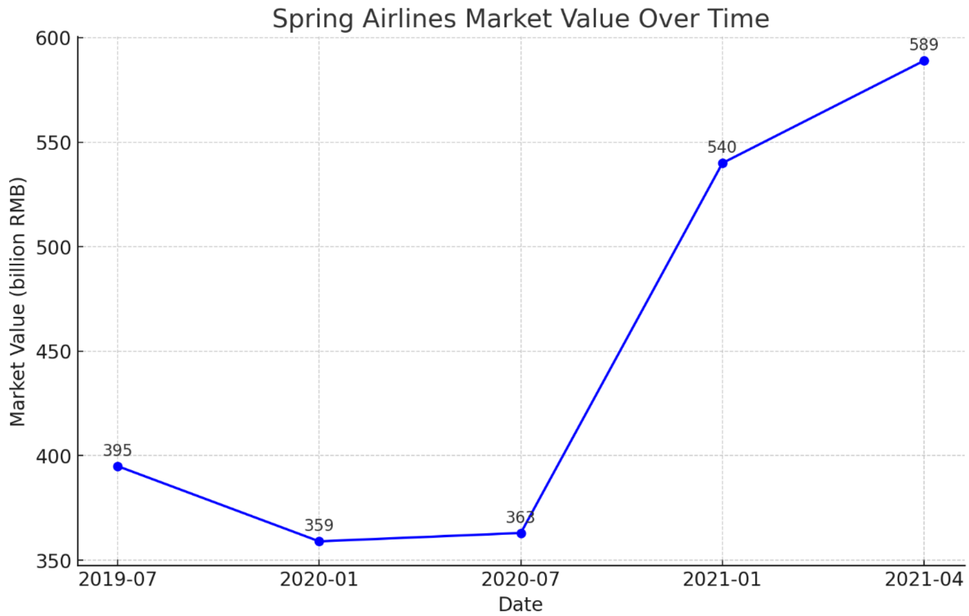

Figure 5: Spring airlines historical market value (Photo/Picture credit: Original).

When faced with such a situation, investment companies should increase the frequency of valuations, always maintain judgments on changes in the epidemic situation, and reasonably reflect them in valuations. For example, when the government strengthens control and the number of new cases decreases, it should increase the frequency of valuations for airlines. expectations. In addition, judge the particularity of the valuation target in terms of operating strategies and market segments, and look for hidden aspects that may have a greater impact on corporate operations, rather than just relying on corporate cash flow data and comparisons with peers. For example, note that Chunqiu The airline's low-cost airline attributes that distinguish it from other airlines and the possible impact of the joint airline consumer group, as well as the positive impact of Spring and Autumn's unique business strategy. Only in this way can obtain the most reasonable valuation of the enterprise and increase the return on investment.

6. Conclusion

Through research, this paper finds that the COVID-19 pandemic has a greater impact on discounted cash flow method and market method. After the impact of the COVID-19 pandemic, the discounted cash flow method and the market method in the valuation model have exposed their shortcomings. The former relies too much on investment firms' research on target companies, so it is hampered by the epidemic and the accuracy of its valuation is greatly reduced. The latter requires accurate market data, which cannot be updated in a timely manner due to the epidemic, resulting in lower valuations. Therefore, it understands that the COVID-19 pandemic has had a considerable impact on the global private equity market. But from another perspective, the shock has also brought new opportunities to the private equity market, with fintech, healthcare, pharmaceuticals, and biotechnology industries not declining, but increasing. Starting from the impact of COVID-19 on the private equity market, this study is the first to study the relationship between COVID-19 and private equity valuation, so that investors can make timely adjustments when similar major events occur in the future. It is also hoped that scholars and researchers of all parties can take this experience to study a more reasonable private valuation model to cope with more challenges in the future. This article does not address the impact of COVID-19 on other valuation models. The impact of the epidemic on the private equity market is

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comprehensive, so other valuation models will also be affected to a certain extent, and other valuation models can be analyzed in the future to further deepen the research on this topic.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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The Combined Effects of Financial and Market Indicators on the Valuation of New Listings: Evidence from the Biopharmaceutical Sector

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Abstract: This study confirms that financial and market data have a significant impact on the valuation of newly listed companies, especially in the biopharmaceutical industry. Using multiple linear regression models, this paper found significant differences in the impact of EBITGR and EBITDAGR on price-to-earnings ratio (P/E Ratio) across years. Other indicators such as Total Asset Turnover, Return on Assets (ROA) and Debt to Equity Ratio (D/E Ratio) have weaker explanatory power and unstable influence. In addition, fluctuations in market valuations of listed companies are influenced by market sentiment and the macroeconomic policy environment. In high-growth, high-risk industries such as biopharmaceuticals, regulatory policies and listing structure reforms in the market can cause structural changes in model performance. At the same time, changes in market sentiment and regulation can also affect the explanatory power of financial indicators to some extent. Further analyses showed that market preferences for valuation changed over time during the study period, especially when the market moved significantly, driven by regulatory policy and the external environment. This makes the conclusions of the study's findings subject to uncertainty in different market environments. Overall, this study reveals a number of key factors affecting the market valuation of newly listed companies and highlights the importance of the interaction between market data and financial indicators. In future research, more attention should be paid to the role of different time periods, market conditions and industry characteristics to avoid potential valuation traps and provide more informative support to market investors and managers.

Keywords: Financial Performance, Market Indicators, Firm Valuation, Biopharmaceutical Sector.

1. Introduction

In today's increasingly globalized capital markets, initial public offerings (IPOs), as an important part of the transformation of a company's capital structure, have not only attracted extensive academic attention, but are also a key topic in financial practice. The issue of valuation of newly listed companies, especially how firm financial data and market data affect their valuation, has become a focus of attention for both researchers and practitioners [1].

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It is well known that a company's financial data, such as earnings, liabilities, and cash flow, are fundamental factors in assessing the intrinsic value of a company. Traditional financial theories suggest that these data can reflect a company's operating conditions and future profitability, and are the core variables that affect company valuation [2]. However, in a highly complex and volatile market environment, relying on traditional financial data alone can no longer fully explain a company's market valuation. Market data, including external factors such as macroeconomic conditions, industry trends, and investor sentiment, have an equally important impact on company valuation [3]. Especially in the IPO process, the impact of market data may be more significant due to information asymmetry and market uncertainty.

Although existing studies have explored the impact of financial and market data on firm valuation from different perspectives, there is still a relative lack of systematic research on this particular group of just-listed firms [4]. In addition, the existing literature is divided in explaining how these two types of data work together in the valuation process of just-listed companies. On the one hand, some scholars argue that the impact of market data is particularly prominent at the IPO stage, as market sentiment and macroeconomic factors may have a significant impact on share prices in the short term [5]. On the other hand, there is also the view that financial fundamentals remain key in determining a company's long-term valuation even at the IPO stage [6].

In view of this, this paper employs regression analysis to conduct an empirical study on companies that have gone public in the last three years. By analysing the impact of financial data (e.g. profitability, debt level and cash flow situation) and market data (e.g. pre-IPO market sentiment, macroeconomic indicators and industry growth rates) on IPO valuation, this study aims to reveal the specific mechanisms by which these factors act on the valuation of newly listed companies [7].

The aim of this paper is to explore how these factors individually and collectively contribute to the market valuation of IPO firms, not only expanding the theoretical framework on firm valuation, but also providing empirical support for IPO pricing in practice, providing deeper insights for investors, and for managers, understanding how financial and market data affect firm valuation, and providing practical references in decision-making processes [8].

2. Method

2.1. Data Selection

Based on the available data, this paper selected Chinese A-share listed companies from 2021 to 2023 as the sample. The sample is screened and processed based on the following criteria: 1) listed biopharmaceutical companies, 2) companies with assets between 500 million and 1 billion, 3) companies with P/E ratios greater than 0, and 4) excluded missing sample data. In order to prevent the influence of abnormal or missing sample data on the experimental analyses and results, this paper selected 17 sample companies from 386 biopharmaceutical companies, and the statistical data were obtained from the Wind Information financial terminal database. All other financial data were obtained from China Stock Market and Accounting Research (CSMAR) database and National Bureau of Statistics.

2.2. Variable Construction

The P/E ratio is one of the most commonly used and understood valuation metrics by investors. It is a direct reflection of the price the market is willing to pay per unit of earnings and thus provides a visual representation of the market's expectations of a company's future profitability. By using the P/E ratio as the dependent variable, the study is able to provide insights that are consistent with the perspectives of market participants, and the P/E ratio not only reflects current market valuations, but is also considered an important predictor of a company's future profitability. A high P/E ratio may imply that the market expects the company to achieve higher earnings growth [9]. Therefore, analyzing the relationship between P/E ratios and other financial indicators can help predict a company's future performance. The variables are derived in the following Table 1.

Table 1: Variable Description.

Type	Variable	Symbol	Variable definition
Dependent	Price-to-Earnings Ratio	P/E	Price per Share divided by Earnings per Share (EPS)
Independent Control	Total Asset Turnover Ratio	ATO	Net Sales divided by Total Assets
	Return on Assets	ROA	Net Income divided by Average Total Assets
	Debt to Equity Ratio	D/E	Total Liabilities divided by Shareholders' Equity
	Earnings Before Interest and Taxes Growth Rate	EBITGR	EBIT_current year minus EBIT_previous year, then divided by EBIT_previous year
	Earnings Before Interest, Taxes, Depreciation, Amortization Growth Rate	EBITDAGR	EBITDA_current year minus EBITDA_previous year,then divided by EBITDA_previous year
	Net Profit Margin	NPM	Net Profit divided by Revenue
Control	Firm Size	Size	Total assets are in the order of magnitude

2.3. Modelling

To study the effect of Total Asset Turnover Ratio, Return on Assets, Debt to Equity Ratio, Earnings Before Interest and Taxes Growth Rate, Earnings Before Interest, Taxes. Depreciation, Amortization Growth Rate, Net profit margin, on firm valuation P/E establish Eq (1) where P/E is the dependent variable and Controls denote each control variable.

$$P/E_{i,t} = \alpha_0 + \alpha_1 ATO_{i,t} + \alpha_2 ROA_{i,t} + \alpha_3 D/E_{i,t} + \alpha_4 EBITGR_{i,t} + \alpha_5 EBITAGR_{i,t} + \alpha_6 NPM_{i,t} + \sum Control_{i,t} + \sum IND + \sum YEAR + \varepsilon_{i,t} \quad (1)$$

3. Empirical Results

3.1. Descriptive Statistics

Table 2 shows descriptive statistics for P/E, as well as variables for other financial indicators. The mean P/E is 35.80, with a standard deviation of 12.28 and a range from 16.54 to 57.38, Indicating significant differences in valuations between companies. The standard deviation of both ROA and NPM is 0.9, indicating that there is not much difference in profitability between companies.

Table 2: Summary statistics.

Variable	N	Mean	S.D.	Min.	Max.
P/E	34	35.80	12.28	16.54	57.38
ATO	34	0.80	0.23	0.44	1.48
ROA	34	0.15	0.09	0.05	0.36
D/E	34	0.38	0.27	0.13	1.15
EBITGR	34	0.26	0.57	-0.40	2.56
EBITDAGR	34	0.23	0.39	-0.25	1.26
NPM	34	0.18	0.09	0.06	0.39

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Table 3 presents the results of the correlation analysis of all variables in this study. Most of the correlation coefficients are less than four, indicating a significant difference between them. The positive correlation between EBITDAGR and NPM is reasonable, because when a company's EBITDA increases, it means that its core profitability is enhanced, cost control is better, and operational efficiency is improved. Therefore, more income can be converted into net profit, thereby improving the net profit margin.

Table 3: Correlation matrix.

Variable	P/E	ATO	ROA	D/E	EBITGR	EBITDAGR	NPM
P/E	1.00						
ATO	1.84	1.00					
ROA	79.77***	1.25***	1.00				
D/E	-2.94	0.06	-0.09	1.00			
EBITGR	3.20	0.08	0.06**	0.13	1.00		
EBITDAGR	9.77*	0.20*	0.12***	0.13	1.36	1.00	
NPM	86.24	0.38	0.92	-1.01**	1.84*	1.92***	1.00

Note: *p < 0.1, **p < 0.05, ***p < 0.01.

3.2. Regression Results

Table 4 presents the results of a multiple regression analysis of the relationship between the price/earnings ratio (P/E) and several financial indicators, specifically for companies in the biopharmaceutical industry. The analysis and interpretation of each variable is presented below.

Table 4: Regression results for the impact of P/E on financial performance.

Variables	P/E
ATO	27.630
	(23.369)
ROA	42.400
	(194.995)
D/E	10.457
	(7.319)
EBITGR	-17.371*
	(9.864)
EBITDAGR	24.826*
	(16.309)
NPM	47.361
	(166.298)
YEAR	YES
INDUSTRY	YES
N	34
R-Squared	0.510

Note: *p < 0.1, **p < 0.05, ***p < 0.01.

Although asset turnover shows a positive coefficient (27.630), suggesting that higher asset turnover may theoretically enhance the P/E ratio, this result is statistically insignificant, possibly due to the fact that in the biopharmaceutical industry, the effect of asset turnover is more attenuated or is more significantly affected by other variables that are not included (e.g., investment in R&D). Similarly, return on assets (ROA), although also exhibiting a positive coefficient (42.400), is similarly statistically insignificant (with a standard error of 194.995), possibly due to the industry characteristics that lead to higher fluctuations in ROA or the fact that the market reacts to the short-

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term financial performance of a company much less than it does to its future potential and R&D achievements.

Meanwhile, the positive coefficient (10.457) of Debt to Equity Ratio (D/E) does not reach statistical significance (with a standard error of 7.319), reflecting the market's insensitivity to the financial structure of biopharmaceutical companies, placing more emphasis on their research capabilities and long-term growth potential. On the contrary, the significant negative correlation of EBITGR (coefficient of -17.371, $p < 0.1$) suggests that the market is concerned about the risks that may be associated with the growth of profits, and therefore manifests itself as valuation pressure in the P/E reflection.

The significant positive correlation of EBITDAGR (coefficient of 24.826, $p < 0.1$) indicates that the market is optimistic about the improvement in the underlying profitability of the companies, which is expected to enhance their market value and attractiveness. Finally, although Net Profit Margin (NPM) exhibits a positive coefficient (47.361), it is not statistically significant enough (with a standard error of 166.298), suggesting that the market may be focusing more on the long-term potential of a biopharmaceutical company than on its short-term profit performance when evaluating it.

This analysis shows that while the direct impact of most financial metrics on the P/E ratios of biopharmaceutical companies is insignificant, the growth rates of EBITGR and EBITDAGR have significant negative and positive impacts on the P/E ratios, reflecting the market's assessment of a company's future risk and growth potential, respectively. These findings emphasize the market's sensitivity to the growth prospects of biopharmaceutical companies and the complexity of its response to their financial health [10].

Focus on EBITDAGR for investors' investment decisions in the biopharmaceutical industry: EBITDAGR (Earnings Before Interest, Tax, Depreciation, and Amortization Growth Rate) has a significant positive impact on the P/E ratio. This suggests that when evaluating biopharmaceutical companies, investors should consider their long-term growth potential rather than focusing solely on current or short-term earnings. Possible risks associated with earnings growth: EBITGR (Earnings Before Interest and Tax Growth Rate) has a significant negative correlation with P/E ratio, which may reflect the high risks associated with high growth. Investors should be cautious and consider the potential risks when investing in high growth companies. Evaluate financial metrics holistically. Although single metrics such as return on assets (ROA) and net profit margin (NPM) do not show statistically significant impact, they are still important when evaluating a company's financial health holistically. Investors should combine multiple financial metrics to make a more comprehensive investment decision.

3.3. Robustness Check

The results of the multiple regression analyses of Table 5 comparing 2021 and 2022 can provide some robustness checks for investment decisions in the biopharmaceutical industry, especially in the context of considering the impact of the epidemic on the market and company operations. Below are the key insights gained from the analyses of the two annual data and their implications for investment strategies:

Table 5: Robustness results for the impact of P/E on financial performance.

Variables	2021	2022
ATO	14.490	14.173
	(56.095)	(42.932)
ROA	-220.84	5.839
	(438.289)	(295.540)

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Table 5: (continued).

D/E	5.778	15.082
	(10.376)	(11.897)
EBITGR	-20.537**	-135.334**
	(12.652)	(56.432)
EBITDAGR	37.569**	179.632**
	(23.479)	(81.845)
NPM	258.609	48.930
	(390.833)	(259.363)
YEAR	YES	YES
INDUSTRY	YES	YES
N	17	17
R Square	0.601	0.665

Note: *p < 0.1, **p < 0.05, ***p < 0.01.

In multi-year financial analyses of companies in the biopharmaceutical industry, this paper pays particular attention to the relationship between price-to-earnings (P/E) ratios and EBIT growth rates (EBITGR) as well as EBITDA growth rates (EBITDAGR).2021 data shows a significant negative correlation between EBITGR and P/E ratios (coefficient of -20.537, $p < 0.05$) , which suggests that although the company has achieved profit growth, the rate of growth may have fallen short of market expectations or the market is concerned about the potential risks associated with this, leading to a negative impact on the company's valuation. Meanwhile, the positive correlation between EBITDAGR and P/E (37.569, $p < 0.05$) suggests that the market is positively evaluating underlying profitability improvements as an important indicator of a company's long-term growth potential.

The negative impact of EBITGR is even more pronounced going into 2022 (coefficient of -135.334, $p < 0.05$), which may be related to the economic uncertainty during the COVID-19 outbreak and the market's avoidance of risky investments, especially given the unique challenges and pressures faced by the pharmaceutical industry. However, the further increase in the coefficient of EBITDAGR to 179.632 ($p < 0.05$) continues to demonstrate the market's positive perception of companies that are able to maintain or enhance their underlying profitability, as they are able to effectively manage operational efficiencies and improve their competitiveness in the marketplace.

The performance of the biopharmaceutical sector received significant market attention during the COVID-19 outbreak. This attention was primarily reflected in the surge in demand for vaccines, therapies, and related medical devices and technologies. As a result, the outbreak may have exacerbated sensitivity to the negative impact of EBITGR, as the market may have been concerned that even earnings growth could be exposed to subsequent business uncertainty and regulatory risk. At the same time, underlying profitability growth (as indicated by EBITDAGR) may have been positively assessed by the market in the context of the epidemic as it may represent the company's resilience and potential market leadership in response to the crisis.

Investors should focus on the negative impact of EBITGR and consider diversification to reduce the high risk arising from a single investment. Focus on underlying profitability and on investments in companies that show strong EBITDAGR, which may demonstrate stronger earnings and growth potential in the midst of ongoing market turmoil [11].

4. Conclusion

This analysis draws several key findings from regressing the P/E ratios of biopharmaceutical companies against a number of financial metrics for the years 2021 and 2022. First, EBIT growth rate (EBITGR) exhibits a significant negative correlation with P/E ratios, suggesting that despite profit growth, the market remains wary of the sustainability and risks associated with that growth. In contrast, EBITDAGR is significantly positively correlated with the P/E ratio, suggesting that the market is positive about underlying profitability improvements. This trend is more consistent in both years, suggesting that the market performance of the biopharmaceutical industry is closely related to its underlying business activities in the particular context of the epidemic. In addition, other financial metrics such as Asset Turnover (ATO), Return on Assets (ROA), Debt to Equity Ratio (D/E), and Net Profit Margin (NPM) do not reach statistically significant levels of influence on the P/E ratio, but provide an important perspective on a company's operational efficiency and capital structure. Overall, these results reveal that the market valuation of biopharmaceutical companies is influenced by a variety of financial indicators, with EBITGR and EBITDAGR having the most significant impact.

Although this study provides valuable insights, there are some limitations. Firstly, the relatively small sample size (N=34) may limit the generalizability and robustness of the statistical results. Second, the model fails to include all potential variables that may affect the P/E ratios of biopharmaceutical companies, such as specific data on R&D investment, competitive market conditions, regulatory changes and macroeconomic conditions. In addition, long-term trends and cyclical fluctuations may not be adequately captured as the data only covers two years. Financial data may often be heteroskedastic, i.e., the variance of the model's error term varies with the dependent variable, which violates the basic assumption of ordinary least squares. This, if not adequately addressed, may lead to reduced validity of statistical inference.

Future research could enhance the breadth and depth of the study by expanding the sample and including more years of data. At the same time, the inclusion of more control variables, such as R&D expenditures and new product launches, may provide a finer-grained explanation of the P/E ratios of biopharmaceutical companies. In addition, consideration of industry-specific risk factors and macroeconomic indicators, such as changes in interest rates and pharmaceutical policy adjustments, would also make the model more complete. Considering the possible long-term impact of the COVID-19 outbreak on the biopharmaceutical industry, future research should further explore the mechanisms by which the outbreak affected the financial performance and market valuation of companies. In addition, comparative analyses of biopharmaceutical companies in emerging markets and different geographic regions may reveal differences in market structure and corporate behavior on a global scale. In summary, this study provides a preliminary but important perspective for understanding the market valuation dynamics of the biopharmaceutical industry and informs investors and company management to make more informed decisions in an uncertain market environment.

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A Study on the Performance of Mergers and Acquisitions in the Context of State-Owned Enterprise Reform: The Case of Ansteel and Benxi Steel

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Abstract: The State-owned Assets Supervision and Administration Commission emphasizes that promoting the reorganization of state-owned enterprises (SOEs) can focus their advantageous resources, which plays a positive role in addressing issues such as the uneven distribution of state-owned capital, inefficient resource allocation, and homogenized development. This paper, set against the backdrop of SOE reform and central enterprise reorganization, uses the merger and reorganization event of Ansteel Group and Benxi Steel Group as a case study to investigate how central enterprise reorganization can improve the performance of central enterprises, based on the theory of synergistic effects. The study finds that under the theory of synergistic effects, after the reorganization of Ansteel Group and Benxi Steel Group, the operational, financial, and managerial synergistic effects of Ansteel Group continue to be realized, thereby enhancing the performance level of Ansteel Group. This paper aims to demonstrate the improvement of enterprise performance through central enterprise reorganization and calls on other central enterprises to actively respond to the national requirements for mergers and reorganizations, offering suggestions for subsequent reorganizations of central enterprises.

Keywords: Ansteel Group, Merger and Reorganization, Synergy Effect, Performance Evaluation

1. Introduction

On June 30, 2020, the 14th meeting of the Central Comprehensive Deep Reform Commission was convened, and the "State-owned Enterprise Reform Three-Year Action Plan (2020-2022)" was reviewed and adopted, officially commencing the three-year initiative for state-owned enterprise reform. The initiation of this action plan signifies a further deepening of state-owned enterprise reform and an enhancement of policy enforceability. The plan calls for prominent and influential state-owned enterprises to undergo strategic reorganizations and professional integrations, driving resources to converge towards advantageous and core enterprises. It aims to resolve issues of homogenized competition and redundant construction, thereby strengthening the market competitiveness and international influence of state-owned enterprises.

This paper examines the reorganization event of Ansteel Group and Benxi Steel Group within the context of the state-owned enterprise reform and the three-year action plan, providing empirical evidence on how central enterprise reorganizations can improve enterprise performance from operational, financial, and managerial synergy effects. It offers robust support for other central and state-owned enterprises to actively respond to policy requirements.

2. Theoretical Foundation - Synergy Effect Theory

The concept of synergy was first introduced by the American scholar Ansoff, who understood synergy as: "The ideal state of the matching relationship between the company and the acquired enterprise. Previous business literature often described synergy as '2+2=5', implying that the overall performance of a company after acquiring another company is better than the sum of the two companies' original performances." [1] Ansoff's interpretation emphasizes the economic significance of synergy, partly attributed to the benefits of economies of scale [2]. Weston further subdivided synergy effects into operational, financial, and managerial synergy effects. [3] Specifically, operational synergy refers to the increased efficiency of production and business activities under economies of scale following corporate mergers and reorganizations [4][5]; financial synergy pertains to the achievement of financial objectives post-merger and reorganization[6], mainly manifested in improvements in growth capacity, profitability, operational capability, and debt-paying ability [7][8]; managerial synergy is reflected in the enhanced management efficiency following corporate mergers and reorganizations [6].

3. Research Design

3.1. Research Method

The research method employed in this paper is the single-case study method, for the following reasons: (1) This study focuses on how Ansteel Group and Benxi Steel Group improved Ansteel's enterprise performance through mergers and reorganizations within the context of state-owned enterprise reform, which is a "how" type of question; (2) Compared with other research methods, the case study method is more targeted and suitable for studying relatively new phenomena; (3) The merger and reorganization event of Ansteel Group and Benxi Steel Group is typical, and an in-depth analysis of how Ansteel improved enterprise performance after the case is beneficial for reference and comparison by other state-owned enterprises undergoing mergers and reorganizations.

3.2. Case Selection

This paper follows the theoretical typical sampling principle [9], selecting Ansteel Group as the case study object for the following main reasons:

(1) Enterprise typicality. As a large state-owned enterprise directly managed by the central government, Ansteel Group is the first large-scale integrated iron and steel enterprise restored and constructed in New China and the earliest established steel production base. It plays an irreplaceable role in China's economic construction and the development of the steel industry, known as "the eldest son of the Republic's steel industry" and "the cradle of New China's steel industry." Ansteel, a Fortune Global 500 company, has nine major production bases across China, with large production scale, extensive area, and high level, making it an important and well-known supplier domestically and internationally. In enterprises with a long history, the effect of organizational inertia is more pronounced. Ansteel Group, established in 1916, has a long history, making it a typically representative enterprise for study.

(2) Case enlightening. As a typical case of central enterprise reorganization, studying the reorganization case of Ansteel Group and Benxi Steel Group not only proves that actively conforming to the advanced policies of the State Council can bring operational advantages to enterprises but also

provides inspiration for other central and state-owned enterprises to carry out mergers and reorganizations.

3.3. Data Sources and Collection

This paper combines primary and secondary data sources and collection methods. Primary data sources include listed company annual reports, policy documents, etc. Secondary data sources include various public materials, such as reports from the State-owned Assets Supervision and Administration Commission website, policy interpretations, news reports, authoritative platform analysis reports, etc. In addition, this paper also uses materials from databases like CNKI and official public accounts that are considered reliable after screening as references.

4. Background and Motivation for the Reorganization of Ansteel Group and Benxi Steel Group

4.1. Operational Synergy Effects

With the continuous growth of China's economy, the scale of the national steel industry has been expanding and its industrial competitiveness has been continuously improving. However, at the same time, the international competitiveness of the steel industry urgently needs to be enhanced. At the beginning of 2021, the Ministry of Industry and Information Technology issued the "Guiding Opinions on Promoting the High-Quality Development of the Steel Industry," which further promoted the merger and reorganization between Ansteel Group and Benxi Steel Group. In addition to the requirements of the national macro environment, the reorganization of Ansteel Group and Benxi Steel Group is also a need for their own development. Both Ansteel Group and Benxi Steel Group are located in Liaoning Province and are the two major steel giants in the province, with similar product categories and roughly the same sales markets. Before the reorganization event, the product prices of the two companies were significantly lower than those in the Central and Southern China regions, and the reason for this situation was that the two companies were engaged in a "price war" in their respective regions, resulting in a negative competitive situation. Therefore, to respond to the national needs and improve the operating conditions of the two companies, on August 20 of the same year, the State-owned Assets Supervision and Administration Commission of Liaoning Province transferred 51% of the equity of Benxi Steel Group to Ansteel Group without compensation, making Benxi Steel Group a holding subsidiary of Ansteel Group.

4.2. Motivations for Reorganization

4.2.1. Requirements under the Background of State-Owned Enterprise Reform

On July 26, 2016, the State Council issued the "Guiding Opinions on Promoting Structural Adjustment and Reorganization of Central Enterprises." The purpose of issuing this "Opinion" is to implement the decision-making deployment of the Party Central Committee and the State Council on deepening the reform of state-owned enterprises, and to propose the promotion of structural adjustment and reorganization of central enterprises. The key tasks in the "Opinion" include "four batches," which are "consolidating and strengthening a batch," "innovating and developing a batch," "reorganizing and integrating a batch," and "cleaning up and exiting a batch." The reorganization of Ansteel Group and Benxi Steel Group belongs to the "reorganizing and integrating a batch," promoting the strong alliance of the steel industry and promoting the professional integration of the two.

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4.2.2. Enhancing International Competitiveness

The reorganization of Ansteel Group and Benxi Steel Group is conducive to the overall planning and rational development of the most concentrated iron ore resources in China, enhancing the supply capacity of self-owned iron ore, and cultivating world-class enterprises with global competitiveness, achieving high-quality development of the new Ansteel.

5. Performance Evaluation of Ansteel Group and Benxi Steel Group Reorganization Based on Synergy Effects

5.1. Operational Synergy Effects

Following the merger and reorganization of Ansteel Group and Benxi Steel Group, both the operating income and net profit saw a significant increase in 2021 (Figure 1). Post-reorganization, Ansteel Group's operating income reached 383.057 billion yuan, ranking it second in the country and third in the world. This leapfrogged Ansteel Group to become a "star" in China's steel industry, enhancing its international influence and competitiveness.

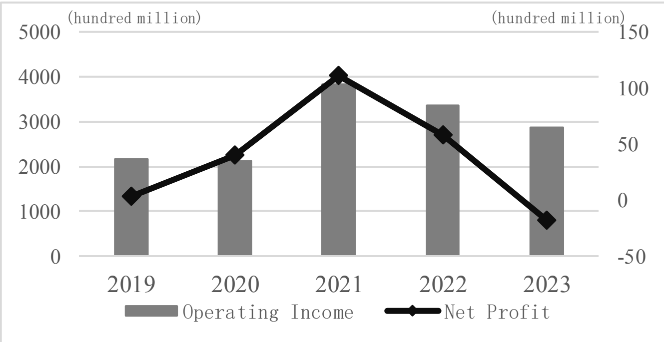

Figure 1: Ansteel Group's Operating Income and Net Profit from 2019 to 2023
Data Source: Compiled based on the annual reports of Ansteel Group from 2019 to 2023.

After the successful reorganization, Ansteel Group boasts a crude steel output of 63 million tons, becoming the largest "aircraft carrier" in North China, following Baosteel Group. Concurrently, with the integration of Ansteel and Benxi Steel, the economies of scale will gradually emerge. The new Ansteel Group will evolve into a global enterprise with world-class scale, costs, and products, steadily progressing towards the goal of becoming a global iron ore resource company.

5.2. Financial Synergy Effects

5.2.1. Growth Capability

As depicted in Figure 2, following the merger and reorganization in 2021, Ansteel Group achieved peak levels in both total asset turnover rate and operating income growth rate. In 2021, the total asset turnover rate of Ansteel Group reached a high of 44.62%, and the growth rate of operating income reached 39.63%. From 2022 to 2023, there was a general trend of significant decline in both total asset growth rate and operating income growth rate. This is attributed to the exceptionally strong performance of the newly reorganized Ansteel Group post-2021. However, it is anticipated that the synergistic effects will continue to positively impact the new Ansteel Group, and overall, the growth capability is expected to show an upward trend post-reorganization.

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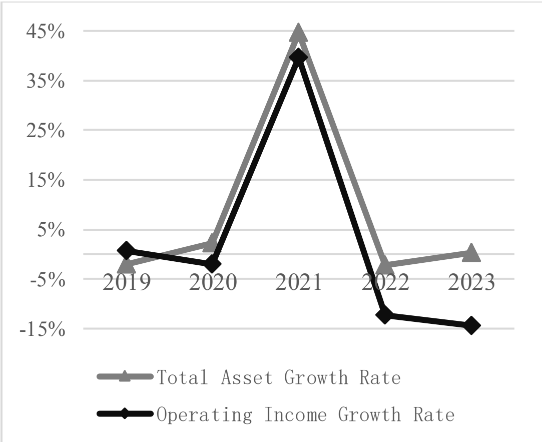

Figure 2: Ansteel Group's Total Asset Growth Rate and Operating Income Growth Rate from 2019 to 2023

Data Source: Compiled based on the annual reports of Ansteel Group from 2019 to 2023.

5.2.2. Profitability

As shown in Figure 3, Ansteel Group's net profit margin showed a stable upward trend from 2019 to 2021, indicating an enhancement in profitability following the merger and reorganization; the gross profit margin fluctuated slightly but overall trended upward during the same period, with the reorganization contributing to Ansteel Group's profitability in the short term. However, after 2022, both the net profit margin and gross profit margin of Ansteel Group exhibited a downward trend due to external environmental factors. In 2022, influenced mainly by the global economic downturn and a decrease in demand for steel products, steel prices plummeted, leading to an expanding loss across the steel industry and a weak cyclical market with low prosperity. Overall, this paper posits that Ansteel Group's profitability is expected to improve when the market outlook improves.

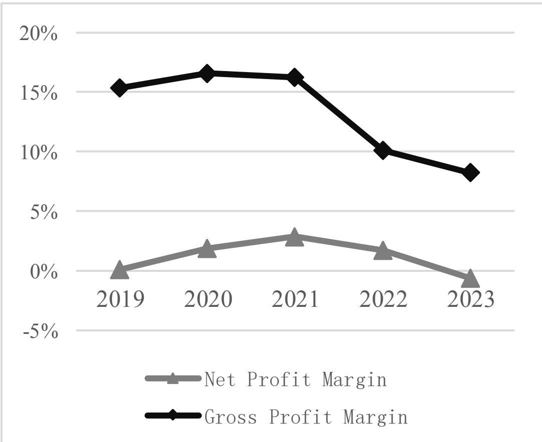

Figure 3: Ansteel Group's Net Profit Margin and Gross Profit Margin from 2019 to 2023

Data Source: Compiled based on the annual reports of Ansteel Group from 2019 to 2023.

5.2.3. Debt-Paying Ability

(1)Short-term Debt-Paying Ability

The optimal range for the current ratio is 1.5 to 2.0, and the quick ratio should be around 1. Figure 4 illustrates the changes in Ansteel Group's short-term debt-paying ability. Overall, Ansteel Group's current and quick ratios have been poor, showing low levels. From the perspective of the current ratio,

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although there was an increase after the merger and reorganization in 2021, it remains below the normal level. Regarding the quick ratio, there has been little change after the reorganization, and it remains at a low level. Considering both the current and quick ratios, the merger and reorganization between Ansteel Group and Benxi Steel Group did not improve Ansteel Group's low debt-paying ability. Additionally, the low cash ratio of Ansteel Group from 2019 to 2023 also confirms its poor short-term debt-paying ability.

（2）Long-term Debt-Paying Ability

Figure 5 shows the changes in Ansteel Group's long-term debt-paying ability from 2019 to 2023. In terms of the debt-to-asset ratio, Ansteel Group's overall debt-to-asset ratio has not fluctuated significantly, indicating that the merger and reorganization with Benxi Steel Group did not have a substantial impact on Ansteel Group's long-term debt-paying ability. Looking at the equity ratio, Ansteel Group's equity ratio has been fluctuating within a normal range, further confirming that the reorganization event had little overall impact on Ansteel Group's long-term debt-paying ability.

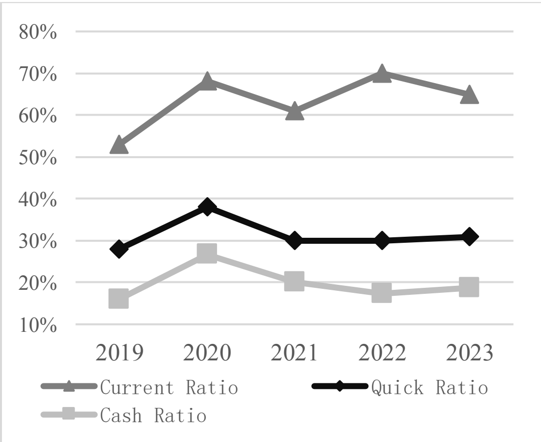

Figure 4: Changes in Ansteel Group's Short-term Debt-Paying Ability

Data Source: Compiled based on the annual reports of Ansteel Group from 2019 to 2023.

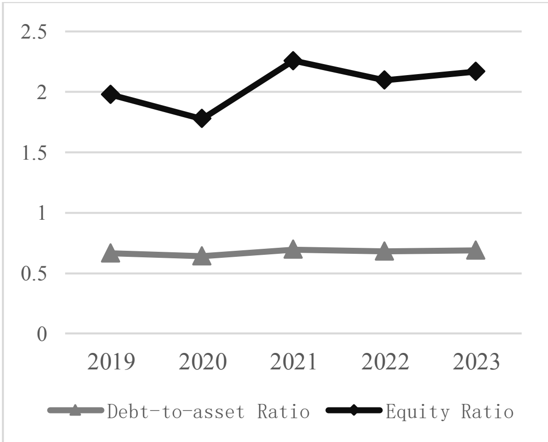

Figure 5: Changes in Ansteel Group's Long-term Debt-Paying Ability

Data Source: Compiled based on the annual reports of Ansteel Group from 2019 to 2023.

Considering both short-term and long-term debt-paying abilities, the merger and reorganization of Ansteel Group and Benxi Steel Group did not bring an improvement in Ansteel Group's debt-paying ability. This paper suggests that this may be due to the overall unremarkable debt-paying ability in the steel industry.

5.3. Managerial Synergy Effects

In this paper, the analysis of the managerial synergy effects mainly selects asset management capability indicators to analyze the merger and reorganization event of Ansteel Group and Benxi Steel Group. As shown in Figure 6, the inventory turnover rate, total asset turnover rate, and accounts receivable turnover rate of Ansteel Group all show a significant decline after 2021, indicating that the managerial synergy effect has been prominently realized after the merger and reorganization of Ansteel Group and Benxi Steel Group.

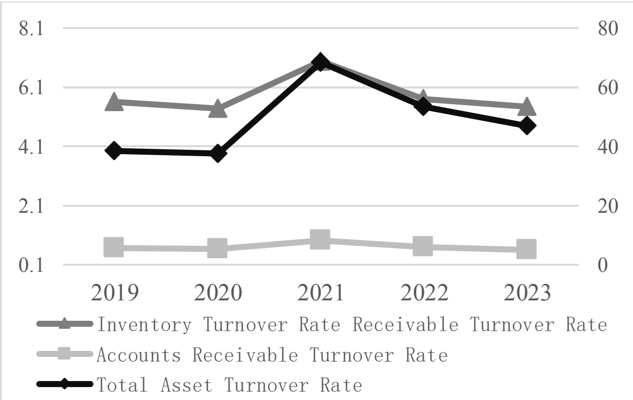

Figure 6: Changes in Ansteel Group's Inventory Turnover Rate, Total Asset Turnover Rate, and Accounts Receivable Turnover Rate from 2019 to 2023

Data Source: Compiled based on the annual reports of Ansteel Group from 2019 to 2023.

6. Research Conclusions and Implications

Driven by national requirements and their own needs, Ansteel Group and Benxi Steel Group completed a merger and reorganization on August 20, 2021, with Benxi Steel Group officially becoming a subsidiary of Ansteel Group. The analysis in this paper shows that after the reorganization event, Ansteel Group has effectively leveraged operational synergy, financial synergy, and management synergy. The merger between Ansteel Group and Benxi Steel Group has brought about a "1+1>2" effect for Ansteel Group, transforming the previous "disorderly confrontation" into a win-win situation of "mutual support." The reorganization event of Ansteel Group and Benxi Steel Group is a typical case of large-scale central enterprise reorganization, and the results of the synergy effect and the improvement of corporate performance have confirmed the advantages of state-owned enterprise reform in promoting the reorganization of central enterprises. This paper provides evidence for the improvement of corporate performance through central enterprise reorganization, and it is suggested that central enterprises and state-owned enterprises should actively respond to reorganization policies according to their own needs to achieve the goal of improving corporate performance.

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The Study of an Urban Social Resilience Evaluation Index System under the Context of Public Health Emergencies

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Abstract: This paper focuses on urban social resilience under the context of public health emergencies. It constructs an evaluation index system based on the theories of resilience and urban resilience, urban and social vulnerability, system coupling and coordination, risk and chaos, as well as a review of the current state of domestic and international research. A BP comprehensive evaluation model was established and applied. The study found that among 21 cities, except for Shanghai, Beijing, Shenzhen, Chengdu, Nanjing, and Hangzhou, the social resilience levels of the remaining 15 cities are below the average level.

Keywords: Public Health Emergencies, Social Resilience, Mega and Super-Large Cities.

1. Introduction

The rapid development of socio-economics and the increasing trend of aging populations have accelerated urban social processes, while the issues of social development have become increasingly apparent. Global pandemics and nuclear leakages have posed significant threats to urban residents' lives [1]. Against this backdrop, urban social resilience has gradually emerged as a new research direction, bringing the society's ability to prevent, respond to, and recover from public health emergencies into the public eye[2]. Considering the post-epidemic era as a recent major public health emergency faced by cities, and mega and super-large cities can more prominently demonstrate the impact of events on the city. Therefore, how to scientifically evaluate urban social resilience remains a problem that the academic community and the practical field urgently need to solve.

Currently, domestic and international scholars have conducted some research in the field of urban resilience evaluation. The research mainly focuses on disaster risk governance, multiple disturbance impacts, and dynamic change process analysis in the direction of theoretical framework construction[3]; in the direction of comprehensive index evaluation, scholars mainly establish an index system of different urban resilience elements based on the connotation of urban resilience, calculate the resilience index to comprehensively evaluate the level of urban resilience [4]; in the direction of remote sensing models, scholars focus on the spatial heterogeneity and spatiotemporal evolution process of urban resilience [5]. In addition, scholars' evaluation of urban resilience also includes resilience network evaluation, functional model assessment, resilience maturity model evaluation, and other multifaceted research[6].

However, starting from the existing literature, existing research mainly focuses on the comprehensive evaluation of urban resilience under the existing urban structure, and there is less research on the dimension of urban social resilience from the perspective of public health emergencies.

Moreover, most of them are theoretical studies, and the research angles are mostly concentrated on the community level rather than the city level, and there is no unified analysis of indicators related to urban social resilience combined with practical application [7]. It can be seen that establishing a scientific and comprehensive urban social resilience evaluation index system to deal with public health emergencies has become an urgent need in the current academic community and social practice.

This paper takes mega and super-large cities in the post-epidemic era as the research object, aiming to use grounded theory and the DPSIR conceptual model to construct an urban social resilience evaluation index system based on the background of public health emergencies. By using the combination of entropy weight method - variation coefficient method for weighting and BP neural network comprehensive evaluation method, a new urban social resilience evaluation model is established. An application analysis of 21 mega and super-large cities across the country is conducted to comprehensively assess the capabilities of the city's social dimension in the face of public health emergencies, providing a scientific basis for government decision-making, improving the public's cognition and understanding of public health emergencies, and promoting the stable and harmonious development of society.

2. Comprehensive Evaluation Index System

2.1. Data Sources

In this paper, a collection of previous research literature was conducted. Through academic databases such as CNKI (China National Knowledge Infrastructure), Baidu Academic, and official websites of the National Emergency Management Department and the National Standardization Management Committee, 24 relevant literatures and documents that are in line with this research were identified. Based on Grounded Theory, Nvivo 14.0 was used to randomly code 2/3 of the collected literature, totaling 16 samples, for open coding analysis. This was followed by manual open coding to identify different index subjects, with the remaining 1/3 used for theoretical saturation testing [8].

2.2. Evaluation Index System

To verify the accuracy and comprehensiveness of the dimensions of urban social resilience under public health emergencies as defined in this paper, the DPSIR conceptual model was introduced, drawing on the coding ideas of Grounded Theory for exploratory research on the evaluation index system of urban social resilience under public health emergencies, forming the results of qualitative research. Through the collection and coding process of raw data, the evaluation index system of urban social resilience under public health emergencies is summarized into the 5 main dimensions of the DPSIR model: Driving force, Pressure, State, Impact, and Response, with 10 axial codings and 22 open codings, thus forming 10 secondary indicators and 22 initial tertiary indicators, as shown in the table.

Table 1: Evaluation System

Target Layer	Criterion Layer	Element Layer	Indicator Layer
Urban Social Resilience Evaluation Index	Driving Force :D	Economic Development Driving Force (D1)	D11 Per Capita Disposable Income (Yuan)
			D12 Fiscal Revenue (Billion Yuan)
		Social Development Driving Force (D2)	D21 Non-elderly Population Proportion (%)
			D22 University and Above Education Population per 100,000 People (People)

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Table 1: (continued).

Pressure: P	Emergency Service Pressure: P1	D23 Proportion of Non-disabled Population (%)
		P11 Proportion of General Public Service Expenditure in Local Government Expenditure (%)
		P12 Proportion of Disaster Prevention and Emergency Management, Public Safety Expenditure in Local Government Expenditure (%)
	Medical Supply Pressure: P2	P21 Number of Doctors per 10,000 People
		P22 Number of Hospital Beds per 10,000 People
Status: S	Social Relationship Network: S1	S11 Urban Coverage Rate (%)
		S12 Number of College Students per 10,000 People
	Organizational Support Capability: S2	S21 Proportion of Social Security and Employment Expenditure in Local Government Expenditure (%)
	Organizational Support Capability: S2	S22 Proportion of Health and Wellness Expenditure in Local Government Expenditure (%)
Impact: I	Industrial Structure and GDP: I1	I11 Share of the Tertiary Sector in GDP (%)
		I12 Per Capita GDP (10,000 Yuan)
	Information Transmission and Material Transportation Capability: I2	I21 Fixed Broadband Household Penetration Rate (%)
		I22 Total Volume of Posts and Telecommunications Business (Billion Yuan)
Response: R	Promotion and Education: R1	R11 Proportion of Cultural Media Expenditure in Local Government Expenditure (%)
		R12 Proportion of Education Expenditure in Local Government Expenditure (%)
	Scientific and Technological Innovation Capability: R2	R21 Proportion of Science and Technology Innovation Expenditure in Local Government Expenditure (%)
		R22 Proportion of Employment in the Science and Technology Sector (%)
		R23 Proportion of Employment in the Creative Industries (%)

3. Empowerment by Combination of Entropy Weight Method and Variation Coefficient Method - Construction and Application of BP Neural Network Evaluation Model

Through the normalization of the collected data, the model employs a combination of the entropy weight method and the variation coefficient method for empowerment, followed by simulation with a Backpropagation (BP) neural network, ultimately resulting in an integrated evaluation analysis model based on the combination of the entropy weight method and variation coefficient method, as well as the BP neural network.

DOI: 10.54254/2754-1169/95/20241123

3.1. Data Sources

This paper is based on the updated data from the seventh national census, selecting samples for model application [9]. Data from 21 mega and super cities across the country are comprehensive and updated quickly. The social resilience indicators data for each city in 2022 are chosen as the network learning samples. Among them, Shanghai, Harbin, Kunming, and Zhengzhou have not yet released the 2023 statistical yearbook during the writing process of this paper. Therefore, the national economic and social development statistical bulletins for 2022, as well as the quarterly and monthly statistical data for the whole year of 2022, are selected to integrate and calculate the specific social indicator data for each city in 2022. This is done to better train the learning samples, making the evaluation results more convincing. All relevant evaluation indicators for the level of urban social resilience under public health emergencies are quantitative indicators, and the indicator data can be obtained from official websites and statistical materials for direct quantification or formula-derived quantification.

3.2. Determination of Expected Values in BP Neural Network

Training Training requires a comparison of expected values with output values to meet the error requirements. Based on the weights determined by the combination of the entropy weight method and the variation coefficient method and the summation of standardized data weighted by these weights, all expected values are obtained. That is, the expected values for the level of social resilience in 21 mega and super cities under public health emergencies are shown in Table 2.

Table 2: Expectations of social resilience in 21 national megacities

Cities	Expected Value
Chengdu	0.5455
Hangzhou	0.4464
Beijing	0.4199
Shanghai	0.3998
Shenzhen	0.3762
Nanjing	0.3127
Changsha	0.2781
Wuhan	0.2850
Foshan	0.2622
Xi'an	0.2316
Kunming	0.2718
Guangzhou	0.2289
Dongguan	0.2469
Jinan	0.2620
Zhengzhou	0.2366
Tianjin	0.2265
Qingdao	0.2249
Dalian	0.2159
Harbin	0.1798
Shenyang	0.1959
Chongqing	0.1613

3.3. BP Neural Network Simulation Training

This paper selects 19 cities as training samples. The remaining cities with extreme expected values, Chengdu and Chongqing, are chosen as test samples to illustrate the universality of the evaluation model.

(1) Input Layer: In the neural network model, the number of nodes in the input layer typically reflects the complexity of the features or indicators involved in the model. In this paper, 22 third-level indicators are selected as input nodes, which means the model takes into account a wide range of evaluation factors, thereby more comprehensively analyzing the performance of urban social resilience in public health emergencies.

(2) Hidden Layer: Combining the situation of urban social resilience and existing research, this paper adopts the following calculation formulas to determine the number of nodes in the hidden layer [10]:

$$L = \sqrt{n+m} + a, L = \sqrt{nm}, L = \frac{n+m}{2}, L = log_2 n$$

Where L represents the number of nodes in the hidden layer, n represents the number of nodes in the input layer, and m represents the number of nodes in the output layer. The value of a ranges from 1 to 10 and a is taken as an integer [11]. This paper calculates the approximate range of the number of hidden layer nodes to be [4, 16]. Through multiple trials and adjustments, when the number of hidden layer nodes is set to 16, the training observed that the error reached a minimum value of 0.000256. Therefore, this paper selects 16 as the number of nodes in the hidden layer.

(3) Output Layer: The node is set to 1 and the rating is divided. As shown in Table 3.

Table 3: Division of toughness level and grade

Evaluation Grading	Output Result Value	Resilience Level
A	(0.51, 1.00]	High Resilience
B	(0.42, 0.51]	Moderately High Resilience
C	(0.33, 0.42]	Moderate Resilience
D	(0.24, 0.33]	Moderately Low Resilience
E	(0.15, 0.24]	Low Resilience

Utilizing MATLAB R2021a software, the neural network is configured with 22 neurons in the input layer, 16 neurons in the hidden layer, and 1 neuron in the output layer. The training function trainlm is employed, with a learning rate of 0.05, a default momentum factor of 0.9, a training precision requirement of 1×10−41×10−4, a maximum number of training epochs set to 10,000, and a training target function error goal of 1×10−41×10−4 [133-135]. Sample data is then input into the model. Through the BP neural network training, relevant training comparison values are obtained, and the experimental results indicate that the expected output values are close to the actual output values.

Model Validation Results The well-trained model is applied to Chengdu and Chongqing for validation, and the output results are presented in Table 4.

Table 4: Comparison table of the expected sample and the output results of training

City	Training Value	Expected Value	Absolute Error	Relative Error
Chengdu	0.543652245	0.545490264	0.001838019	0.34%
Chongqing	0.162624535	0.161282348	0.001342187	0.83%

In summary, the evaluation model established in this paper performs well in approximating both the training and test samples, thus it is considered effective and can be used to assess the social resilience levels of other cities.

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4. Comprehensive Evaluation Results Analysis

The study found that the current average level of urban social resilience in China is 0.28609. Among the 21 cities, except for Shanghai, Beijing, Shenzhen, Chengdu, Nanjing, and Hangzhou, the social resilience levels of the remaining 15 cities are below the average. This indicates that although many cities in China have started to pay attention to the development and construction of urban resilience, there is a significant disparity in the current levels of social resilience. The scoring and resilience levels of each city are shown in Figure 1.

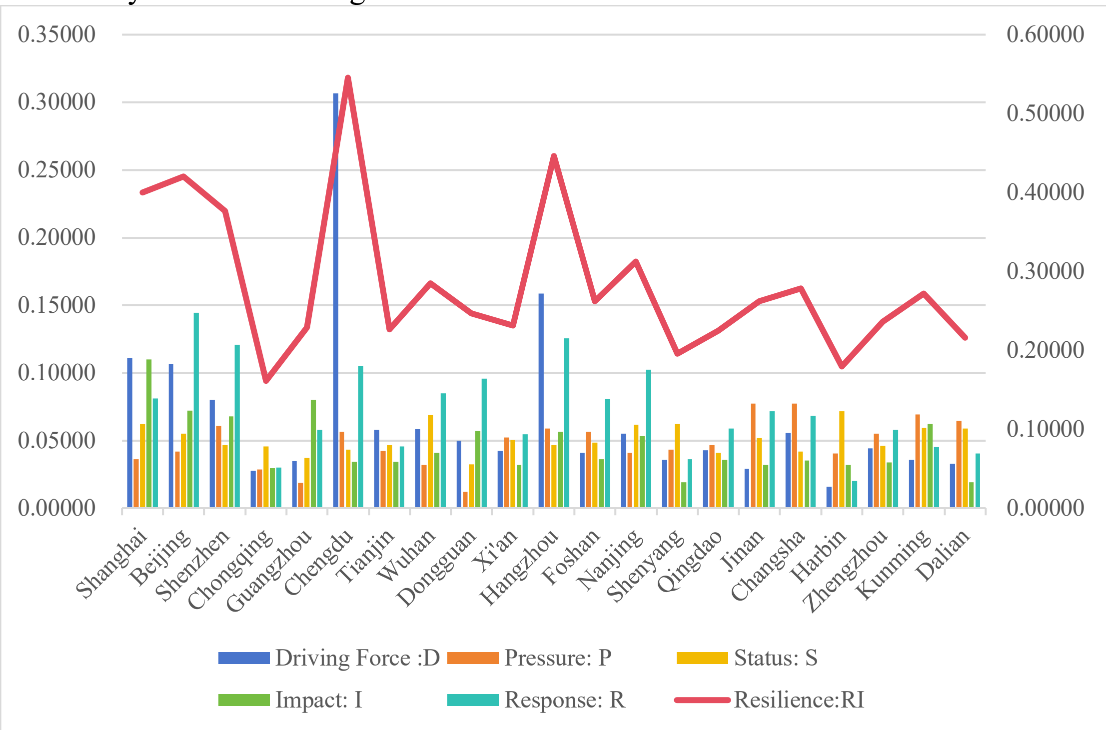

Figure 1: Score status and resilience level chart of each city

5. Conclusions

Firstly, this paper constructs an evaluation index system for urban social resilience under public health emergencies. Focusing on the social resilience of cities in the context of public health emergencies, the paper establishes common evaluation indicators from the five dimensions of the DPSIR conceptual model. It also optimizes and constructs the index system by combining grounded theory for the urban level under public health emergencies. This index system includes ten aspects: economic development and social development at the driving force level, emergency services and medical supplies at the pressure level, social relationship networks and organizational support capabilities at the state level, industrial structure and GDP as well as information transmission and material transportation capabilities at the impact level, and promotion and education and scientific and technological innovation capabilities at the response level.

Secondly, this paper constructs an evaluation model for urban social resilience under public health emergencies based on the BP neural network, using 21 mega and super cities as sample data for the application study. By employing the combination of the entropy weight method and the variation coefficient method for empowerment, a BP neural network simulation model is constructed. The model is trained based on samples from 21 mega and super cities across the country and simulated using MATLAB software. It reflects the resilience situation in various dimensions of large cities nationwide and retains the data of the test cities to verify the model's effectiveness, that is, whether it

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can reflect the social resilience of cities. This model only requires objective data and does not need subjective scoring by experts, thus obtaining evaluation results and having a broad application prospect.

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Does Failure Tolerance of the Board of Directors Affect Investment Efficiency?

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Abstract: Based on the perspective of failure tolerance, this paper measures the board's failure tolerance by whether the company's performance failing to meet the board's expectations leads to the mandatory replacement of managers. On this basis, the paper selects data from A-share listed companies in China from 2010 to 2022 to study the impact of board failure tolerance on corporate investment efficiency. The research finds that board failure tolerance can significantly improve corporate investment efficiency, both inhibiting over-investment and alleviating under-investment.

Keywords: Agency Conflict, Executive Team Stability, Failure Tolerance Theory

1. Introduction

China's economy has maintained rapid growth for a long time, but the goals of economic development have undergone qualitative changes. The report of the 19th National Congress of the Communist Party of China proposed a shift from a "high-speed growth stage" to a "high-quality development stage." Enterprises are the micro-foundation of economic development, and their efficient development is crucial for promoting high-quality economic development. For micro-enterprises, investment is the foundation for enhancing corporate value, and investment decision-making is the core of the three major financial decisions. Investment efficiency plays an important role in corporate development. Only highly efficient investments can enable companies to maintain a competitive advantage in fierce market competition and achieve sustainable development. However, high investment does not necessarily mean high efficiency. There is a contradictory phenomenon in China of high investment but low efficiency, with listed companies exhibiting inefficiencies in the form of over-investment or under-investment. According to the CSMAR database statistics, about 61% of companies exhibit under-investment, and about 39% exhibit over-investment. This indicates that there are inefficient investment behaviors among China's listed companies, with under-investment being more prevalent than over-investment. Both over-investment and under-investment deviate from ideal investment states, causing numerous problems for business operations and leading to increased risks of stock price crashes [1] and damage to corporate value [2].

In the modern corporate structure characterized by the separation of ownership and management, the control of the business is no longer in the hands of shareholders but is delegated to experienced senior managers. As investment is a critical way for a company to create value, the decision-making power for investments largely lies with senior managers. Managers, in pursuit of their own interests, may often sacrifice the interests of stakeholders such as shareholders and creditors when making investment decisions, thereby negatively impacting corporate investment efficiency. Therefore, it is particularly important to motivate senior managers to improve corporate investment efficiency. Existing literature mainly explores the impact of board governance [3] and management incentives [4] on corporate investment efficiency from an internal perspective based on agency theory and optimal contract theory. However, the inherent riskiness, long-term nature, and unpredictability of corporate investments make performance measurement difficult, thus limiting the motivational effectiveness of standard performance-based compensation mechanisms.

Given the limitations of traditional standard performance-based compensation mechanisms in motivating managers to make investment decisions, Manso [5] proposed the failure tolerance theory oriented towards innovation incentives. This theory points out that compensation mechanisms strictly linked to performance can lead managers to pursue short-term performance, resulting in myopic behaviors. It further suggests establishing a new type of incentive mechanism: tolerating early failures of managers and rewarding success. The failure tolerance theory provides a new theoretical perspective to mitigate the conflicts of interest between shareholders and corporate managers. Thus, can the board's introduction of a failure tolerance incentive mechanism motivate managers' investment behavior, leading them to make investment decisions with a greater focus on the company's long-term value and maximizing shareholder wealth?

The academic contributions of this paper mainly lie in the innovation of the measurement method of board failure tolerance. This paper reviews the measurement methods of board failure tolerance and finds that existing literature mainly measures it from the perspective of performance decline, using the sensitivity of managerial forced turnover to short-term performance changes [6, 7] and the stickiness of executive compensation [8]. This paper starts from whether managerial forced turnover occurs when the board's expectations are not met, providing a new measurement method for board failure tolerance and enriching the failure tolerance theory.

2. Research Hypothesis

The failure tolerance theory proposes that an incentive mechanism should be established to tolerate early failures and reward long-term successes [5]. A failure-tolerant board is characterized by "emphasizing rewards and light punishments" and "rewarding excellence without penalizing failure" [9], which alleviates managers' short-sighted behaviors, enhances their adventurous spirit and risk-taking ability, reduces agency costs, and thereby improves corporate investment efficiency.

From the perspective of personal costs and benefits, managers consider the potential returns and personal costs when making investment decisions. New investments require managers to invest more time and effort and bear higher risks. When managers incur high personal costs from new investments and the returns are uncertain, they tend to abandon some projects with positive net present values [10], resulting in under-investment. However, a failure-tolerant board provides managers with protection from failure and rewards for investment success [5], reducing the personal costs of investment and providing the necessary incentives. This motivates managers to pursue new investments and make high-quality investment decisions based on the goal of maximizing the company's long-term value, thus alleviating the problem of under-investment caused by concerns over personal costs and subsequently improving corporate investment efficiency.

From the perspective of job security for managers, a failure-tolerant board does not replace managers due to short-term performance not meeting expectations, ensuring job security for managers. This security makes managers more likely to make high-quality investment decisions based on the company's long-term value. On one hand, when managers expect a short tenure, they may avoid investing in high-risk new projects due to concerns about job and income security, leading to a tendency to maintain previous investment projects [11] and resulting in under-investment. On the other hand, when managers expect a short tenure, they have a strong motivation to engage in self-

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serving investments that sacrifice long-term shareholder interests [12], leading to over-investment. A failure-tolerant board provides managers with the expectation or promise of a longer tenure [8], allowing managers to enjoy the delayed returns from investments during their term. Therefore, managers will consider the company's long-term value when making investment decisions, alleviating under-investment and over-investment issues, and thereby enhancing corporate investment efficiency.

From the perspective of executive team stability, if the board cannot tolerate short-term performance not meeting expectations and replaces managers, it will exacerbate managerial short-sighted behaviors [13], reduce the quality of internal control [14], and lead to inefficient investment problems. Conversely, if the board provides high tolerance and does not replace managers due to short-term performance not meeting expectations, the executive team can maintain high stability. On one hand, a stable executive team is a guarantee for making high-quality investment decisions. A stable executive team can reduce the likelihood of conflicts among team members [15], leading to more coordinated and efficient communication, thus making decisions that are more beneficial for the company's development. On the other hand, a highly stable executive team is more focused on the company's long-term development. When the team is very stable, the interests of team members align with the company's long-term value, allowing them to enjoy the long-term benefits from investments. Executives will have the willingness and motivation to focus on the company's future development, considering long-term returns in their investment decisions, reducing agency costs [16], and suppressing inefficient investment behaviors.

In summary, based on the failure tolerance theory, board failure tolerance reduces the personal costs of managers' new investments to a certain extent, ensures job security for managers, and improves the stability of the executive team. This allows managers to make high-quality investment decisions from the perspective of the overall interests of the company, thereby improving investment efficiency. Based on the above analysis, the first research hypothesis of this paper is proposed:

Hypothesis H1: Board failure tolerance can significantly improve corporate investment efficiency.

3. Research Design

3.1. Sample Selection and Data Sources

This paper selects A-share listed companies on the Shanghai and Shenzhen stock exchanges from 2010 to 2022 as the initial research sample. The original sample was processed as follows: (1) excluding financial and insurance companies; (2) excluding ST, *ST, and PT companies; (3) excluding companies with missing data. To eliminate the potential impact of extreme values, all continuous variables were winsorized at the 1st and 99th percentiles. The data used in this paper are all sourced from the CSMAR database.

3.2. Variable Design

3.2.1. Dependent Variable: Investment Efficiency

The dependent variable in this paper is corporate investment efficiency. Referring to Richardson's residual measurement model [17], the deviation between a company's actual investment and the predicted optimal investment level is used to measure inefficient investment. The specific model (1) is as follows:

$$Inv_{i,t} = \alpha_0 + \alpha_1 Growth_{i,t-1} + \alpha_2 Lev_{i,t-1} + \alpha_3 Cash_{i,t-1} + \alpha_4 Age_{i,t-1} + \alpha_5 Size_{i,t-1} + \alpha_6 Return_{i,t-1}$$

$$+\alpha_7 Inv_{i,t-1} + \sum Industry/Year + \varepsilon_{i,t-1} \quad (1)$$

where *Inv* represents investment expenditure; *Growth* is the growth rate of operating revenue; *Lev* is the asset-liability ratio; *Cash* is the ratio of cash and cash equivalents to total assets; *Age* is the natural logarithm of the observation year minus the listing year; *Size* is the natural logarithm of total assets; *Return* is the stock return.

The residuals obtained from the regression of the above Richardson model are used to measure investment efficiency (*Inveff*). The absolute value of the residual indicates the level of investment inefficiency: the larger the absolute value, the lower the investment efficiency. A positive residual indicates over-investment (*Overinv*); a negative residual indicates under-investment (*Underinv*), measured by the absolute value of the residual.

3.2.2. Independent Variable: Board Failure Tolerance

Following Manso's [5] proposal of the failure tolerance theory, which advocates for tolerating early failures, scholars have begun to measure this variable. Di Junpeng et al. [18] used the average tenure of managers to measure a company's failure tolerance towards its managers. Zhu Bing et al. [6] measured a company's tolerance towards managers by examining the sensitivity of forced managerial changes to short-term performance. They argue that if managers are dismissed due to a short-term decline in corporate performance, it indicates a low level of failure tolerance.

Thus, this paper defines board failure tolerance as follows: when the board does not change managers due to actual corporate performance failing to meet expectations, the board is considered failure-tolerant [6]. Referring to the studies by Zhu Bing et al. [6] and Chen Xiude et al. [8], this paper constructs a dummy variable to measure board failure tolerance. Specifically, the sample where actual earnings per share (EPS) is lower than the analysts' forecast mean is retained. The difference between actual EPS and the analysts' forecast EPS mean is divided into high and low groups based on the annual industry median. If the difference is above the median and no forced managerial change occurs in the following year[1], the board is considered failure-tolerant, assigned a value of 1. If the difference is below the median and a forced managerial change occurs in the following year, the board's failure tolerance is low, assigned a value of 0. The specific measurement method of board failure tolerance is shown in Table 1.

There are two main reasons for using analyst forecasts as the board's performance expectations: Firstly, when the board evaluates whether corporate performance has declined, merely comparing the performance difference between this year and last year cannot fully account for external factors such as market environment and industry competition. Analysts, as important information intermediaries in the capital market, analyze and publish earnings forecasts based on their professional ability and information-gathering advantages. These forecasts reflect the capital market's expectations for company performance to a certain extent, helping to alleviate the information asymmetry between investors and listed companies [19]. Therefore, comparing this year's performance with the analysts' forecast mean, rather than directly comparing the performance difference between this year and last year, incorporates market expectations and industry trends, avoiding the aforementioned incomplete considerations. Secondly, considering the optimistic bias in analyst forecasts [20], this paper categorizes the difference between corporate performance and analysts' forecast mean into high and

[1] Managerial changes are categorized into forced changes and non-forced changes. This study considers non-forced changes in managers as voluntary changes that do not involve whether the board tolerates failure. Zhu Bing et al.'s research categorizes "dismissal," "resignation," and "personal reasons" as types of forced managerial changes, and categorizes "retirement," "end of term," "change in controlling rights," "health reasons," "improvement of corporate governance structure," "involvement in a case," and "end of agency" as types of non-forced managerial changes. However, some CEOs' voluntary resignations may also be disclosed as "personal reasons." Therefore, building on Zhu Bing et al.'s research, this study categorizes "personal reasons" as non-forced managerial changes rather than forced managerial changes.

low groups when constructing the variable. When the difference is large, it indicates that the actual corporate performance is far below the board's expected level. If the board does not enforce a managerial change at this time, it shows a certain level of failure tolerance. Conversely, when the difference is small, and the board enforces a managerial change, it indicates the absence of failure tolerance. Therefore, this paper uses analyst forecasts as the board's expectations for executive performance. If the actual corporate performance is below the analysts' forecast mean, the board will consider whether the executives have exerted maximum effort in managing the company.

Table 1: Measurement Method for Board Failure Tolerance

	Difference Above Median	Difference Below Median
Non-forced managerial change	1	-
Forced managerial change	-	0

3.2.3. Control Variables

Referring to the approach of Yan Zichun et al. [21], this paper selects firm size, asset-liability ratio, revenue growth rate, return on assets, free cash flow, listing duration, board size, proportion of independent directors, CEO duality, stock return, and ownership nature as control variables. Additionally, industry and year effects are controlled for in the analysis.

3.3. Model Construction

This paper constructs model (2) to test Hypothesis H1 and Hypothesis H2. The specific model is as follows:

$$Ineff_{i,t}(Overinv_{i,t}/Underinv_{i,t}) = \alpha_0 + \alpha_1 RR_{i,t-1} + \alpha_2 Controls + \sum Industry + \sum Year + \varepsilon \quad (2)$$

Where: $Inveff_{i,t}$ is the investment efficiency of firm i in period t ($Overinv_{i,t}$ indicates over-investment and $Underinv_{i,t}$ indicates under-investment). RR_{t-1} is the board failure tolerance of firm i in period t-1. Since the impact of board failure tolerance on corporate investment efficiency has a lagging effect, we examine the influence of board failure tolerance in period t-1 on investment efficiency in period t. *Control* represents the control variables. The model adopts a "two-way fixed effects model" to account for relevant fixed effects. *Year* and *Industry* are the year and industry fixed effects, respectively. α_0 is the intercept term. α_1 is the regression coefficient of the independent variable RR_{t-1}. α_2 is the regression coefficient of the control variables. ε is the error term.

4. Empirical Results

4.1. Descriptive Statistics

Table 2 reports the descriptive statistics of the main variables in this study. Among the total 9,102 samples, approximately 36.8% of the samples exhibit over-investment issues, while about 63.2% of the samples exhibit under-investment issues. The mean value for over-investment samples is 0.049, with a maximum value of 0.898. The mean value for under-investment samples is 0.031, with a maximum value of 0.271. This indicates that inefficient investment is prevalent among Chinese listed companies, with under-investment being more common and over-investment being more severe. The

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mean value of the dummy variable for board failure tolerance (RR) is 0.885, indicating that 88.5%2 of the sample firms exhibit the characteristic of board failure tolerance.

Table 2: Descriptive Statistics Results

Variables	N	mean	sd	min	P25	Median	P75	max
Inveff	9102	0.038	0.047	0	0.011	0.025	0.046	0.898
Overinv	3350	0.049	0.067	0	0.009	0.025	0.061	0.898
Underinv	5752	0.031	0.028	0	0.012	0.025	0.041	0.271
RR	9102	0.885	0.319	0	1	1	1	1

4.2. Regression Results Analysis

Table 3 reports the regression results of the impact of board failure tolerance on corporate investment efficiency. L.RR represents the one-period lagged board failure tolerance. Column (1) shows the regression results of board failure tolerance on corporate investment efficiency. It can be seen that the regression coefficient of the variable L.RR with *Inveff* is significantly negative at the 1% level, indicating that board failure tolerance can significantly suppress inefficient investment and improve investment efficiency. Columns (2) and (3) in Table 3 show that the regression coefficients of L.RR with *Overinv* are significantly negative at the 5% level, and the regression coefficients of L.RR with *Underinv* are significantly negative at the 1% level. This indicates that board failure tolerance can both inhibit over-investment and alleviate under-investment. Thus, hypothesis H1 is validated.

Table 3: Impact of Board Failure Tolerance on Investment Efficiency

	(1) *Inveff*	(2) *Overinv*	(3) *Underinv*
L.*RR*	-0.0057***	-0.0068**	-0.0051***
	(-3.798)	(-2.008)	(-4.535)
_cons	0.0747***	0.0707**	0.0953***
	(5.607)	(2.276)	(9.559)
Controls	Yes	Yes	Yes
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
N	9102	3350	5752
adj. R^2	0.125	0.185	0.101
F	31.2982	18.6945	15.9617

Note: Values in parentheses are t-values, “***”, “**”, and “*” denote significance at the 1%, 5%, and 10% levels, respectively.

4.3. Endogeneity Test

The empirical tests above used the lagged independent variable by one period to mitigate reverse causality issues. However, the results may still be influenced by sample selection bias and endogeneity problems due to omitted variables. To address these concerns, this study employs two-period lagged variables, propensity score matching, and controls for firm fixed effects. The regression results are consistent with the main regression results, indicating the robustness of the conclusions.

[2] Chen Xiude et al.’s research data shows that approximately 80% of listed companies tolerate failure, which is similar to the statistical results of this study. Hence, the definition and data collection process of this study are reasonable, and the obtained data are valid.

5. Conclusion and Implications

This paper, from the perspective of failure tolerance, measures board failure tolerance based on whether a manager is forcibly replaced when the company's performance falls short of the board's expectations. Using data from A-share listed companies in China from 2010 to 2022, this study examines the impact of board failure tolerance on corporate investment efficiency. The following conclusions are drawn: Board failure tolerance significantly improves corporate investment efficiency by both curbing over-investment and alleviating under-investment. Based on the current research findings, this paper offers the following recommendations for companies: Emphasize board governance and fully leverage the role of the board to enhance corporate investment efficiency. Companies can construct incentive mechanisms that tolerate failure to effectively boost managers' risk-taking spirit, reduce their personal costs, and ensure job security. Such fault-tolerant incentive mechanisms can motivate managers to consider the long-term interests of the company, make higher-quality investment decisions, and ultimately improve corporate investment efficiency.

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The Relationship Between AI and Unemployment Rate and the Solution

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Abstract: Technological advancements and significant strides in artificial intelligence have undeniably propelled economic growth. Integrating AI into production processes enhances productivity and efficiency. AI systems can operate continuously without breaks, and advanced technologies minimize the risk of human errors, producing high-quality goods and reducing costs. Ever since the inception of ChatGPT, the discourse surrounding the potential replacement of human labor by artificial intelligence has been a recurring theme. However, specific industries within the job market are resistant to being replaced by artificial intelligence, as they require distinct human qualities like creativity, emotion, and decision-making skills. These professions require problem-solving, interpersonal skills, emotional understanding, moral decision-making, and various unique human talents. This paper analyses the relationship between AI and the unemployment rate and the solution. It revealed the temporary decline in production efficiency, including short-term production efficiency reduction and long-term productivity improvements. Various policies can be implemented to address the issues mentioned, including initiatives to enhance education and improve the transparency of AI applications.

Keywords: Artificial intelligence, Unemployment rate, High-skilled employees, Production efficiency

1. Introduction

The emergence of artificial intelligence has significantly impacted and transformed the labor market, ushering in substantial changes while concurrently opening up new avenues for employment and expansion. The evolution of artificial intelligence has dramatically influenced the labor market, leading to substantial transformations and paving the way for the emergence of fresh employment prospects and areas for growth. The proliferation of artificial intelligence has sparked profound changes in the labor market, revolutionizing its landscape and generating novel opportunities for employment and advancement.

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In a research report released on March 27th, Goldman Sachs analysts Joseph Briggs and Devesh Kodnani highlighted the significant impact of artificial intelligence breakthroughs, predicting that approximately 300 million jobs globally will be displaced by generative AI. However, for around 7% of American workers, over half of their job responsibilities could feasibly be carried out by AI, rendering them more susceptible to being replaced. A paper from OpenAI revealed that, according to analyses of machine large language models conducted by scholars and businesses, an estimated 80% of the U.S. workforce will experience some level of impact from ChatGPT on at least 10% of their job tasks.

Indeed, the interplay between artificial intelligence and the contemporary labor market can be categorized into two distinct phenomena: coexistence and substitution. A portion of artificial intelligence technology within the labor market involves coexisting alongside the workforce, encompassing functionalities like voice assistants, image recognition, and natural language processing. These tasks are ones that were previously beyond the capability of the human workforce.

Nevertheless, there exist artificial intelligence technologies that are poised to supplant segments of the labor force, precipitating a surge in unemployment. According to CNN, projections indicate that by 2027, 69 million novel job opportunities will be generated globally, while 83 million existing jobs will be rendered obsolete within the same timeframe, resulting in a net loss of 14 million jobs. This equates to a 2% reduction in current worldwide employment levels. In the era of AI, numerous professions face the specter of obsolescence. Occupations characterized by simple, repetitive tasks governed by strict rules, data analysis, and predictive functions are particularly susceptible to automation by AI. For instance, cashier positions may be replaced by automated cashier systems, while ticket inspectors could be supplanted by automated ticket readers.

2. Analysis 1

Both the labor market and artificial intelligence have undergone adaptations to align with the ongoing revolution in science and technology.

Following Robert Solow's model, the incorporation of AI technology into production extends to include technology as a crucial factor of production. The productivity gains driven by technology have a considerable impact on economic expansion, capital accumulation, and the demand for labor. A scenario of balanced growth is depicted. The horizontal axis symbolizes the capital-labor ratio (K/L), while the vertical axis represents output (Y). The productivity curve, denoted by the S curve in the graph, illustrates the varying output levels corresponding to different capital-labor ratios. As the capital-labor ratio approaches the equilibrium ratio, the growth rates of capital and output will surpass the growth rate of the labor force, ultimately attaining balanced growth.

AI intervention has the potential to enhance efficiency and boost productivity levels within the labor market. By undergoing career retraining, embracing lifelong learning, and adapting to the evolving nature of work, the labor market has actively undertaken initiatives to adjust to the integration of AI technology.

To address these short-term structural shifts, governments and various institutions have taken proactive measures to mitigate the risks associated with AI technology in the labor market. Primary emphasis has been placed on the establishment of lifelong learning initiatives within the labor market, aimed at aiding workers in consistently enhancing and acquiring new skills to effectively adapt to the ever-evolving technologies and requirements [1].

The source from the "Deploying Generative AI in US State Governments: Pilot, Scale, Adopt" report by the McKinsey Global Institute. It visually represents the implementation of AI across diverse sectors and industries [2].

(1) Innovations in Systems: AI tools can offer coding assistance to facilitate the modernization of outdated IT systems. These tools can analyze legacy COBOL applications, propose alternative code

revisions in different languages, generate technical documentation, and recommend testing scenarios for the updated code.

(2) Tailored Content Creation: AI tools empower swift creation of personalized content, encompassing text, imagery, and voice, enabling governments to cater to the unique needs of residents on a customized basis. For instance, social service case managers can leverage AI content solutions to extract pertinent information from individual cases and offer tailored assistance.

(3) Advanced Skill Development Tools: AI-powered learning platforms can provide customized learning opportunities, pinpoint individual skill deficiencies, and adapt educational content accordingly. Skill enhancement and retraining initiatives can utilize AI-based evaluations to assist employees in acquiring new skills that align with evolving job requirements [3].

In conclusion, the evolving role of AI in educational requirements and work environments can facilitate the delivery of more effective and personalized services, boost workforce productivity, and enhance overall customer experiences.

3. Analysis 2

Temporary Decline in Production Efficiency:

1)Short-term production efficiency reduction

In a short run, production efficiency will reduce. This can be explained by the theory of creative destruction popularized by the Joseph Schumpeter. “Creative destruction describes the deliberate dismantling of established processes in order to make way for improved methods of production.” (Creative Destruction: Out With the Old, in With the New, CAROL M. KOPP, February 20, 2023) Waste of resources means inefficiency. Therefore, in facing the challenges and opportunities brought by AI, the key is to cultivate skills and innovation capabilities that adapt to the new opportunity [4].

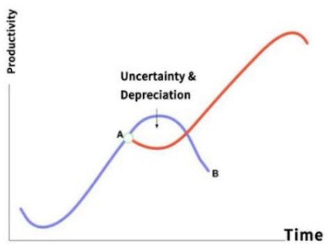

Figure 1: Uncertainty and depreciation

2)Long-term productivity improvements: increase high-skilled employees

In the long term, the demand for labor skills and quality is becoming increasingly pivotal. The data presented in the EUKLEMS Labour Input Data graph illustrates the value added in both low-skilled and high-skilled sectors [5], it is observed that the value added in the low-skilled sector has declined as real GDP has grown, as shown in Figure 2. Conversely, the high-skilled sector has experienced a contrasting phenomenon.

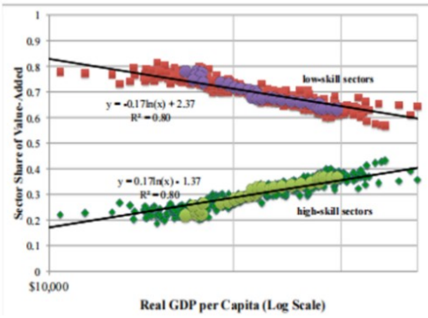

Figure 2: Real GDP and sector share

4. Analysis 3

4.1. Rising unemployment rate in a short run: jobs replaced by AI

Table 1: Jobs replaced by AI

AI matrix	manufacturing industry	service sector
manufacturing industry	**a**	**b**
service sector	**c**	**d**
AI matrix=(1-a)*(1-d)-(0-b)*(0-c)		

The latest wave of AI technology is mainly focus on Generative AI. Even in the field of media, Warner Pictures, Netflix, Disney, etc. are already using AI to create special effects and other simple tasks. There are many traditional jobs can be replaced by AI. Without new developed jobs, it may cause structural unemployment [6].

4.2. Lower unemployment in a long run: use of inter-dependencies

In a long run, the unemployment can be release. The input output model shows a different situation. “Input-output analysis is a form of macroeconomic analysis based on the inter-dependencies between different economic sectors or industries. ”(WILL KENTON, Input-Output Analysis: Definition, Main Features, and Types,July 30, 2021)Assume that a country's manufacturing industry introduces AI technology to improve productivity. We found that AI directly caused productivity increases in the manufacturing sector. Because the introduction of new machine, it increases demand of maintenance personnel, which also lead to an increase in employment opportunities in the service sector [7]. Example not only happen in service sector, but also raw material suppliers, logistics service providers, retailers, etc. These indirectly influences expand its business and meet the demand of the directly influenced one. Therefore, it will provide more opportunity of working and reduce the unemployment rate [8].

5. Recommendation

To address the aforementioned issues, various policies can be implemented, including initiatives to enhance education and improve the transparency of AI applications.

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(1) Facilitating the education: The Robert Solow Growth Model indicates that an increase in any of its constituent elements can drive economic growth, leading to an uptick in output (Y = AL^a K^(1-a)). As the government focuses on addressing the employment challenges, the model emphasizes the importance of boosting labor input (L) to bolster economic growth. Meanwhile, to address the displacement of low-skilled workers by AI, as suggested by the Leontief's Input-Output Model, the government can implement strategies such as enhancing education with a focus on AI-related subjects like data science and computer programming [9].

6. Conclusion

When delving into the impact of artificial intelligence on the job market, we must face an unavoidable reality: although the integration of artificial intelligence technology has brought unprecedented efficiency and innovation to various industries, it is also accompanied by the adjustment of occupational structure. Some traditional and repetitive jobs may be replaced by automation, leading to the risk of unemployment for some workers. However, promoting and improving the transparency of artificial intelligence applications through education can provide us with an effective solution path. Firstly, we need to increase investment in skill training and re education for the workforce to ensure that they have the knowledge and ability to adapt to new technologies. Transparency means enabling the public to understand key information such as the decision-making process, algorithm logic, and data sources of artificial intelligence. The combination of education and transparency can provide strong support for us to address the employment challenges brought about by artificial intelligence. By improving the skills and adaptability of workers, we can strive to prevent individuals from being excluded by technological changes. In short, although the integration of artificial intelligence may bring challenges to the job market, as long as we take the right measures and methods, we can effectively address these challenges.

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