Portfolio Management Based on TMT Sector: Comparative Study between Basic Qualitative and Model-Based Approach

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Abstract. Nowadays, more and more investment techniques are incorporating model-based techniques to facilitate portfolio management process; however, techniques that could predict future stock expected returns are relatively scarce. This study mainly focuses on using model-based methods to evaluate stocks in the TMT (Technology, Media, Telecom) sector based on historical data for the last four years. LSTM (Long Short-Term Memory) neural network and Fama-French three factor models are employed in this study to predict the future expected return of the stocks and further, evaluate whether the stock could come into the optimal portfolio. Efficient frontiers are drawn using the variance of expected return against the mean of future expected return. Then investment utility function is set up along with the efficient frontier to make optimizer to get the best weight of the optimal portfolio. To justify if the model-based approach is robust, comparative study is done between basic qualitative approach and model-based approach. Two parallel approaches will use different methods as well as metrics to evaluate the same set of competitor stocks and generate the optimal portfolio. The results have shown that both approaches have the same optimal portfolio and the model-based approach is justified. Thus, this quantitative model-based approach is robust and applicable for investment since it could generate consistent result as the basic qualitative approach and it is more explicit in data.

Keywords: Portfolio Management; Fama-French Three Factor Model; LSTM Neural Network; Efficient Frontier; Expected Return.

1. Introduction

The study mainly focuses on portfolio management within TMT sector since TMT industry is more of innovation driven strategy and the companies within TMT industry is more volatile in its return and riskier. If the model could adapt well in this industry, then it could be likely to fit all industries.

The research background of this analysis is to identify the best portfolio within TMT sector using machine learning and optimization. Several companies are selected from the TMT sector and their performance is evaluated using the approach introduced in this study. The best portfolio is made based on the evaluation outcome and relevant investment implications are shown using data driven approach. The study, in general, deals with the question of how to evaluate different companies within a particular industry on the stock market. The study will focus on quantitative as well as qualitative research to evaluate the difference between the two.

In this study, two major models contributing to model-based approach are LSTM and Fama-French three factor models. This study favors single layer LSTM since it has a superior fit compared to multilayer counterparts [1]. LSTM neural network has been proven to have a poor fit if it is fed with too many variables [2]. Thus, in this study, LSTM is only fed with stock OHLC (Open, High, Low, Close) data. Also, the study does not consider the famous DQN (Deep Q-Network) neural network since DQN generally does not have an impressive prediction outcome and LSTM has been proven to have quite good predict power [3-5]. In this study, Fama-French three factor model is also employed to predict stock expected return out of index expected return. This model is quite robust from empirical studies and validity is widely recognized [6, 7]. Lastly, the model-based method in this study adopts the efficient frontier to illustrate the tradeoff between mean and variance of expected return, whose validity is also backed by relevant research [8, 9]. An investment utility function has been set up in this study to get the optimal model-based portfolio. The risk-aversion parameter is set to 2, which is derived from the 1983 study concerning this topic [10].

The main research rationale is that the study uses a comparative study between basic qualitative and model-based portfolio management approach. For illustrative purposes, five stocks (AAPL, CAJ, DELL, HPQ, HPE) from the TMT industry is selected and evaluated using basic qualitative approach in the first place. The five stocks are evaluated in terms of the four dimensions: valuation, growth, profitability and payout. From the evaluation of the performances, the optimal portfolio is established based on the rejection rule: a stock is rejected from the optimal portfolio if it does not reach some thresholds of metrics. Then, the model-based approach is applied to get the optimal portfolio using future expected return predicted by a series of models. Fama-French three factor model is fitted firstly to get a linear relationship between stock close price and index close price. LSTM neural network is trained afterwards and is based on index OHLC data for the past three years. The study employs LSTM to get index expected return for the next year. Combining both Fama-French and LSTM model, the study could get the outcome for stock return for the next year. In this way, efficient frontier based on future expected return is established and investment utility function is applied to get the optimal portfolio. Eventually, the optimal portfolios based on basic qualitative and model-based approach are compared in terms of their similarity to check if they are consistent.

The outcome for the study is that portfolio from model-based approach is consistent with its counterparts from basic qualitative approach. Both approaches get the same optimal portfolio and the study concludes that this model-based approach is robust and applicable for investment not only for TMT sector. Also, this approach may be more preferable than basic qualitative approach since it generates explicit data and portfolio weight outcomes.

For the potential improvement of this study, more time-series prediction models other than LSTM could be applied and evaluated to get more precision on the prediction outcome. Also, the study could focus more on other industry sectors to check the eligibility of this method in terms of different investment circumstances. Moreover, Fama-French three factor model is very likely to get overfitted, which could probably to solve by using ridge or lasso regression.

2. Data and Methodology

2.1 Data

The data imported into this study is from Yahoo Finance stock data API. For basic analysis regarding valuation, growth, profitability and payoff, this study employed data ranging from 2018-2021 since the four-year data is capable of generating three growth rate trends. For Fama-French three factor model and LSTM neural network model building, the study incorporated stock and index OHLC data from last three years ranging from Jul 1st 2019 to Jun 30th 2022. This data also comes from Yahoo Finance.

2.2 Methodology

The basic methodology of the study is using basic analysis as well as more model driven approach to test if the two methods will lead to the same optimal portfolio, which means that the advanced portfolio building method is as robust as the basic analysis. The stock tickers chosen are AAPL, DELL, HPQ, CAJ, HPE, which are all from TMT industry since it is assumed that stocks within same industry sector are more comparable. Firstly, basic analysis is applied to the stocks using data from the last four years. The interested stocks are evaluated based on four great dimensions: valuation, growth, profitability and payout. For each dimension, different metrics are calculated and compared while rejection rules are established as well: a stock is rejected from the optimal portfolio if it cannot reach some thresholds in any of the metrics. After generating the optimal portfolio out of the basic approach, model-based methods are employed: Fama-French three factor model and LSTM neural network are built based on stock and index data for the last three years. Admittedly, there is a discontinuity of data between basic analysis and model-based approach; however, since the study concerns about the long-term consistent performance of the stocks. The discrepancy in the time of data will not affect the judgement of the study concerning the performance evaluation for the fact that basic and advanced methods employ different metrics to evaluate the stocks. For the advanced approach, Fama-French three factor model is built based on certain index data. In this study, index return is employed as the indicator for return of some segments of the market. The tickers chosen for Fama-French and LSTM modeling is DJIA, SLY, SPLG, SLYV, SLYG, representing for market return (R_{DJIA}), low cap return (R_{SLY}), large cap return (R_{SPLG}), value stock return (R_{SLYV}) and growth stock return (R_{SLYG}) respectively. The model is fitted as below:

$$R_{it} - R_{ft} = \alpha_{it} + \beta_1\left(R_{DJIA} - R_f\right)_t + \beta_2(R_{SLY} - R_{SPLG})_t + \beta_3(R_{SLYV} - R_{SLYG})_t \quad (1)$$

Additionally, the study uses expected return of 13-week treasury bond to simulate the risk-free rate R_{ft}. For the LSTM neural network, the study predicts the future close price of the indexes of interest using OHLC data for the past three years. The outcome shows the close price of the trading days for the next year i.e., the next 252 trading days. Then the outcome is fed into the Fama-French three factor model to predict the expected return for the chosen stock for the next year. Eventually, the future expected return of the stock is evaluated in terms of its average along with its variance. Using investment utility function and sharpe ratio, the optimal portfolio under model-based approach is generated.

3. Comparative Study betthe studyen Basic Qualitative and Model-Based Approach

3.1 Basic Analysis Regarding Final Optimal Portfolio

The basic approach adopted in this investment study is to split the stock universe into different industry clusters. It should be more reasonable to analyze data from the industry perspective since companies from different industries may have quite different profiting patterns, asset and debt structure, opportunities of growth, etc. The difference in these factors may create confusion when selecting target stock according to the technical statistics. Then, this study evaluates the stocks from TMT industry from statistics of four major sections: valuation; growth; profitability; payout. The conclusion is drawn based on the analysis on the data of the four sections. Due to the inconsistency of data, the study will only analyze stock that has data available for three consecutive years.

3.1.1 Valuation

This study selects the technical statistics as follows: P/E, P/B, PEG. The notion of stock selection according to P/E is that it is preferred to select value stocks which have relatively low P/E ratio: the stock will be favorable if the P/E ratio should be ideally between 10 and 20. For P/B ratio, it is preferred that the stock is a value stock with relatively low P/B ratio. However, considering P/B ratio could be inflated by large ROE value, this criterion is subject to further investigation. Another indicator for valuation assessment is PEG: the firm in question is undervalued if it has a PEG ratio lower than 1.

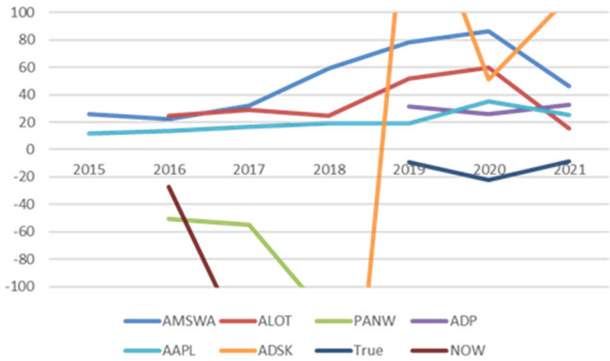

Fig. 1 P/E ratio of target TMT stocks

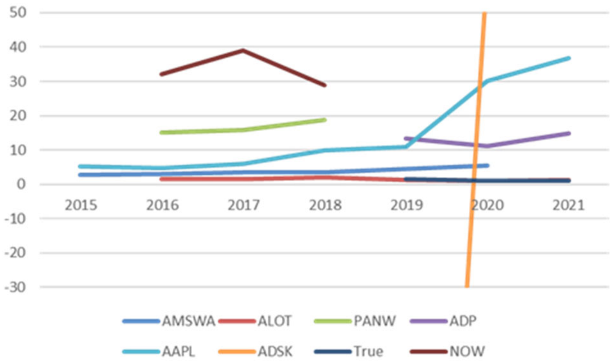

Fig. 2 P/B ratio of target TMT stocks

Table 1. P/E and P/B quantile value of AAPL

	2015	2016	2017	2018	2019	2020
P/E	16.67%	6.25%	15.79%	10.71%	10.00%	20.83%
P/B	77.78%	50.00%	57.89%	67.86%	75.00%	79.17%

* Quantile value shown in this table is within TMT industry. Quantile 0% means the company is considered the most value-based while quantile 100% means the company is the most growth-based. The companies' data is ranked in the following fashion (P/E as example): small positive P/E, large positive P/E, small negative P/E, and large negative P/E

In the case shown above, the study could conclude that the AAPL has the lowest P/E ratio over the period compared to other companies and its P/E ratio is roughly within range 10 and 20. There is a jump in AAPL's P/E ratio between 2019 and 2021 with its peak at 2020. During this period, the AAPL P/E ratio exceeds 20, however, considering the growth nature of the TMT industry, its P/E ratio is more value based compared to its counterparts. As to P/B ratio, it goes unexpected that AAPL's P/B ratio is rising dramatically over recent years since 2019. This phenomenon could be interpreted that the rapid surge of P/B ratio results from the increase in ROE value (since AAPL's P/E ratio does not vary much during the same period). The rise in ROE ratio exhibits the improvement in profiting ability of AAPL as well as promising future potential of growth, which are both preferable traits of stock investment. In general, AAPL has a lower P/E compared to its counterparts, always maintaining its position in the top 25% quantile of the TMT industry. By contrast, its P/B ratio stays in the bottom 50% quantile of the TMT industry, implying robust ROE, great growth momentum and profiting ability.

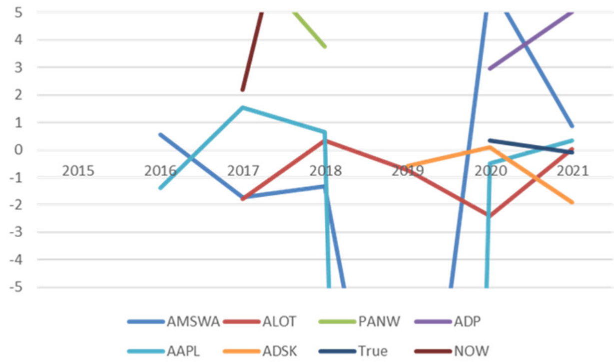

Fig. 3 PEG ratio of target TMT stocks

Another valuation insight is provided by PEG ratio. Generally, low or negative PEG ratio indicates that the firm is undervalued. AAPL shows a great drop between 2018 and 2020, reaching a history lowest PEG of -112 in year 2019. Also, AAPL maintains PEG ratio lower than 1 over the period except for 2017 where its PEG is 1.55, slightly greater than 1. Therefore, generally speaking from PEG perspective, AAPL is concluded to be undervalued stock.

From valuation perspective, AAPL is value based for sure. However, its growth potential may not be fully captured by the market and is undervalued, which may create a good investment opportunity.

3.1.2 Growth

Revenue growth and EBITA growth are selected to be the measurement metrics of growth. High growth rate is preferred but not compulsory for value firms; however, this study will not favor any company with negative growth rate for 2 consecutive years.

In terms of revenue growth, AAPL has negative growth of -7.97% and -1.95% for 2016 and 2019 respectively while its growth recently reaches the peak value of 33.26%. Considering the fact AAPL is a value stock, its growth in revenue from 2019 to 2021 is impressive. Its performance within TMT industry is not outstanding but adequate: its revenue growth quantile in the industry is around 50% generally, indicating that AAPL has roughly beat about 50% of its fair plays. This revenue growth is quite impressive for value companies like AAPL: most companies in TMT industry are growth based rather than value-based. So, it is relatively hard for value stocks such as AAPL to stand out in revenue growth quantile.

Moreover, EBITA growth statistics for AAPL provides more or less similar insights as revenue growth statistics. For 2016 and 2019, AAPL has negative EBITA growth but is not significant (-15.24% and -6.24% respectively). Quantile data concerning EBITA growth of AAPL in TMT section shows that AAPL falls in the bottom half of the section (around 50%), which is consistent with revenue growth quantile in that it beats over 50% of the companies in TMT section in terms of EBITA growth rate.

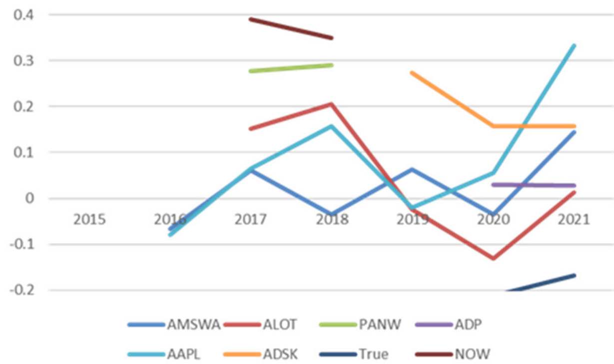

Fig. 4 Revenue growth of target TMT stocks

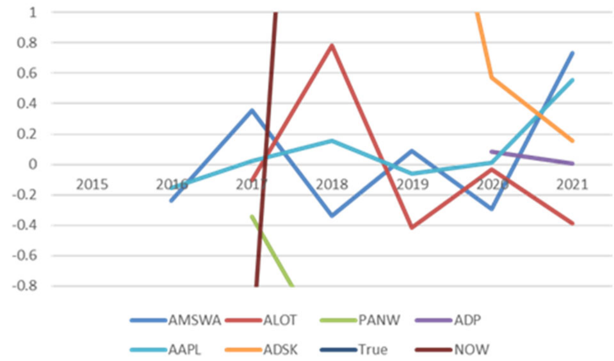

Fig. 5 EBITA growth of target TMT stocks

In summary, AAPL is adequate in terms of growth metrics while its recent trend of revenue as well as EBITA growth should also be given more attention. The mediocre of AAPL growth metrics is not outstanding in TMT section but could still beat about half of the stocks in the section. These quantile statistics indicate that the growth of the company is in good shape since it is a value stock while TMT industry is more of a growth-based logic. Additionally, from overall perspective, revenue growth CAGR over 2016 to 2021 is 9.37% and EBITA growth CAGR is 8.03% over same period, indicating adequate growth dynamics.

3.1.3 Profitability

This study evaluates profitability by measurement as follows: net profit margin; gross profit to asset ratio. These two measurements will provide insights on the cost of generate net profit from the total revenue and the ability to generate gross profit from the company's asset. This study will prefer companies with high net profit margin and high gross profit to asset ratio. In light of the fact that most value firms have relatively heavy asset, value stocks could have relatively low gross profit to asset ratio compared to growth stocks.

The net profit margin of AAPL fluctuates between 20% and 25% over the period. Also, it indicates strong competitiveness when importing quantile values of this metric. The quantile value of net profit margin for AAPL is above 75% throughout 2016 to 2021, meaning that it outperforms 75% of its counterparts in the TMT section. The outperformance implies that AAPL is capable of efficient cost control when generating profit.

For gross profit to asset ratio, AAPL's gross profit to asset ratio has been increasing steadily since 2017. By the end of 2021, AAPL's gross profit/asset reaches all time highest of 46.76%, surpassing 88.46% of its counterparts. Though AAPL has relatively low gross profit to asset ratio from 2015 to 2018, the company is gradually enhancing its ability to generate profit from its asset base. Since AAPL is a value-based firm, its asset should be heavier than other firms in the TMT section. Therefore, the gross profit of AAPL will be impressive and promising if the current trend of increasing gross profit/asset ratio persists.

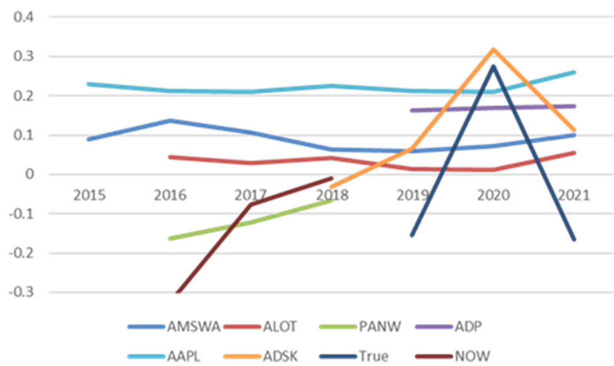

Fig. 6 Net profit margin of target TMT stocks

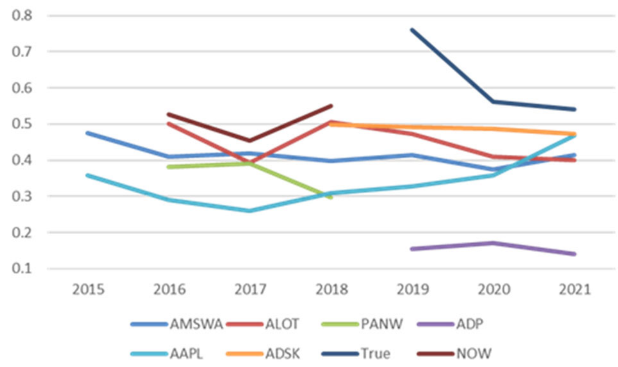

Fig. 7 Gross profit/asset of target TMT stocks

Table 2. Net profit margin and gross profit/asset quantile value of AAPL

	2015	2016	2017	2018	2019	2020
Net profit margin	88.89%	87.50%	88.89%	85.71%	90.00%	75.00%
Gross profit/asset	55.56%	31.25%	47.37%	42.86%	50.00%	58.33%

* Quantile value shown in this table is within TMT industry, taking ascending order (quantile 0% means smallest in value)

Beating most of its counterparts in the TMT section, AAPL has really outperformed in terms of net profit margin. Its ability with cost control in the process of profit generation is favorable from investment perspective. Moreover, AAPL's gross profit to asset ratio is constantly increasing since 2017. This trend, combined with AAPL's enormous asset base, indicate a highly probable profit surge in the future.

3.1.4 Payout

Finally, the study employs dividend yield as the measurement to assess the companies' payout performance.

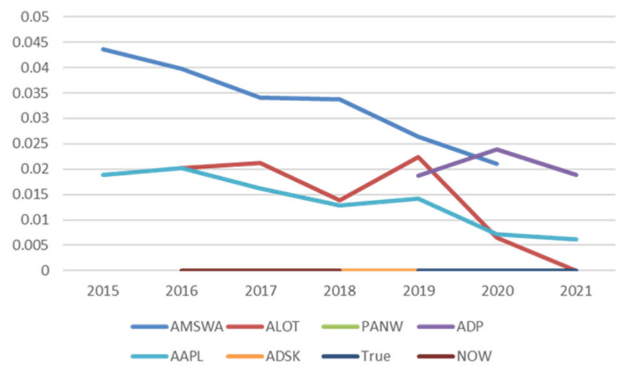

Fig. 8 Dividend yield of target TMT stocks

Dividend yield of AAPL oscillates down from 2015(1.89%) to 2021(0.62%), which indicates that the payout of AAPL is inadequate and diminishing. According to quantile data within TMT section, AAPL constantly beats over 77% of the its counterparts throughout the timeframe. More importantly, AAPL's dividend yield quantile grows from 80% to 95.83% from 2019 to 2021 while in the very same period, its dividend growth has decreased from 1.42% to 0.62%. This implies that industry scope dividend yield drops dramatically in recent years of 2019 to 2021 and AAPL shows a somehow resilient trend to the industry level dividend yield recession.

Consequentially, AAPL's dividend yield may seem inadequate and diminishing from absolute value while it shows a resilient trend against the overall drop in dividend yield on the TMT industrial level. Also, the dividend yield quantile data indicates that few company within TMT industry will outperform AAPL and exhibit positive dividend yield growth. Therefore, AAPL may have inadequate payout ability, but it does not prevent it from being a good investment in its industry stock universe.

3.2 Basic Qualitative Approach

The competitors for the analysis are given as DELL, HPQ, CAJ, HPE. For all these competitors, the study will choose similar indicators as before: P/E ratio, P/B ratio, PEG ratio, EPS growth rate, revenue growth, gross profit margin, gross profit to asset ratio, dividend yield. The performance of competitors is also considered in terms of four aspects: valuation (P/E ratio, P/B ratio, PEG ratio), growth (EPS growth rate, revenue growth), profitability (gross profit margin, gross profit to asset ratio) and payback (dividend yield).

The aim of our analysis of competitors in the industry would be choose the best stock or best group of stocks. However, the study will constrain on the number of best stock group to less than half of the total competitor population, i.e., best stock group will have 2 stocks at most.

3.2.1 Valuation

Firstly, the study evaluates the valuation of relevant competitors in the industry using P/E, P/B and PEG.

For P/E ratio, the study follows the criteria that negative P/E ratio will not be tolerated if the stock is to be selected for the final portfolio. For DELL, it has preferable P/E ratio between 10 and 20 most of the time; however, it has a negative value P/E ratio for 2018. HPE also has a negative P/E ratio for 2020 and it has greatest volatility in terms of P/E. The study may take CAJ into consideration since it is highly undervalued. For AAPL and HPQ, both are in preferable P/E range most of the time and is generally undervalued stock.

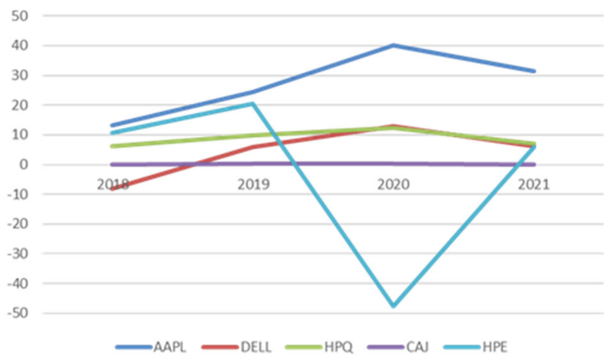

Fig. 9 P/E ratio of competitor stocks

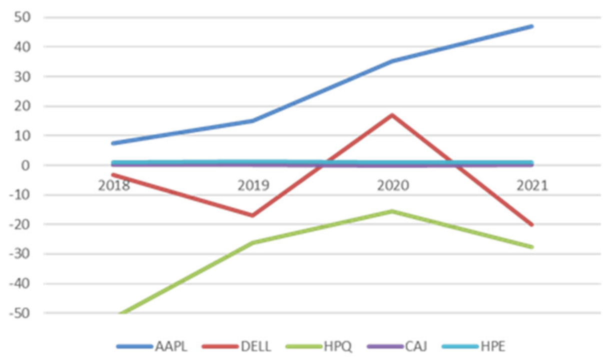

Fig. 10 P/B ratio of competitor stocks

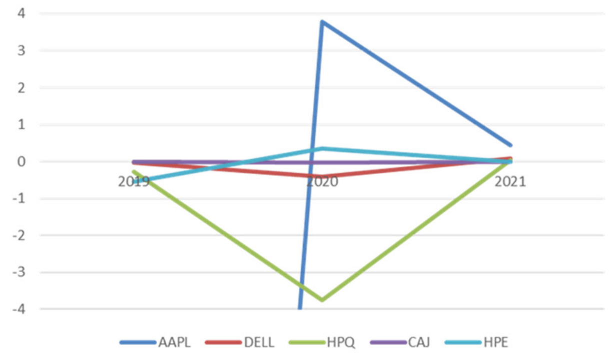

Fig. 11 PEG of competitor stocks

For P/B ratio, the selection principle is more or less the same: the study do not tolerate negative P/B. As a result, HPQ and DELL are all ruled out. CAJ still has a quite low P/B, which is consistent with its P/E ratio and indicates that it is highly undervalued. Combined with HPE's high volatility P/E and low P/B, the study can conclude that HPE has large equity but high volatility of EPS, which is not a desired trait for good investment. AAPL's P/B ratio is high and steadily increasing, which also implies higher ROE in recent years.

For PEG ratio, all data shows value less than 1.0 except for AAPL in year 2020. This is tolerable since year 2020 is the year filled with passive views: most stock experience undervaluation in this year. Only the companies with strong growth momentum and resilience to the pandemic stands out and get overvalued. Also, people in pandemic will be more risk averse in terms of asset management. Thus, AAPL's temporary high PEG ratio will not be a suffice evidence to rule it our from best portfolio. All other stocks behaved quite normally: with PEG under 1 constantly, they are undervalued generally.

3.2.2 Growth

Secondly, the study evaluates the growth metrics for competitors. Two measurements are chosen: EPS growth rate and revenue growth rate.

For EPS and revenue growth rate, the study will not consider companies with negative growth rate for two consecutive years. Though most of the competitors experience increasing growth rate, they perform badly from overall time period. AAPL on the other hand, maintains positive EPS growth rate over the period and has a revenue growth in the leading position among its competitors.

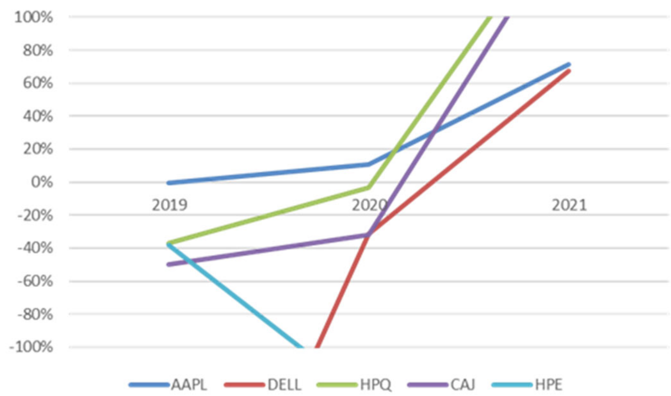

Fig. 12 EPS growth rate of competitor stocks

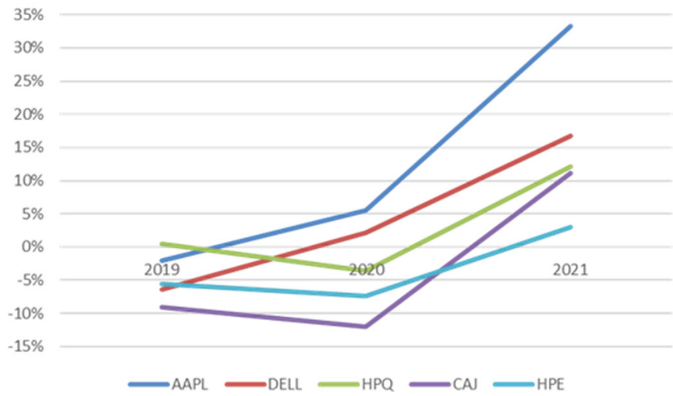

Fig. 13 Revenue growth rate of competitor stocks

3.2.3 Profitability

Thirdly, the study evaluates the profitability of competitors with metrics as gross profit margin and gross profit to asset ratio.

For gross profit margin, the study could conclude from the graph shown below that there is stratification in the data. Each competitor forms a stratum. The ranking in terms of this metric is easy to observe. Also, for gross profit to asset ratio, the data is also stratified into 2 parts: upper three (AAPL, HPQ, CAJ) and lower two (HPE, DELL). Considering the stratification from overall perspective the study can derive that only AAPL and CAJ stay in the upper stratum for both of the metrics, indicating that they are more capable of generating profit from revenue and their asset's profiting ability is outstanding.

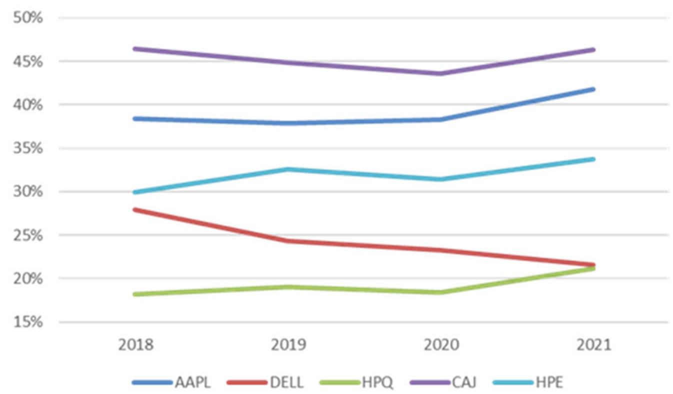

Fig. 14 Gross profit margin of competitor stocks

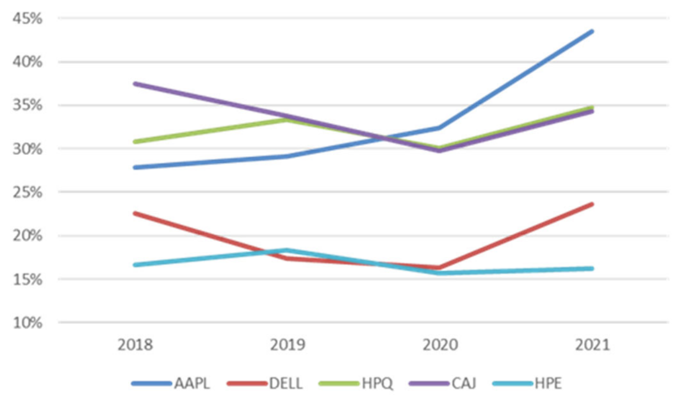

Fig. 15 Gross profit/asset of competitor stocks

3.2.4 Payout

Lastly, the study evaluates the payback of competitors with dividend yield.

For dividend yield, the study could see that HPQ and HPE have the largest dividend yield of about 3.5%. AAPL's dividend yield is constantly decreasing and stays at low level. DELL and CAJ has no dividend distribution for most of the time period. Many competitors have payback consistently lower than other firms with high payback. However, this drawback does not prevent them from entering the best portfolio: more dividend yield may imply more risk since the firm may give too much to its investors. Thus, the study could not properly rule out firms with low or zero dividend yield. The data provides the insight that HPE and HPQ outperform other stocks in payback metric. AAPL, DELL and CAJ fall behind.

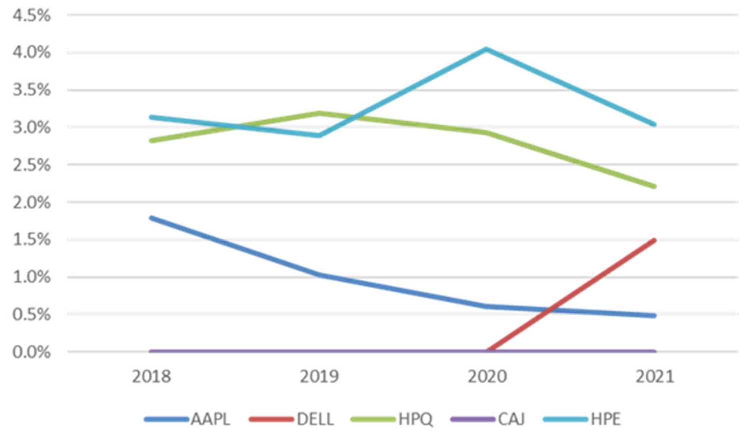

Fig. 16 Dividend yield of competitor stocks

3.3 Model-Based Approach

When the study considers all these metrics and rule out firms based on our threshold of data, the study could get to the conclusion that AAPL should be the only stock in the portfolio. This result also aligns with the portfolio data generated from our neural network prediction (LSTM) for the next year return and efficient frontier analysis. In portfolio selection process, the study generated predicted data for the next 252 trading days (1 year ahead) using LSTM neural network and optimized a best portfolio based on certain statistics: Sharpe ratio and Utility function respectively. Our definition of investment utility function is as follows:

$$U = E(R) - 0.5\times 2 \times var(R) \tag{2}$$

The parameter 2 is derived from Hanson and Singleton's 1983 study. The result is shown below in the table. The study could conclude that best utility portfolio is a better choice than best sharpe portfolio since it has significant higher return and utility score with small drop in sharpe ratio. Thus, from statistical perspective, the study can conclude that 100% position in AAPL is the best choice.

Table 3. Best Sharpe and Best Utility portfolio component based on predicted price data for the next 252 trading days

	AAPL	DELL	HPQ	CAJ	HPE	return	sharpe	utility
Best Sharpe	56.91%	19.01%	24.08%	0.00%	0.00%	3.47%	1.61	1.31
Best Utility	100.00%	0.00%	0.00%	0.00%	0.00%	5.38%	1.50	1.80

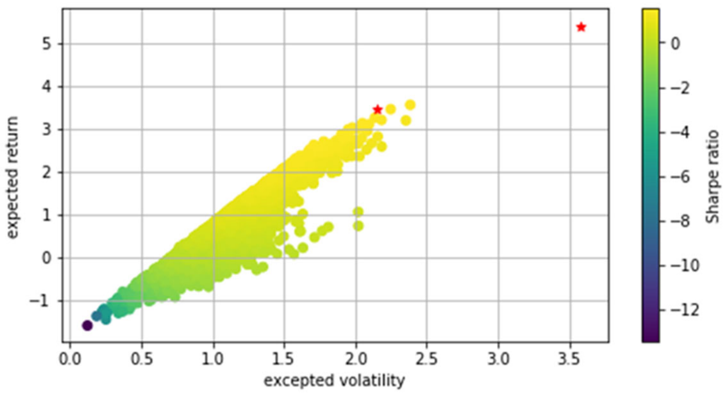

Fig. 17 Best sharpe and best utility portfolio on efficient frontier

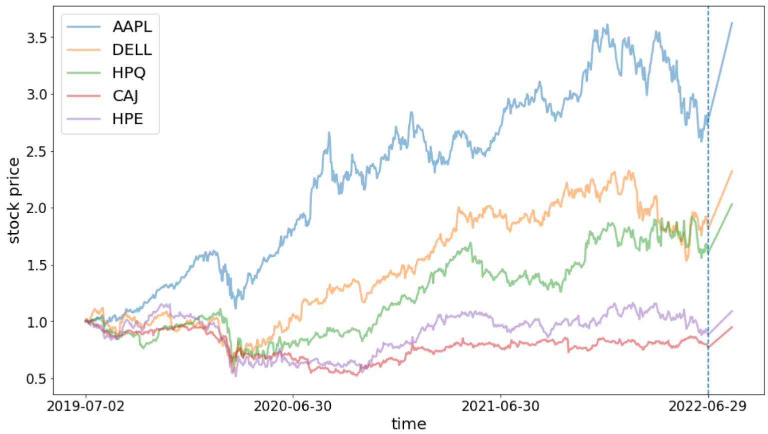

Fig. 18 Prediction result for competitor stocks using LSTM(next 30 days exhibited)

4. Conclusion

The study incorporates data from Yahoo Finance for the last four years and employs both basic qualitative and model-based quantitative approach to evaluate stocks for the optimal portfolio. In this study, LSTM and Fama-French three factor models are introduced and fitted to get model-based optimal portfolio. The model-based optimal portfolio is then compared to the one generated from the basic approach. Eventually, the study concludes that the optimal portfolio is the same for both basic and model-based approach. Moreover, though both basic qualitative and model-based approach are subject to arbitrary choices of parameters such as rejection rule and investment utility function, the model-based approach is more robust than basic approach in that it shows investors the actual future expected return. The model built in the study could be used for not only TMT sector stocks but also other stock clusters within one industry sector. Also, this study illustrates that when compared to basic qualitative approach, model-based approach is more charming since it could provide more data driven outcomes and more insights on future returns. This study; however, does not consider the disparate effect between different models. In order to get a more precise model to predict future expected return, multiple models should be tested and compared. Employing hyperparameter tunning could also be a solution to find the best prediction for the future returns.

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