International Journal Of Engineering Research And Development
e- ISSN: 2278-067X, p-ISSN: 2278-800X, www.ijerd.com
Volume 20, Issue 7 (July, 2024), PP. 63-72

Applying Quantile Regression on Factor Analysis for Evaluating Stock Selection Strategies for Taiwan Stocks

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ABSTRACT
Factor analysis selects stocks by studying which factors will affect stock returns. However, the amount of stocks to be purchased based on the selected factors is usually important but not well-considered in factor analysis. Quantile regression can be used to evaluate the performance of factors at different return quantiles, further improving the accuracy and robustness of stock selection, especially on how much percentasge of stocks of highest (or lowest) factor values to invest.
This study applies quantile regression on factor analysis and proposes a stock selection strategy combining both analysis. The experimental results show that choosing the quantile with the largest impact coefficient appearing on the tail of head of quantile regression analysis can significantly improve the return rate of the investment portfolio and reduce risk. Finally, this study uses data from the Taiwan stock market over the past 20 years for backtesting, verifying the effectiveness of the proposed strategy.
The research results provide investors with a more objective and structured evaluation approach for stock selection methods in hope to make more accurate investment decisions.

Date of Submission: 01-07-2024 Date of Acceptance: 11-07-2024

I. INTRODUCTION

Quantitative stock trading (Marshall et al., 2008) refers to the use of quantitative methods to determine whether a particular stock can generate excess returns in the future, assess its risk, and how to form an efficient portfolio. The factor model studies which factor(s) will affect stock returns. Harvey and others counted a total of 316 different factors published in top journals. The growth rate of factor discovery has increased from one factor in the 1960s (Sharpe, 1964) to about 50 factors per year from 2004 to 2012 (Harvey et al., 2016). Most of factors are based on company characteristics; for example, the scale factor observes that the return of small companies is always higher than that of large companies (Lai et al., 2022).

The Fama & French three-factor model (Fama et al., 1993) and five-factor model (Fama & French, 2015) set the theoretical foundation for factor analysis. However, as for the proportion of each factor to be bought, the Fama & French three-factor model only distinguishes between two groups of sizes, and the value factor is cut into three groups (Fama et al., 1993). Such a rough stock screening will select a very large number of stocks. Furthermore, existing research has proven that the relationship between company characteristic factors and stock returns is nonlinear (Romano & Wolf, 2013), so the choice of factor value quantiles is critical for determining the final stock returns of the factor in actual trading. The factor-based investment return should be very dependent on the nonlinear high return rate of stocks with extreme quantile returns. Therefore, how to find the exact quantile of the effective factors is an important detailed consideration in actual factor-based stock trading. This study proposes adding quantile regression analysis to factor analysis to more accurately evaluate and understand the portfolio returns.

Figure 1 analyzes the relationship between the Enterprise Value to Sales ratio (EV/S) factor and the quantile of overall stock returns using Compound Annual Growth (CARG) as the measurement for Taiwan Stock Market for the years of 2000-2023. The x-axis represents the quantile of returns (percentile), and the y-axis represents the regression coefficient of the EV/S factor and stock returns at that quantile. The solid red line represents the regression coefficient of the EV/S factor with stock returns when quantiles are not distinguished. Without distinguishing quantiles, the overall impact of the EV/S factor on stock returns is much lower than the impact of the EV/S factor on stock returns at specific quantiles. Significant impact exists between the highest quantile of stock returns and the EV/S factor (although the direction is negative), which is not the case for the lowest quantile.

Similar to Figure 1, Figure 2 represents the results for the Price to Invested Capital ratio (P/IC) factor. The red line represents the estimated value of OLS regression, the red dashed line represents the 95%

confidence interval of OLS regression, the black line represents the estimated value of quantile regression, and the gray area represents the 95% confidence interval of quantile regression. It can be observed that there is not much difference between the two different regression methods at the 50% to 70% quantile, but the difference becomes larger as it moves towards the extreme quantile.

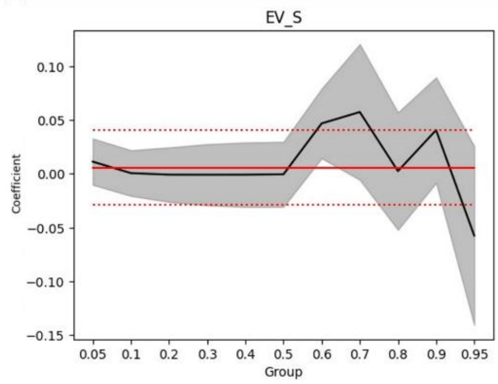

Figure 1: The regression coefficient of the quantile regression of the CAGR on the EV/S factor in the Taiwan stock market for years 2000-2023

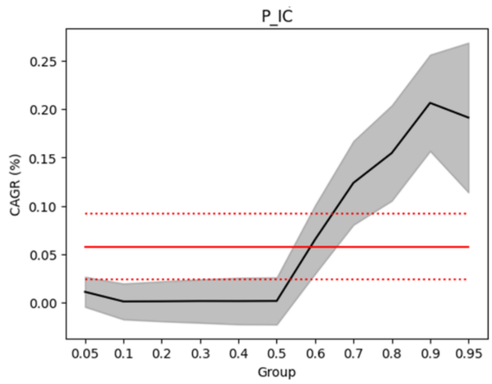

Figure 2: The regression coefficient of the quantile regression of the CAGR on the P/IC factor in the Taiwan stock market for years 2000-2023

If only the OLS coefficients of factor regression analysis are used, both the EV_S factor and the P_IC factor have a positive impact on stock returns. However, through quantile analysis, P_IC is the factor of choice to obtain high returns more effectively where only the stocks with top 5-10% of the factor values need to be purchased to enjoy the expected return. Investors to use funds effectively will want to find out the exact quantile cut-off points that are statistically effective in factor research to reduce the number of stocks purchased and at the same time increase the rate of return. This study focuses on the following research topics:

1. Provide analysis capabilities to combine quantile regression into the factor analysis,
2. For a variety of different factors, provide a consistent basis to compare the performance between different factors with their quantile regression in order to select a robust investment portfolio
3. Using actual data in the Taiwan stock market to validate and captures the impact of factors and different quantiles on returns through quantile regression, improves the accuracy and robustness of stock selection strategies, and determines which factors and their corresponding quantiles perform better in the Taiwan stock market.

II. LITERATURE SURVEY

Three area of related researched are surveyed in this section: factor models, quantile regression, quantitative trading.

2.1 Factor Analysis

Fama & French proposed the three-factor model in the 1990s, which is an extension of the Capital Asset Pricing Model (CAPM). This model introduces two additional factors: the market value factor (SMB) and the value factor (HML), used to explain the changes in asset returns. The market value factor measures the return difference between small-cap stocks and large-cap stocks, while the value factor compares the returns of high market value and low market value stocks (Fama et al., 1993). Fama & French further expanded their model and proposed a five-factor model, adding the profitability factor (RMW) and the conservatism factor (CMA) (Fama & French, 2015). These factors consider the impact of company profitability and conservatism on asset returns, making the model more comprehensive in explaining changes in asset returns. Harvey and others have counted a total of 316 different factors published in top journals (Harvey et al., 2016). Many factors can be simply divided into the following three categories (Lai et al., 2022). The first category is the Economic and theoretical-based factors, such as the Capital Asset Pricing Model (CAPM) proposed by Sharpe. The second is the Statistical factors based on Ross's Arbitrage Pricing Theory (APT), extracted to explain changes in asset returns as much as possible. The third is the Company characteristic-based factors, which are based on company characteristics (including historical returns), such as the market value factor (SMB) and the value factor (HML) in the Fama and French three-factor model.

2.2 Quantile Regression

The traditional Ordinary Least Squares (OLS) method mainly focuses on the average value of the dependent variable under given independent variable conditions. This method ignores the distribution of the data, so its predictive ability is poor for data with extreme values and distribution tails (Maiti, 2021). Quantile regression analysis aims to explore the conditional distribution of the dependent variable at different quantiles. It was proposed by Koenker and Bassett in 1978 and was first used to study the relationship between different income levels and a series of indicators such as occupation and education level (Koenker & Bassett, 1978). The characteristic of quantile regression is that it does not make any distribution assumptions about the population, and the estimated parameters are determined by the original distribution of past samples. Quantile regression is a non-parametric model, the estimation process is carried out by simulating repeated sampling, and the processing process is more complicated than least squares regression. In practical applications, for the estimation of tail-end distribution data, the quantile regression model is more accurate than the least squares regression; but if it is not aimed at the estimation of both tail ends, the difference between the quantile regression and the least squares regression model results is not large (Allen & Powell, 2011). Quantile regression analyzes the difference in the impact of each explanatory variable on the explained variable under different quantiles, which is also one of the characteristics of quantile regression.

Unlike ordinary least squares that can only get a single prediction value, quantile regression can get a set of prediction values by giving different weights to the data. These predictions represent the percentage of observations with high weights, that is, the quantiles of the return distribution, which can take any value between 0 and 1. For example, if an investor wants to understand the effect of the market value factor on high-yield stocks, they can set $\tau=0.9$. If they are interested in the relationship between low-yield stocks and the market value factor, they can set $\tau=0.1$.

2.3 Quantitative Trading

Quantitative trading use historical financial data, combined with statistical analysis and mathematical model building, to convert trading logic into code, forming a trading system to assist investors in finding the most suitable investment portfolio and improving investment performance (Ta et al., 2018). The advantage of quantitative trading is that it uses computers to calculate entry and exit signals, which can effectively eliminate the impact of human emotions, minimize investment risk, and maximize investment returns (Dellavigna & Pollet, 2009). Backtesting is an indispensable part of the development process of quantitative trading strategies. It evaluates the effectiveness and potential risks of the strategy by simulating the performance of the strategy on past data (Bailey et al., 2016) (Bailey et al., 2015). In quantitative trading, performance metrics are an important means to evaluate trading strategies. Common performance indicators include Annual Return (AR), Compound Annual Growth Return (CAGR), Annual Volatility, Sharpe Ratio, and Maximum Drawdown (MDD), etc. These indicators can help investors evaluate the risk and return of the strategy (Lo, 2002).

III. Design of the System Flow and Experiments

This study systematically examines the effectiveness of factors, including single-factor stock selection and quantile regression models, and compare the analysis results for commonly used factors. Through the quantile regression model, analyze the impact of different variables at specific quantiles to improve the accuracy and robustness of the stock selection strategy. The following will explain how the system flows and how the experiments are designed for validating the actual data from Taiwan Stock Markets.

3.1 Single-factor stock selection

Single-factor stock selection is a strategy that solely relies on a financial indicator or market data to screen stocks. The execution of single-factor stock selection includes the following steps:

(1) Factor selection: Common factors include fundamental factors (such as price-to-earnings ratio, price-to-book ratio, dividend yield, etc.) and technical factors (such as momentum, volatility, etc.). Past literature, for example Tortoriello (2009), will be the main source of factors used for validation in this study.
(2) Factor ranking: Stocks are ranked according to the selected factor. Usually, investors will choose to invest in a portion of stocks with the highest or lowest factor values. For example, if the price-to-earnings ratio is chosen as the factor, you may choose to invest in stocks with the lowest price-to-earnings ratio in the ranking.
(3) Factor re-ranking and stock replacement: After a period of time, the factors of each stock will change, so it is necessary to re-rank the factors and replace the stocks to maintain the logical consistency of the factor ranking stocks in the research. The period from each stock replacement to the next stock replacement is called the "backtesting window" (Pardo, 2008).
(4) Portfolio construction and profit risk calculation: Build a portfolio based on the sorting results of each window. Investors can choose different numbers of shares and allocation ratios based on risk preferences and the amount of funds.
(5) Establish relevant parameters of the factor analysis model and compare and evaluate across factors: Store the results of each factor analysis for the purpose of analyzing and comparing this factor with other factors individually and mutually.

3.2 Quantile regression

Quantile regression was proposed by Koenker and Bassett in 1978 to study the impact of different variables at specific quantiles. The form of the quantile regression model is as follows:

$$Qy(\tau \mid X)=X\cdot\beta(\tau) \qquad (1)$$

where, $Qy(\tau \mid X)$ represents the τ-th quantile of the dependent variable y given the independent variable X, and $\beta(\tau)$ is the regression coefficient of the τ-th quantile. This method can analyze variables at different quantiles, thus obtaining a set of different regression results.
The impact of individual factor values on stock performance is usually a nonlinear problem. Quantile analysis can help determine how much a valid factor needs to be invested in order to achieve the expected investment effect. Therefore, when constructing a quantile regression model, we divide each factor into multiple groups and calculate the compound annual growth rate (CAGR) of each group. The specific steps are as follows:

(1) Data segmentation and grouping: Sort each factor according to its value and divide it into several groups.
(2) Calculate CAGR: Calculate the CAGR for each group, with CAGR as the dependent variable (y) and group number as the independent variable (X).
(3) Regression analysis: Use quantile regression to perform regression analysis at different quantiles (for example, 0.1, 0.5, 0.9), and compare the regression results at different quantiles.

This study constructs a single-factor stock selection model through the influence coefficient of different capital return quantiles of the factor, and tests its results to determine the appropriate quantile. Figure 3 shows the quantile regression results of the EV_S factor on CAGR, where different quantiles (such as 0.1, 0.5, 0.9) correspond to different slopes. Figure 1 shows the slope comparison of the EV_S factor under different quantile regressions, clearly pointing out that the slopes at certain quantiles have higher significance and predictive power.

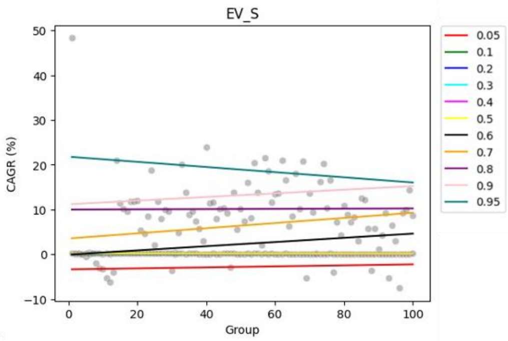

Figure 3: Scatter plot of CAGR and group numbers for the EV/S factor

Table 1: Comparison of EV/S factor investment portfolios constructed based on quantile regression

	QR(0.05)	QR(0.5)	QR(0.95)
Q1	6.39%	20.10%	20.10%
Q2	3.50%	12.88%	12.88%
Q3	6.83%	12.25%	12.25%
Q4	7.05%	10.96%	10.96%
Q5	12.14%	12.14%	12.14%
Q6	12.32%	12.62%	12.62%
Q7	10.84%	6.93%	6.93%
Q8	12.17%	6.90%	6.90%
Q9	13.06%	3.67%	3.67%
Q10	12.50%	5.83%	5.83%
Q1 – Q10	-6.11%	14.27%	14.27%

Table 1 shows the backtest results of the stock selection model constructed by the EV/S factor through different quantile regression coefficients. Among them, QR(0.05) represents the single-factor stock selection model constructed by the influence coefficient of the 0.05 quantile, QR(0.5) represents the single-factor stock selection model constructed by the influence coefficient of the 0.5 quantile, and QR(0.95) represents the single-factor stock selection model constructed by the influence coefficient of the 0.95 quantile. The analysis shows that QR(0.95) and QR(0.5) have higher significance in predicting CAGR, while the predictive effect of QR(0.05) is more general. The results of this experiment can provide suggestions for choosing quantiles. Choosing the quantile of the influence coefficient (larger slope) can more accurately reflect the direction of future stock performance.

3.3 Single-factor stock selection and Quantile Regression

Based on the quantile regression model, which can correct the problem in factor analysis that it is difficult to determine how much percentage of stocks to invest in for a valid factor, this study constructs the following stock selection strategy process that combines factor selection and quantile analysis:

(1) Regression model application: Based on the experimental results of the previous section, choose the quantile model with the largest absolute value of the slope, because this model has the highest sensitivity to changes in returns.

(2) Return prediction: Use the selected quantile regression model to predict the future CAGR. The formula is as follows:

$$CAGRi=\beta(i,0)(\tau)+\beta i(\tau)\cdot Xi+\epsilon \qquad (2)$$

where $\beta(i,0)$ is the intercept term, $\beta i(\tau)$ is the regression coefficient of the i-th factor at the τ-th quantile, and Xi is the group number corresponding to different stocks of the i-th factor.

(3) Stock sorting and selection: Sort stocks according to the predicted CAGR and select stocks with the highest predicted returns for investment.

The exact method proposed here uses quantile regression to perform regression analysis at different quantiles, fully utilizing the information of factors at different return levels, thereby improving the accuracy and robustness of the stock selection strategy.

IV. EXPERIMENTS DATA AND FACTOR SELECTION

The backtesting data time is from January 1, 2000 to December 31, 2023. The Taiwan stock price data and financial report data are gathered from the Taiwan Economic Journal (TEJ, 2024) database. The Taiwan stock market selects all listed and OTC companies, a total of 1775 stocks. Among them, stock price information (opening price, highest price, lowest price, closing price, average price) uses the dividend-adjusted stock price.

4.1 Factor Selection for the Experiments

There are many factors to choose from. Tortoriello (2009) explains that factors can be divided into seven types of factors: profitability factors, valuation factors, cash flow factors, growth factors, asset allocation factors, momentum factors, and risk signal factors. This study will analyze the effective factors from these types and backtest them on Taiwan stocks. The following describes the definition and calculation method of each factor: (1) Earnings per share (EPS), (2) Price-to-earnings ratio (PE), (3) Enterprise value multiple (EV/EBITDA), (4) Enterprise value to sales ratio (EV/S), (5) Free cash flow price ratio (FCF/P), (6) Cash return on invested capital (CROIC), (7) Free cash flow to operating income ratio (FCF/OI), (8) Return on equity (ROE), (9) Return on invested capital (ROIC), (10) Price-to-book ratio (PB), (11) Price-to-sales ratio (PS), (12) Market value to invested capital ratio (P/IC), (13) Operating cash flow to equity ratio (OCF/E), (14) Price momentum (Momentum).

4.2 Experiment Results and Validation

A series of regression analysis combining single factors and quantiles with all Taiwan stock data from February 2000 to December 2023 are conducted. When conducting quantile regression, each factor was sorted and divided into 100 groups for backtesting. The trading strategy was to buy and hold and change stocks every month (i.e. the aforementioned backtesting window is each month in this study to reflect the most current financial data change), calculate the CAGR of each group, apply the quantile regression procedure as proposed, take the group number as the explanatory variable x, and CAGR as the dependent variable y. The slope estimates of OLS and non-quantile regression are drawn into two different pictures. For example, Figure 4 is a scatter plot of P/IC factor CAGR and group number. From this figure, it can be seen that the slope of the median regression presents a downward-left and upward-right tilt, indicating that there is a positive effect between the P/IC factor group number and the median of CAGR, that is, the larger the group number, the larger the CAGR. However, at higher quantiles (0.95) and lower quantiles (0.05), the results of quantile regression differ greatly from median regression. When the regression line is steeper at higher quantiles, and the regression line slope approaches 0 at lower quantiles, it indicates that the same factor has a completely different impact on different quantiles of CAGR. The steep regression line indicates that the P/IC factor has a greater impact on the high quantile of CAGR.

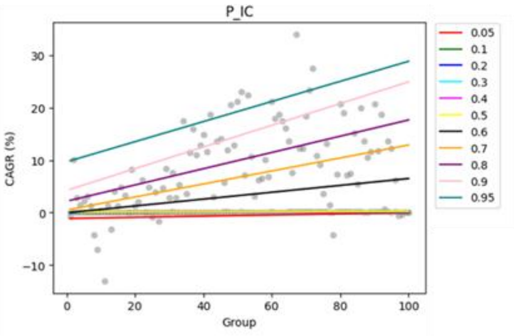

Figure 4: Scatter plot of CAGR and group numbers for the P/IC factor

Figure 2 is the regression coefficient estimate of the P/IC factor at different return quantiles. The red line is the estimate value of OLS regression, the red dashed line is the 95% confidence interval of OLS regression, the black line is the estimate value of quantile regression, and the gray area is the 95% confidence interval of quantile regression. It can be observed that there is not much difference between the two different regression methods at the 50% to 70% quantile, but the difference between the two is greater towards the extreme quantile.

This study conducted a quantile regression analysis on all the factors listed in the beginning of this Section, one by one into the proposed quantile regression procedure, and the results of the regression coefficient line graphs and scatter plots of each factor were organized as shown in Figures 5 and 6, and more detailed data records are in Table 2.

Observing Figures 5, 6 and Table 2, you can choose the quantile where the regression line of each factor is steepest, such as the 70% quantile for the EPS factor, the 95% quantile for the EV/S factor, the 80% quantile for the ROE factor, and the 95% quantile for the PB factor.

Factor	OLS coefficient	Quantile										
		0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.95
EPS	-0.032*	-0.069**	-0.001	-0.001	-0.001	-0.001	-0.001	-0.053**	-0.096**	-0.055	-0.037	0.044
PE	0.065**	0.068**	0.004	0.002	0.002	0.002	0.003	0.027**	0.068**	0.126**	0.177**	0.241**
EV_EBITDA	0.002	0.013	0.007	0	-0.001	-0.001	-0.001	0.032*	-0.052	-0.046	0.066**	-0.023
EV_S	0.006	0.011	0.001	-0.001	-0.001	-0.001	0	0.047**	0.058	0.002	0.041	-0.058
FCF_P	-0.047**	-0.024**	0	0	0	-0.001	0	-0.038*	-0.109**	-0.077*	-0.115**	-0.14*
CROIC	-0.023	-0.006	0	0	0	0	-0.001	-0.063**	-0.074**	-0.047	-0.013	-0.02
FCF_OI	-0.004	-0.013*	0	0	0	0	-0.001	-0.047**	-0.021	-0.022	0.034	0.016
ROE	-0.047**	-0.059**	-0.038**	-0.001	-0.001	-0.001	-0.002	-0.064**	-0.098**	-0.121**	-0.045	-0.035
ROIC	-0.049**	-0.083**	-0.021*	-0.001	-0.001	-0.001	-0.001	-0.071**	-0.106**	-0.087**	-0.03	-0.017
PB	-0.019	-0.05**	0	-0.001	-0.001	-0.001	-0.001	0.001	0.028	-0.168**	-0.262**	-0.387**
PS	0.01	-0.003	0.001	-0.001	-0.001	-0.001	-0.001	0.028*	-0.002	0.023	-0.077**	-0.156**
P_IC	0.058**	0.011	0.001	0.001	0.002	0.002	0.002	0.065**	0.124**	0.155**	0.207**	0.191**
OCF_E	-0.063**	-0.051**	-0.002	-0.001	-0.001	-0.001	-0.001	-0.077**	-0.11**	-0.108**	-0.132**	-0.099*
MOM	-0.004	0.053**	-0.001	-0.001	-0.001	-0.001	-0.001	0.039	-0.032	-0.042	0.019	-0.004

Table 2: Impact coefficients of OLS and quantile regression for each factor

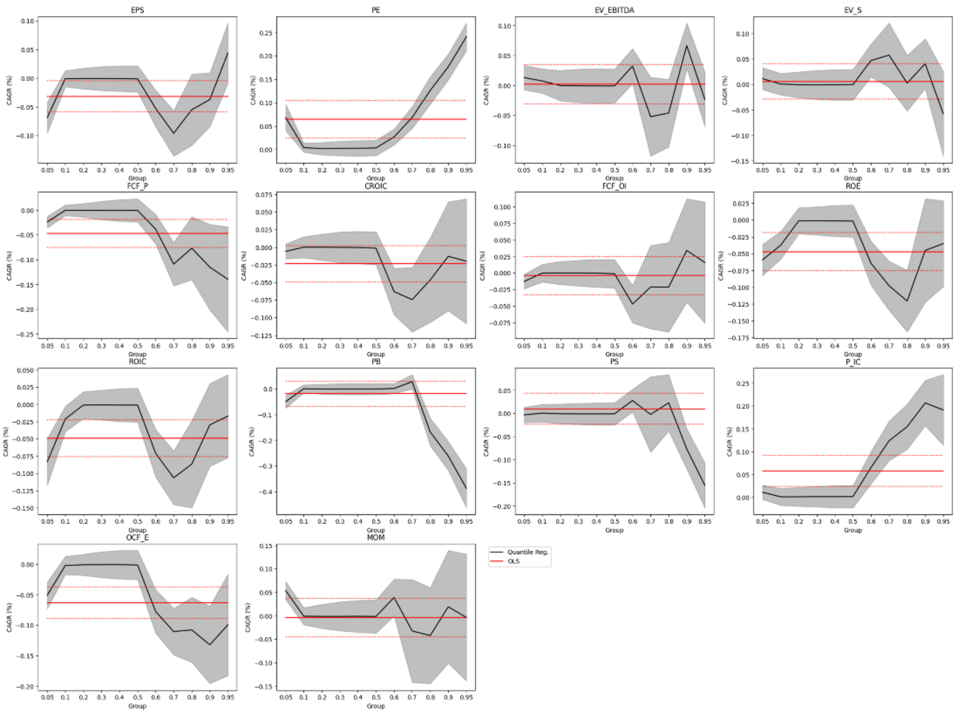

Figure 5: OLS and quantile regression coefficients for each factor

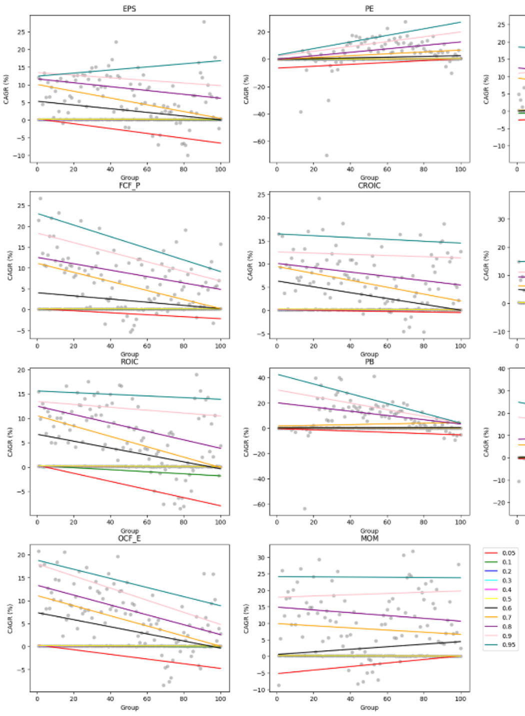

Figure 6: Scatter plot of CAGR and group numbers for each factor

Using different factor regression lines with the steepest slopes, stocks are sorted and divided into 10 groups. After buying and holding the first group and the top five groups, the backtesting comparison results are shown in Table 9. It can be observed that the EV/S factor has the highest CAGR while the EV_EBITDA factor is the lowest. According to Figures 7 and 8, we can observe the relationship between the impact coefficient of the steepest slope of each factor regression line and CAGR and MDD. In Figure 7, it can be observed that CAGR has a positive relationship with the impact coefficient, but it is not obvious, indicating that as the impact coefficient becomes larger, although CAGR has a trend to become larger, it is not obvious. In Figure 8, the regression line presents a positive relationship from low left to high right, indicating that the larger the impact coefficient, the smaller the MDD and the lower the risk.

Table 3: performance results of holding the first group and the top five groups for each factor

factor	Holding the first Group		Holding the first 5 Groups	
	CAGR	MDD	CAGR	MDD
EV_S	20.10%	-39.14%	12.19%	-51.52%
PS	12.32%	-29.02%	12.19%	-52.14%
ROE	12.11%	-44.12%	11.67%	-54.51%
PB	12.11%	-28.90%	14.01%	-43.90%
ROIC	11.67%	-49.48%	11.64%	-55.27%
OCF_E	11.61%	-48.86%	10.87%	-57.27%
P_IC	11.58%	-29.54%	12.95%	-52.39%
FCF_P	10.83%	-61.08%	9.41%	-60.60%
EPS	9.15%	-50.66%	11.00%	-55.00%
PE	8.49%	-67.51%	10.13%	-64.58%
FCF_OI	7.10%	-60.94%	9.81%	-60.52%
CROIC	5.85%	-63.81%	9.76%	-59.86%
MOM	4.96%	-69.97%	9.38%	-55.51%
EV_EBITDA	1.67%	-69.40%	12.44%	-51.86%

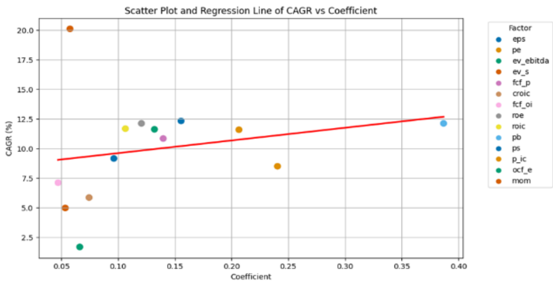

Figure 7: Scatter plot of the maximum absolute impact coefficient of each factor and CAGR.

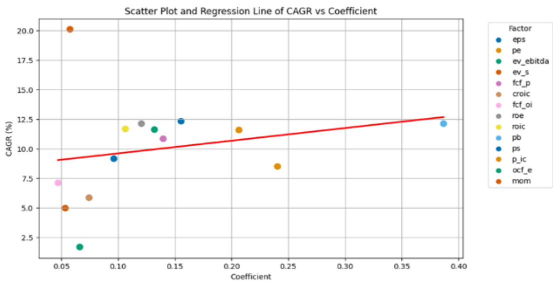

Figure 8: Scatter plot of the maximum absolute impact coefficient of each factor and MDD.

Through this experiment, we can understand that different quantiles found through quantile regression may have completely different impacts on returns at different quantiles, so choosing quantiles is more important. Based on the above results, it should be chosen that the absolute value of the impact coefficient (the slope of the regression line) is the largest quantile that can best reflect the direction of future stock performance differences, and better stocks can be selected and bought and held. Through Figures 7 and 8, it can be further observed that the impact coefficient and CAGR have a positive relationship but the trend is not obvious, and the same line has a positive relationship with MDD but the trend is more obvious. Therefore, if you want to reduce the risk of the investment portfolio, you can choose the return quantile with a larger absolute value of the impact coefficient.

V. CONCLUSION

This study adopts the quantile regression model to analyze the performance of factors at different return levels, thereby improving the accuracy and robustness of the stock selection strategy. The experimental results show that by choosing the quantile with the largest absolute value of the slope for return prediction and stock sorting, this method fully utilizes the information of the factor at different return levels, thereby constructing a more predictive investment portfolio and achieving a better Compound Annual Growth Rate (CAGR). In addition, this study incorporates the interaction of group numbers and time into the quantile model to examine the robustness of factors in different windows. The experimental results show that the CROIC and EV/EBITDA factors have higher robustness in different time windows and can maintain consistent returns and risk performance under different market conditions. Furthermore, the experimental results of this study show that there is a significant relationship between the impact coefficient and CAGR and Maximum Drawdown (MDD). A larger impact coefficient usually means a higher CAGR and a lower MDD, indicating that choosing a quantile with a larger impact coefficient to construct a single-factor investment portfolio can help improve the return of the portfolio and reduce risk.

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