The Influence of Quality Information on Stock Performance: A Sentiment Analysis from Online Review

Huiming Liu[1], Su Wu*[2], Chongwen Zhong*[3], Ying Liu[4]

[1]huiming@icbc.com.cn,* [2]Corresponding author: wusu@tsinghua.edu.cn,* [3]Corresponding author: zhongchongwen@bipt.edu.cn, [4]LiuYing-Amy@bistu.edu.cn

[1]Postdoctoral Research Center Industrial and Commercial Bank of China Beijing, China

[2]Department of Industrial Engineering Tsinghua University Beijing, China

[3]School of Economics and Management Beijing Institute of Petrochemical Technology Beijing, China

[4]School of Economics and Management Beijing Information Science and Technology University, Beijing, China

Abstract. Companies' stock performance could be affected by various factors like breaking news or annual report. We consider that products' quality could also be a crucial factor that influence the stock performance. In this study, the quality characteristics are extracted from the customer online review to measure the products' quality level. We use reinforcement learning models to show that quality information could improve the stock trade policies by increasing the profitability and risk of maximum drawback. The relationship between stock performance and quality level also is explored. This paper demonstrates the importance of quality information and manager could design better products by using the results of our study.

Keywords: sentiment analysis; customer online review; reinforcement learning

1 Introduction

How to measure the impact of products' quality on companies' profits and revenue is an important research area. In the era of big data, companies could obtain various type of quality data. Take JingDong or Amazon for example, customers can evaluate the product experience and service process on the products website. These reviews could contain customers' comments on quality level [1-2]. This quality information could influence customers' demand thus products' competitiveness and sales would be affected.

The increase in companies' product sales or customer satisfaction can also increase the company's profit return. Moreover, when the company is a public listed company, the stock price of the company may be affected. For example, Samsung mobile phone products occupy an

ICBBEM 2024, March 29-31, Wuhan, People's Republic of China

DOI 10.4108/eai.29-3-2024.2347418

absolute monopoly position in the Android mobile phone market. However, Samsung's market value fell by nearly $20 billion after the explosion of the Samsung Note series of mobile phone in August 2016. Meanwhile, although researchers have discussed the impact of quality-related events on stock price, few of them revealed a clear relationship between quality and stock performance [3-4].

To solve this problem, we mine product's quality characteristics from customer online reviews. We adopt quality characteristics as features and examined their impact in reinforcement learning models. Finally, we discuss the fluctuation of company's stock price during the change of products' quality level. In sum, our paper answers these two problems: (1) How do quality characteristics improve to the stock trade policies? (2) What are the predictive and lagging effects of product's quality level?

Our paper contributes to previous studies along these two paths: (1) first, we explore the usage of quality characteristics on stock trade policies by using reinforcement learning policies. (2) second, we show the different performance of stock indicators during the fluctuation of products' quality level. More importantly, we find the predicative and lagging effects of quality level.

In addition, our research finds that when the quality of products is at different levels, some stock indicators of companies are also will be affected. For example, when the quality of the product is recognized by the customer, the daily investment return of the company's stock will show the improvement. Our study once again illustrates the product quality could correlate with stock information tightly.

2 Literature Review

2.1 Stock Trade Policies

Researchers discussed how to obtain abnormal profit based on stock information. Prior literature confirmed that the optimization models were effective in stock trading models [5-6]. Isaenko (2018) found that if trading fees of the T-bills securities portfolio were proportioning to their total price, then the securities' monthly revenue and Sharpe value were decreased simultaneously. Mansour et al. (2019) used multi-objective optimization to balance the weights of risk, return and volatility in a portfolio.

Besides, the Markov Decision Process (MDP) has contributed to the development of man-machine counteraction, chess game and other scenarios. Therefore, researchers have attempted to used DQN model to optimize the portfolio by decreasing the state space and the training speed was enhanced [7].

Similarly, other studies adopted both deep learning and reinforcement learning in stock trade policy analysis [8-9]. Vo et al. (2019) used a bidirectional LSTM model to predict stock return. This framework could significantly enhance stock return as well as Sharpe ratio while the volatility was decreased. Aboussalah and Lee (2020) transformed the discrete state spaces into continuous action spaces and multiple state spaces. A more profitable portfolio was obtained. Vidal and Kristjanpoller (2020) focused on the volatility of gold asset. The CNN-LSTM model was used to decrease the noise and the heterogeneity of instability in the traditional time series model. The effectiveness of the prediction of volatility was improved.

Also, the heuristic algorithms were discussed in the stock trading models [11]. Ramezanian et al. (2019) added a graph model and multi-layer network to predict stock return, volatility and other indicators based on genetic algorithm. Authors found that the accuracy of genetic algorithm outperformed other time series model like GARCH or ARIMA models.

3 Method

3.1 Data Collection and Preprocessing

Apple corporation's products are our research sample in this study. Table 1 showed that iPhone, Macbook and iPad are the main types of Apple's products. These three types are most important for Apple corporation. We conjecture that the performance of these three types of products could be representatives of Apple's operating condition.

Table 1. Sample information.

Brand	Model	# of Review
iPhone	7, 8, SE et al.	14323
Macbook	Macbook Pro 12 inches et al.	2424
iPad	iPad Air, iPad Pro inches et al.	1987

We match company's stock basic information (e.g. close price, open price) with customers' reviews according to daily data. Two cases may occur: first, one product may obtain several reviews on the same day. We combine all quality information into a single vector to represent the day's quality level. Second, weekends have no stock trading operations but customers may publish their comments. We combine weekends' quality information into the last trading day.

We transform each customer's online review into a quality characteristics vector. Company's daily trade information is matched to online reviews. We use products' quality characteristics in stock trade policies.

We use datareader.data in the Pandas module to download the stock price of Apple. The stock information data is from the Yahoo Financial section. We obtain each day's highest, lowest, opening, closing, trading volume, and adjusted closing price.

We use latent Dirichlet distribution (LDA) to extract products' quality characteristics. LDA creates documentation-topic model and topic-word model to assign keywords in each text to a topic. In LDA, each topic's word cannot be directly observed, but is obtained by the weighted summation of the words. In addition, some topics can be merged into one topic to improve the interpretability of the model. Therefore, we set several topics for the LDA model in advance. The final topics are obtained after the results. Since we have all the topics of the products, we define these topics as the quality characteristics of the product.

The customers' emotional attitude is calculated by using sentimental lexicon [12]. The sentimental lexicon is used to add all word's mapping emotional value to a single value. This value is used to evaluate a quality characteristic's emotion. The higher the emotion value of the word, the higher the positive emotion the word contains. Our study divides each customer review into punctuation sentences. Products' quality information can be represented by a vector. Each vector's element is the value of product's quality characteristic's value.

Table 2 showed the components of the vector. Each review has been successfully transformed into structured data. The quality characteristic represents the product's using attribute. Also, the quality characteristic is measured by a quantitative number. Therefore, we could use quality characteristics to evaluate products' quality levels quantitatively.

Table 2. Structure review for reviews.

Online review	Quality characteristic 1	……	Quality characteristic 20
r=1	3.2	……	7.5
r=2	2.9	……	3.4
r=3	0.6	……	2.2
……	……	……	……
r=18734	4.2	……	9.2

3.2 Stock Trade Policies

We design the following product quality characteristic policies: based on the sentimental lexicon [13], we calculate product's quality characteristics value. If one quality characteristic's value is larger than previous value, then we add this quality characteristic with an auxiliary variable and this auxiliary variable equals to 1. On the contrary, if one quality characteristic's value is smaller than previous value, then we add this quality characteristic with an auxiliary variable and this auxiliary variable equals to -1. Each quality characteristic's auxiliary variable is defined as the tendency of quality characteristic.

We use reinforcement learning models to demonstrate the effectiveness of products' quality characteristics. The features in the reinforcement learning models include two parts: first, the basic stock indicators (e.g. open price, close price). Second, the quality characteristic tendency for each quality characteristic. Thus, we define two policies for reinforcement learning models: if the policy only considers the first part of features, then this policy is defined as the basic stock feature policy. If the policy considers the first and second part of features, then this policy is defined as the basic stock feature policy with products' quality characteristics information. Then we compare the stock evaluation performance for these two policies.

The three indicators (annualized return, Sharpe ratio, maximum drawdown) are used to measure the performance of stock trade policies in reinforcement learning models. Annualized return shows the profitability. The Sharpe ratio measures the balance between risk and revenue. The maximum drawdown is defined as the volatility of stock and calculated by the difference between the stock price and the subsequent lowest stock price and the stock price.

3.3 Stock Performance and Products Quality Level

In previous section we discuss the effectiveness of quality characteristic on stock trade policies. To deeply understand the role of products' quality, we seek to explore the tendency of stock performance within different quality level periods.

We first define the products quality level and stock performance. The product quality level is calculated by summing all quality characteristics value to obtain a new variable named quality level. There are three types of quality levels: high-quality level, medium-quality level, and low-quality level. For those days with top 5% quality level, these days is defined as high-quality level days. For those days with medium 5% quality level, these days is defined as medium-quality level days. For those days with low 5% quality level, these days is defined as low-quality level days.

The stock performance is measured by three indicators: Daily revenue ratio, Daily trade volume ratio and Daily max down. The Daily revenue ratio measures stock's return in comparison of last day. Daily trade volume ratio is calculated by the ratio of intraday trade volume on total trade volume. Daily max drawdown shows the difference of highest and lowest price, which demonstrates stock's fluctuation. Table 3 shows the detail of the definition of these indicators.

Table 3. Stock indicators.

Indicators	Definition
Daily revenue ratio	The natural logarithm of the ratio of stock open and close price
Daily trade volume ratio	The ratio of daily trade volume to total trade volume
Daily max drawdown	The ratio of difference of between highest and lowest and highest price

The stock performance's tendency within different quality level periods would be demonstrated in this part. We would like to discuss the impact of quality level on these stock indicators.

4 Results

4.1 Stock Trade Policies

We used the reinforcement learning models to examine the quality characteristics from new perspectives. We used value-based models (e.g. DQN), policy-based models (e.g. Policy-Gradient) and combination models (e.g. Actor-Critic). The stock basic indicators were one part of features in these reinforcement learning models. The quality characteristics were another part of features in these reinforcement learning models.

The following trading rules were defined in these models: the agent had three states in the trading process: buying, selling or holding. We assumed that the agent could trade at most 20000 shares and at least 100 shares for buying and selling states. The holding state showed that the agent made no operation on this trading day. The trading fee is 0.39% according to the requirement of Tiger Securities. The reward function was defined as the daily return on total stock account. The total stock account included the stock's market value and cash.

Table 4 showed the results on annualized return. We found that the basic stock feature policy was outperformed by basic stock feature policy with products' quality characteristics information. In particular, the models with basic stock feature policy had quite low annualized return in DDQN and Actor-Critic, which demonstrated the effectiveness of quality information.

Table 4. Annualized return of reinforcement learning models.

	DQN	DDQN	DQN-Prioritized-Replay
basic stock feature policy	0.216	0.030	0.522
basic stock feature policy with products' quality characteristics information	0.483	0.649	0.654
	Dueling-DQN	Policy-Gradient	Actor-Critic
basic stock feature policy	0.216	0.030	0.522
basic stock feature policy with products' quality characteristics information	0.483	0.649	0.654

For Sharpe ratio, the results showed in Table 5 were like the results of annualized return: the models with basic stock feature policy with products' quality characteristics information had larger Sharpe ratio than models with basic stock feature policy. Meanwhile, for DQN, DDQN, DQN-Prioritized-Replay, the performance of basic stock feature policy with products' quality characteristics information in these models is better than that of Policy-Gradient model. Therefore, we conjectured that value-based models were more suitable than policy-based models for Sharpe ratio.

Table 5. Sharpe ratio of reinforcement learning models.

	DQN	DDQN	DQN-Prioritized-Replay
basic stock feature policy	0.597	0.364	1.047
basic stock feature policy with products' quality characteristics information	1.348	1.306	1.626
	Dueling-DQN	Policy-Gradient	Actor-Critic
basic stock feature policy	0.320	1.649	0.483
basic stock feature policy with products' quality characteristics information	0.882	1.708	0.228

Table 6 showed the results of the maximum drawdown. In DQN, DDQN, Dueling-DQN, Policy-Gradient and Actor-Critic, basic stock feature policy was better than basic stock feature policy with products' quality characteristics information. In contrast, the maximum drawdown of basic stock feature policy with products' quality characteristics information was smaller than that of basic stock feature policy only in DQN-Prioritized-Replay. Therefore, we found that quality information couldn't bring more advantages in respect of maximum drawdown.

Table 6. Maximum drawdown of reinforcement learning models.

	DQN	DDQN	DQN-Prioritized-Replay
basic stock feature policy	0.134	0.054	0.217
basic stock feature policy with products' quality characteristics information	0.195	0.305	0.207
	Dueling-DQN	Policy-Gradient	Actor-Critic
basic stock feature policy	0.158	0.198	0.035
basic stock feature policy with products' quality characteristics information	0.183	0.206	0.049

In reinforcement learning models, we showed that quality information could improve the annualized return and Sharpe ratio while the improvement of maximum drawdown was not significant. Therefore, we conjectured that considering the quality information in the stock trade policies should enhance the stock revenue by improving the profits. However, the quality information in policies may result in more stock fluctuation with larger maximum drawdown.

4.2 Stock Performance and Products Quality Level

In this section, we discussed the stock performance's tendency within different quality levels' intervals. We have summarized three types of quality level days in Method section. Figure 1-Figure 3 displayed the results. In these three figures, the horizontal axis "time distance" denoted the distance between real samples occurrence time and the defined quality level days. For example, "5" meant that we used 5 days after the defined quality level days. Meanwhile, "-5" meant that we used 5 days before the defined quality level days. Therefore, Figure 1-Figure 3 could demonstrated the tendency of stock performance before and after some quality level days.

Figure 1 showed that Daily revenue ratios of high-quality level days had surpassed the ratios of medium-quality level days and low-quality level days after the quality level days. Therefore, company's stock performance has been improved after its products were rated highly by customers. On the other hand, we showed that this tendency was not significant before the quality level days.

We also showed that the difference between medium-quality level days and low-quality level days was not significant. In contrast to the positive of satisfied quality characteristics, it seemed that unsatisfied quality characteristics may not bring negative impacts on daily revenue ratio.

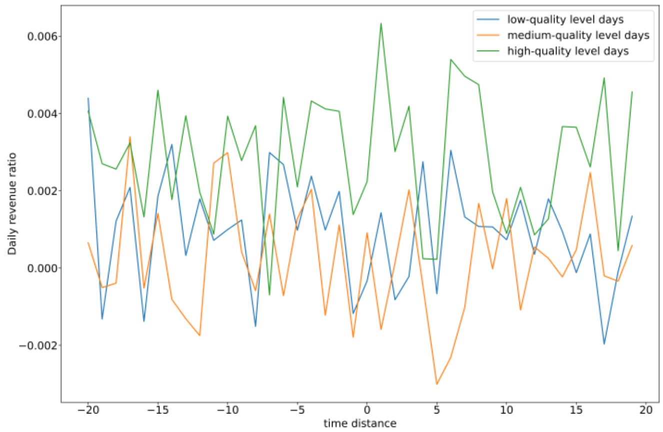

Fig. 1. Daily revenue ratio within quality level days.

Figure 2 showed the daily trade volume ratio within different quality levels days. Before the quality level days, both high-quality level days and low-quality level days have more daily trade volume ratio than medium-quality level days. This phenomenon demonstrated that stock could perceive the change in quality level thus the trade volume could be increased.

In contrast, the difference between low-quality level days and medium-quality level days was not as significant after the quality level days. However, the Daily trade volume ratio of high-quality level days increased drastically. Therefore, we showed a crucial phenomenon that the investors may make greater trading actions before the change in quality level. However, the investors adjust the positions of the stock more frequently if the products have more positive quality rating.

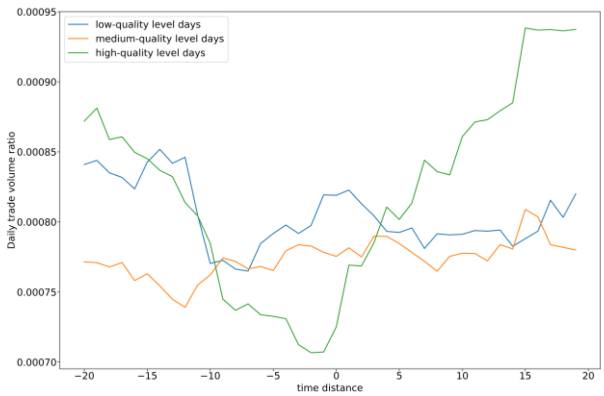

Fig. 2. Daily trade volume ratio within quality level days.

The results of daily maximum drawdown were displayed in Figure 3. The performance of this indicator was quite significant among these different quality level days. The high-quality level days had the largest daily maximum drawdown while the low-quality level days had the smallest daily maximum drawdown. We conjectured that the more satisfied customers had with the products, the more discrepancy between stock's highest price and lowest price.

Also, we found that the daily maximum drawdown of medium-quality level days and low-quality level days was quite stable before or after the quality level days. However, the daily maximum drawdown of high-quality level days was larger before and after the sample days. The value was quite low near the quality level days. Thus, we conjectured that the stock price fluctuated more drastically for high-quality level days.

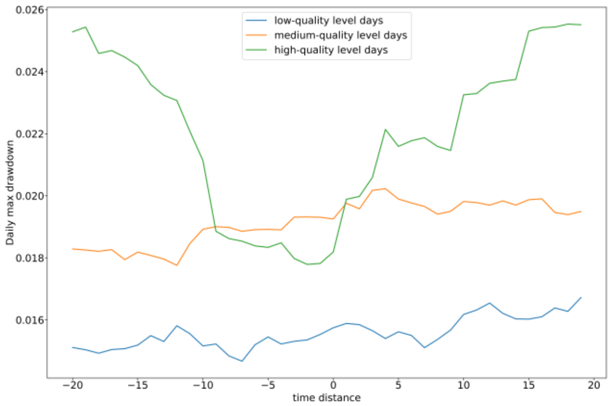

Fig. 3. Daily maximum drawdown ratio within quality level days.

5 Discussion

We also focus on stock indicators of profits (e.g. annualized return,) or risk (e.g. Sharpe ratio, maximum drawdown). We conjecture that profits and risk are the two most important aspects to evaluate stock's performance. Importantly, products' quality performance could have a direct impact on stock's profits and risk [14]. Thus, this study enlightens researchers and practitioners that quality characteristics may not be significant for stock's all indicators. The application of our research should be cautious.

Our study displays the predictive and lagging effects of quality level on stock performance. Previous literature mentions that companies' performance would change if their products' quality has positive or negative news [15]. These studies could use event study methodology to demonstrate the effects of quality level fluctuation [16].

Our study uses sentimental analysis to extract customers' satisfaction or dissatisfaction and transform the emotion into a quality level score. This approach broad the literature on the effects of quality management. Besides, we propose a research framework that include stock trade policies and stock indicators fluctuation. This framework overcoming a crucial shortcoming that discusses stock performance from a biased perspective.

6 Implication

Our study finds a crucial phenomenon that quality characteristics could improvement stock's profits but its fluctuation could also enhance. Stock could fluctuate in a quite short time although its profits would increase later. However, in mutual funds or other asset management areas, maximum drawdown would sometimes be more important than profits. The fund manager would face pressure of money withdrawal if the maximum drawdown is high. Therefore, our study would provide insights that investors should carefully use quality-related trade policies to prevent potential fluctuation.

We also show the lagging and predictive effects of quality level on stock indicators. However, the lagging effects are sometimes more significant than the predicative effects. This finding demonstrates that investors should give different weights to the lagging and predictive effects. For example, fund managers may slow down theirs trading actions before some important events happen. On the contrary, the trading actions may be swift if the fund managers could observe more valuable information.

7 Conclusions

This study discusses the quality characteristics from customer online review. We use the information of quality characteristics to show the improvement of quality information on stock trade policies. The improvement is demonstrated by enhancing the profitability and increasing the risk of maximum drawback. For the relationship between stock performance and quality level, we also show that stock price was improved after customers publish higher rates. The trade volume also increased when the products obtain higher or lower rates. The stock price fluctuates more frequently for high-quality level days. Our results provide evidence that companies' stock performance could be affected by products' quality level. Managers could use quality information to enhance the stock performance in the product design phase.

References

[1] Basu S. Personalized product recommendations and firm performance [J]. Electronic Commerce Research and Applications, 2021, 48: 101074.

[2] Davras G M. Classification of winter tourism destination attributes according to three factor theory of customer satisfaction [J]. Journal of Quality Assurance in Hospitality & Tourism, 2021, 22(4):496-516.

[3] Fan D, Liang T, Yeung A C, et al. The impact of capacity-reduction initiatives on the stock market value of Chinese manufacturing firms[J]. International journal of production economics, 2020,223: 107533.

[4] He J, Wang X, Vandenbosch M B, et al. Revealed preference in online reviews: Purchase verification in the tablet market[J]. Decision Support Systems, 2020, 132: 113281.
[5] Isaenko S. Optimal mean-reversion strategy in the presence of bid-ask spread and delays in capital allocations[J]. Quantitative Finance, 2018, 18(12): 2051-2065.
[6] Mansour N, Cherif M S, Abdelfattah W. Multi-objective imprecise programming for financial portfolio selection with fuzzy returns[J]. Expert Systems with Applications, 2019, 138: 112810.
[7] Park H, Sim M K, Choi D G. An intelligent financial portfolio trading strategy using deep Q-learning[J]. Expert Systems with Applications, 2020, 158: 113573.
[8] Vo N N, He X, Liu S, et al. Deep learning for decision making and the optimization of socially responsible investments and portfolio[J]. Decision Support Systems, 2019, 124: 113097.
[9] Aboussalah A M, Lee C-G. Continuous control with stacked deep dynamic recurrent reinforcement learning for portfolio optimization[J]. Expert Systems with Applications, 2020, 140: 112891.
[10]Vidal A, Kristjanpoller W. Gold volatility prediction using a CNN-LSTM approach[J]. Expert Systems with Applications, 2020, 157: 113481.
[11] Ramezanian R, Peymanfar A, Ebrahimi S B. An integrated framework of genetic network programming and multi-layer perceptron neural network for prediction of daily stock return: An application in Tehran stock exchange market[J]. Applied soft computing, 2019, 82: 105551.
[12] Liu H, Wu S, Zhong C, et al. The effects of customer online reviews on sales performance: The role of mobile phone's quality characteristics[J]. Electronic Commerce Research and Applications, 2023, 57: 101229.
[13] Hamilton W L, Clark K, Leskovec J, et al. Inducing domain-specific sentiment lexicons from unlabeled corpora[C]//Proceedings of the conference on empirical methods in natural language processing. conference on empirical methods in natural language processing.NIH Public Access, 2016:595.
[14]Candido C J, Coelho L M, Peixinho R M. Why firms lose their ISO 9001 certification: Evidence from Portugal[J]. Total Quality Management & Business Excellence, 2021, 32(5-6): 632-651.
[15] Liu H, Wu S, Zhong C, et al. An empirical exploration of quality management practices and firm performance from Chinese manufacturing industry[J]. Total Quality Management & Business Excellence, 2021, 32(15-16): 1694-1712.
[16] Treacy R, Humphreys P, McIvor R, et al. ISO14001 certification and operating performance: A practice-based view[J]. International journal of production economics, 2019, 208: 319-328.