

**PORTFOLIO OPTIMIZATION FOR SHIPPING & DELIVERY SERVICES WITH
R: BEFORE AND AFTER PANDEMIC COVID-19****Dina Anggraeni^{1)*}, Kris Sugiyanto²⁾, M. Irwan Zam Zam³⁾, Harry Patria⁴⁾**¹ University of Indonesia, dina.anggraeni@ui.ac.id² University of Indonesia, kris.sugiyanto@ui.ac.id³ University of Indonesia, m.irwan01@ui.ac.id⁴ University of Indonesia, harry.patria@sbm-itb.ac.id**Info Artikel :**

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ABSTRACT**Keywords:**
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The objective of this research is to construct an optimum investment portfolio of courier services sector stocks during period 2018-2021 using Modern Portfolio Theory model and to analyse risk and return generated by optimal portfolio before and after Covid-19 using R programming. Furthermore, we would also examine the impact of the Covid-19 on stock prices before and after Covid-19 to formulate investment decisions. The sample are 5 biggest courier services stocks (by market capitalization) that are listed consistently and did not stock split or reverse stock and the number of observations in 4825 stocks prices during the period January 2018 to October 2021. Based on the result of optimum investment research, we can observe that the best performing stocks with high tangency is AMZN, in fact way ahead of other sample emitens. The result will be expected to help investors to bid the best possible portfolio in courier services.

INTRODUCTION

The business of delivering items/goods had been increasing since internet era of marketplace, pioneered by Amazon in US. The practicality of buying goods from anywhere and anytime using online platform has enabled courier services throughout the world reach more and expand the market rapidly. They managed to grow business volume, asset valuation, and ultimately stock price. The pandemic indeed hit hard almost all businesses, but one of the most resilient is courier services. The pandemic which restricts people going out has significantly caused courier services to scale up their business to become the new primary need for survival. This fact has attracted investors to look deeper in the opportunity to include courier services stocks in their portfolio.

In the other hand, Portfolio Optimization involves choosing proportions of assets to be held in a portfolio, so as to make the portfolio better than any other. Simultaneous profit maximization and risk minimization has been a decision rule over the years with the development of the minimax concept providing more interesting insight into the history of risk research (Li, Wu, & Ojiako, 2014). The minimax concept deals with the provision of choice reasons behind an individual's decision choice when faced with a number of possible alternative actions, with the impact of each decision choice unknown (Naslund & Whinston, 1964; Li et al., 2014).

According to Li et al. (2014), the major reason for decision choice was because rational individuals were more likely to seek to maximize expected returns from a decision, but this expectation would be weighted by the probability of an alternative outcome (Simon, 1959). They, therefore, advocated for decision models to come into play. Quantitative and mathematical models have been increasingly applied to decision making and prediction, especially in aspects of business management with highly complex characteristics (Watson & Brown, 1978; Li et al., 2014). Namugaya, Weke, & Charles (2014) employed different univariate Generalized Autoregressive Conditional Heteroscedastic (GARCH) models for modelling stock return volatility on the USE.

From the explanation above, using the Modern Portfolio Theory model to design an ideal investment portfolio of courier services sector stocks for the period 2018-2021, we hope this research will help the investors to analyse the risk and return generated by the optimal portfolio before and after Covid-19. It also will help the investors to study the prospect of delivery and courier sector in the future based on the historical events.

This paper is organized as follows: In Introduction, the background knowledge required to comprehend the choice to include courier services emitens stock in the portfolio and how the portfolio optimization is originated. In Literature review, we explain the theory related to portfolio optimization in our research. Research Method will explain about our methodology, the research framework, data selected and processing in R programming. The result of our research will be explained in Result section and will be concluded in Conclusion.

LITERATURE REVIEW

Model Overview

The portfolio optimization first The Markowitz portfolio theory (1952) provides a method for determining how good a portfolio is based solely on the means and variances of the assets in the portfolio. An investor is intended to be risk averse, thus he or she prefers a low return variance (i.e., low risk) and a high expected return. It is also explained in Xu et al (2016) that Markowitz's mean-variance (MV) model is a quadratic program model in which each stock's variance is adapted for risk measurement. All investors are assumed to be sensible (rational) and risk averse in the model (risk-averse). As a result, it is expected that, given the same amount of risk, investors will prefer assets with a higher return.

It is imperative to note, however, that while this assumption generally applies to investor-selected portfolios, it may not necessarily apply to individual assets, at least in terms of the Markowitz model's risk concept of variance or standard deviation of return. This is because two assets with the same risk; variance or standard deviation of return, might have different effects on portfolio diversification, and so the asset with a greater expected return may be less appealing in the context of a portfolio than the asset with a lower expected return.

In 2017, Ronald et al., employed R statistical computing to conduct portfolio optimization study on the performance of stocks listed at the Uganda Stock Exchange (USE) by including the selection of the proportion of assets to be kept in the portfolio, thereby making the portfolio better than others. GREXP bonds dominate the international market, accounting for more than 60% of the maximum diversified portfolio, according to a portfolio optimization model that includes Markowitz Mean Variance (MV), VaR model, and Mean-Absolute and Deviation Model (MAD). To measure stock performance, risk analyses such as volatility, shape ratio, parity risk, and CVaR are used to determine portfolio optimization. Based on this research, investors can use the data to determine which stocks to include in their investing portfolio to reach the optimal portfolio and avoiding bad investments.

Risk-Based Performance Measures

Ronal et.al (2017) generated the following measures to help us explain overall stock performance in addition to analysing the above models in R.

1) Volatility

The standard deviation is used to measure the degree of volatility in stock prices across time (Bodie et al., 2011). It's a statistical measure of a securities's or market index's return dispersion that may be calculated using standard deviation or variance between returns from the same security or market index (Namugaya et al., 2014).

2) Sharpe Ratio (SR)

Sharpe developed SR in 1966, and it's based on the capital market line (Rana & Akhter, 2015). It's beneficial since SR calculates a security's or index's returns (reward) based on the entire risk (volatility) (Bodie et al., 2011). Because risk is determined by the security's standard deviation, SR provides a risk-return trade-off (Rana & Akhter, 2015). As a result, it explains how an investor gets compensated for taking on more risk. A higher SR indicates a security's superior performance. This reward-to-volatility ratio is used to assess the performance of investment managers.

3) Risk Parity (RP)

In portfolio management, RP is used to focus on risk (volatility) allocation rather than capital allocation. When asset allocations are modified to the same degree of risk, the RP portfolio can achieve a higher SR and be more robust to market downturns than standard portfolios, according to the RP approach (Lee, 2014). This method of building an RP portfolio is identical to that of constructing a minimum variance portfolio, with the exception that each asset contributes equally to overall volatility (Amundi, 2014). RP denotes that each asset (single stock, asset class, or equity sector) contributes equally to the overall portfolio risk (Amundi, 2014).

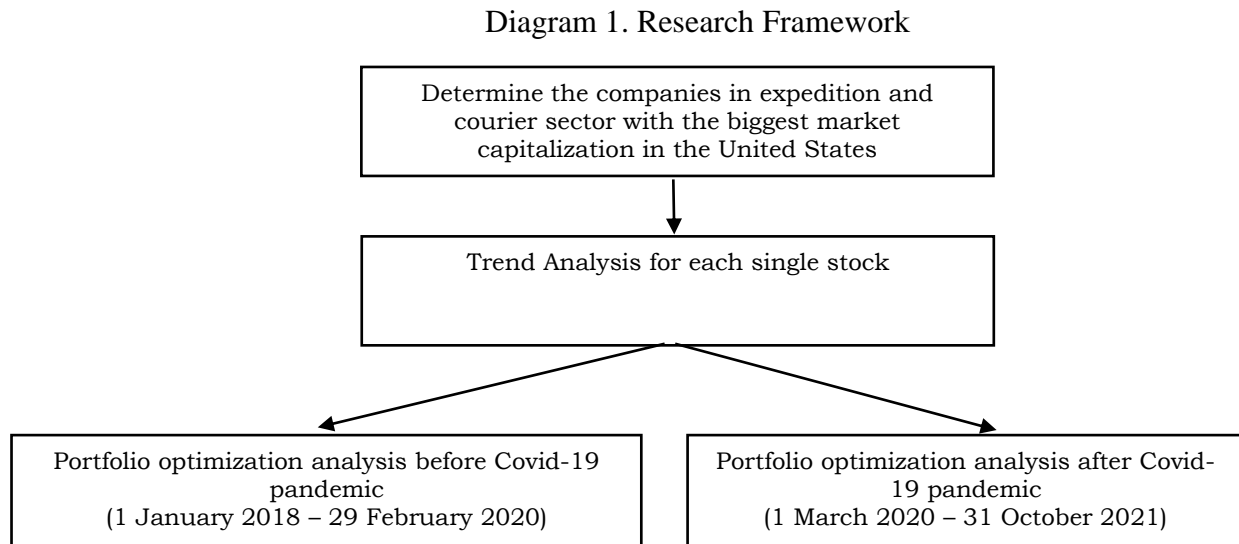
4) Conditional Value at Risk (CVaR) or Expected Shortfall (ES)

ES and CVaR are indices of downside risk (Xu et al., 2016). ES is a risk metric that is used to assess a portfolio's market or credit risk (Xu et al., 2016). When VaR is breached, it is the predicted portfolio loss (Bodie et al., 2011). On extremely bad days, CVaR can be used to assess the degree of expected loss (Xu et al., 2016).

RESEARCH METHOD

Research Framework

The first step in our research is to determine the companies in expedition and courier sector with the biggest market capitalization in the United States. After that, we assess the trend analysis of each single stock, then analyse the portfolio optimization before and after the Covid-19 pandemic. It is briefly described in diagram below.



Data and Sample

This portfolio optimization research is a quantitative method using time series data of daily company stock prices from January 1, 2018 to October 31, 2021. The approach is used to analyse an optimal portfolio for five companies in the expedition and courier sector with the largest market value in the United States before and after Covid-19 pandemic. Using the closing price of the company's shares, the data is retrieved from the yahoo finance website. The following are the five companies:

Table 1. List of companies

No	Code of companies	Name of companies	Market Capitalization	Line of Business
1	AMZN	Amazon.com, Inc.	1.6 trillion	E-commerce, Logistics, AI, Digital Contents.
2	UPS	United Parcel Services	181 billion	Delivery services
3	FDX	FedEx Corporation	67 billion	Delivery Services/Logistics
4	FWRD	Forward Air Corporation	29 billion	Delivery, transportation & transborder shipping
5	AIRT	Air T, Inc	84 million	Air Cargo, Commercial Jet Engines Parts, Aviation Ground Support

Data Collection

Technical data analysis and computations are performed in this study utilizing the R programming. We employ three steps in the R program to determine portfolio optimization before and after the Covid-19 pandemic: downloading portfolio data, trend analysis per share, and portfolio optimization analysis.

1. The first step is to use the tidyquant library to download portfolio data. The code as shown as follows:

```
library(tidyquant)
options("getSymbols.warning4.0"=FALSE)
options("getSymbols.yahoo.warning"=FALSE)

tickers = c("AMZN", "AIRT", "FDX", "FWRD", "UPS")

prices_data <- tq_get(tickers,
                      from = "2018-01-01",
                      to = "2020-02-29",
                      get = "stock.prices")

prices_data_covid <- tq_get(tickers,
                            from = "2020-03-01",
                            to = "2021-10-31",
                            get = "stock.prices")
```

2. The second step is to examine the trend on each stock. The following is the code:

```
prices_data %>%
  group_by(symbol) %>%
  slice(1)

prices_data_covid %>%
  group_by(symbol) %>%
  slice(1)

prices_data_covid %>%
  ggplot(aes(x = date, y = adjusted, color = symbol)) +
  geom_line()

prices_data %>%
  ggplot(aes(x = date, y = adjusted, color = symbol)) +
  geom_line() +
  facet_wrap(~symbol, scales = 'free_y') +
  theme_classic() +
  labs(x = 'Date',
       y = 'Adjusted Price',
       title = 'Price Chart')
```

3. Then the final step is to analyse the portfolio optimization. Before we can show the graph, first we have to calculate the covariance matrix that is gotten from the daily return. The code as shown as follows:

```
log_ret_tidy <- prices_data %>%
  group_by(symbol) %>%
  tq_transmute(select = adjusted,
               mutate_fun = periodReturn,
               period = 'daily',
               col_rename = 'ret',
               type = 'log')

log_ret_tidy_covid <- prices_data_covid %>%
  group_by(symbol) %>%
  tq_transmute(select = adjusted,
               mutate_fun = periodReturn,
               period = 'daily',
               col_rename = 'ret',
               type = 'log')

log_ret_xts <- log_ret_tidy %>%
  spread(symbol, value = ret) %>%
  tk_xts()

log_ret_xts_covid <- log_ret_tidy_covid %>%
  spread(symbol, value = ret) %>%
  tk_xts()

mean_ret <- colMeans(log_ret_xts)
print(round(mean_ret, 5))

mean_ret_covid <- colMeans(log_ret_xts_covid)
print(round(mean_ret_covid, 5))

cov_mat <- cov(log_ret_xts) * 252
cov_mat_covid <- cov(log_ret_xts_covid) * 252
```

Calculation of the level of risk, return, and sharpe ratio:

```
wts <- runif(n = length(tickers))
print(wts)
print(sum(wts))

wts <- wts/sum(wts)
print(wts)
sum(wts)

port_returns <- (sum(wts * mean_ret) + 1)^252 - 1
port_risk <- sqrt(t(wts) %*% (cov_mat %*% wts))
print(port_risk)

port_returns_covid <- (sum(wts * mean_ret_covid) + 1)^252 - 1
port_risk_covid <- sqrt(t(wts) %*% (cov_mat_covid %*% wts))
print(port_risk_covid)

sharpe_ratio <- port_returns/port_risk
print(sharpe_ratio)

sharpe_ratio_covid <- port_returns_covid/port_risk_covid
print(sharpe_ratio_covid)
```

The optimization of the model is carried out in a loop using a random portfolio of 5000.

```
# run this code on 5000 random portfolios.
num_port <- 5000

all_wts <- matrix(nrow = num_port,
                 ncol = length(tickers))
port_returns <- vector('numeric', length = num_port)
port_risk <- vector('numeric', length = num_port)
sharpe_ratio <- vector('numeric', length = num_port)

port_returns_covid <- vector('numeric', length = num_port)
port_risk_covid <- vector('numeric', length = num_port)
sharpe_ratio_covid <- vector('numeric', length = num_port)

# Next lets run the for loop 5000 times
for (i in seq_along(port_returns)) {
  wts <- runif(length(tickers))
  wts <- wts/sum(wts)
  all_wts[i,] <- wts
  port_ret <- sum(wts * mean_ret)
  port_ret <- ((port_ret + 1)^252) - 1
  port_returns[i] <- port_ret
  port_sd <- sqrt(t(wts) %*% (cov_mat %*% wts))
  port_risk[i] <- port_sd
  sr <- port_ret/port_sd
  sharpe_ratio[i] <- sr
}
```

```
for (i in seq_along(port_returns_covid)) {  
  wts <- runif(length(tickers))  
  wts <- wts/sum(wts)  
  all_wts[i,] <- wts  
  port_ret_covid <- sum(wts * mean_ret_Covid)  
  port_ret_covid <- ((port_ret_covid + 1)^252) - 1  
  port_returns_covid[i] <- port_ret_covid  
  port_sd_covid <- sqrt(t(wts) %>% (cov_mat_Covid %>% wts))  
  port_risk_covid[i] <- port_sd_covid  
  sr_covid <- port_ret_covid/port_sd_covid  
  sharpe_ratio_covid[i] <- sr_covid}
```

For the portfolio optimization can be shown as a plot, the code as shown as follows:

- Before Covid-19 pandemic

```
p <- portfolio_values %>%  
ggplot(aes(x = Risk, y = Return, color = SharpeRatio)) +  
  geom_point() +  
  theme_minimal() +  
  scale_y_continuous(labels = scales::percent) +  
  scale_x_continuous(labels = scales::percent) +  
  labs(x = 'Annualized Risk',  
       y = 'Annualized Returns',  
       title = "Portfolio Optimization & Efficient Frontier Before Covid-19") +  
  geom_point(aes(x = Risk,  
                y = Return), data = min_var, color = 'red') +  
  geom_point(aes(x = Risk,  
                y = Return), data = max_sr, color = 'red') +  
  annotate('text', x = 0.26, y = 0.38, label = "Tangency Portfolio") +  
  annotate('text', x = 0.23, y = -0.2, label = "Minimum variance portfolio") +  
  annotate(geom = 'segment', x = 0.196, xend = 0.21, y = 0.029,  
         yend = -0.18, color = 'red', arrow = arrow(type = "open")) +  
  annotate(geom = 'segment', x = 0.262, xend = 0.27, y = 0.164,  
         yend = 0.36, color = 'red', arrow = arrow(type = "open")) +  
  geom_smooth()  
ggplotly(p)
```

- After Covid-19 pandemic

```
p_covid <- portfolio_values_covid %>%  
ggplot(aes(x = Risk, y = Return, color = SharpeRatioCovid)) +  
  geom_point() +  
  theme_minimal() +  
  scale_y_continuous(labels = scales::percent) +  
  scale_x_continuous(labels = scales::percent) +  
  labs(x = 'Annualized Risk',  
       y = 'Annualized Returns',  
       title = "Portfolio Optimization & Efficient Frontier After Covid-19") +  
  geom_point(aes(x = Risk,  
                y = Return), data = min_var_covid, color = 'red') +  
  geom_point(aes(x = Risk,  
                y = Return), data = max_sr_covid, color = 'red') +  
  annotate('text', x = 0.32, y = 0.63, label = "Tangency Portfolio") +  
  annotate('text', x = 0.32, y = 0.25, label = "Minimum variance portfolio") +  
  annotate(geom = 'segment', x = 0.266, xend = 0.26, y = 0.45,  
         yend = 0.28, color = 'red', arrow = arrow(type = "open")) +  
  annotate(geom = 'segment', x = 0.276, xend = 0.28, y = 0.52,  
         yend = 0.61, color = 'red', arrow = arrow(type = "open")) +  
  geom_smooth()  
ggplotly(p_covid)
```

RESULT

Based on statistical data, the average daily stock return for a sample of 5 issuers in the shipping service sector that we chose for the 14 months before the Covid-19 pandemic occurred, namely from January 1, 2018 to February 29, 2020, showed a figure of -0.00723% with an average mean standard deviation 0.02247. Meanwhile, 20 months after the Covid-19 pandemic, from March 1, 2021 to October 31, 2021, the average daily stock return increased to 0.135% with an average standard deviation of 0.04555.

Table 2. Average Daily Return & Standard Deviation of Stock Price

Code	Before Covid-19		After Covid-19	
	Average Return	Standard Deviation	Average Return	Standard Deviation
AIRT	0.00020	0.03575	0.00091	0.08980
AMZN	0.00085	0.01903	0.00129	0.02064
FDX	-0.00106	0.01951	0.00129	0.02753
FWRD	0.00008	0.01590	0.00121	0.02581
UPS	-0.00043	0.01587	0.00207	0.02187

During the Covid-19 pandemic, most business activities were stopped due to lock-down policies and social restrictions implemented by various countries in the world, resulting in a decline in the trend of almost all business entities, including courier services. However, this condition did not last long, where consumer behavior began to change according to the "new normal" conditions, and online transactions began to increase sharply, this had an impact on the courier service business which also increased significantly.

The results of the visualization of the daily stock prices of the 5 delivery service issuers that we chose during the pre-Covid-19 period, namely from January 1, 2018 to February 29, 2020 are as follows:

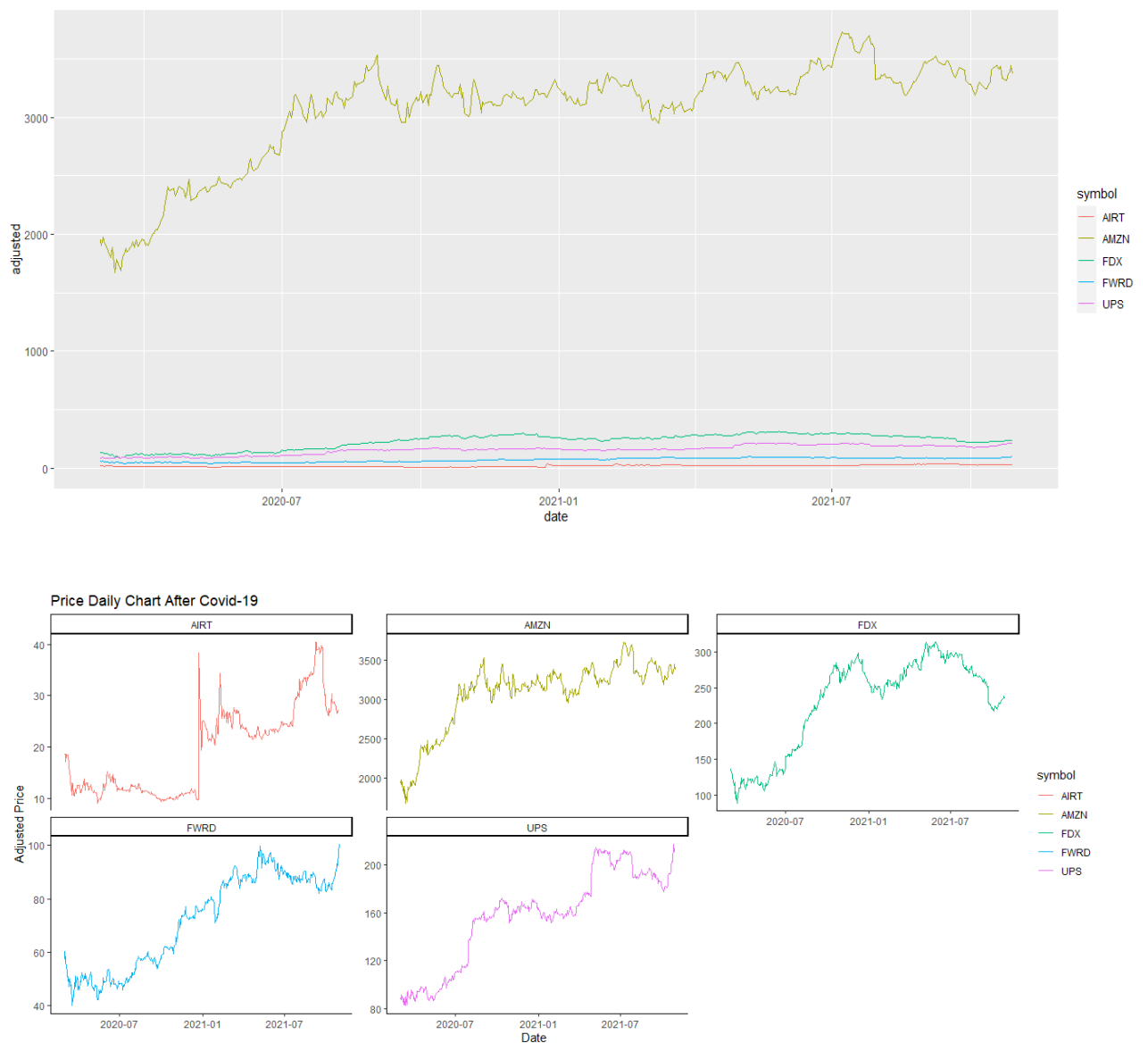
Picture 1. Daily Stock Price Chart Before Covid-19



Prior Covid-19, the daily stock price conditions in the 5 issuers that we selected experienced an upward trend, except for FDX and UPS which recorded declining results due to poor stock performance due to the impact of the trade war between the USA and China as well as several other problems faced These issuers include lawsuits, cut off business relationships with key partners, unable to compete with new competitors and transformation of business strategies to focus on international high-growth markets, global e-commerce, healthcare deliveries, and small and medium-sized businesses.

The visualization results of the daily stock prices of the 5 delivery service issuers that we chose during the post-Covid-19 period, namely from March 1, 2020 to October 31, 2021 are as follows:

Picture 2. Daily Stock Price Chart After Covid-19



After the Covid-19 pandemic, 5 issuers produced stock performance with positive returns due to changes in consumer behavior that preferred online transactions to adjust to new normal conditions and had a direct impact on the delivery service business, which increased significantly. The largest daily average stock return was obtained by FDX because it was able to rise from various business problems and the huge increase in demand for courier services, as well as the performance of the other four issuers who were able to record sharp increases during the period.

Table 3. Looping Portofolio Variance dan Tangency

Attributes	Before Covid-19		After Covid-19	
	Minimum Variance	Tangency	Minimum Variance	Tangency
Return	4,01%	14,83%	45,04%	54,80%
Risk	19,63%	24,37%	26,53%	29,16%
Sharpe Ratio	20,41%	60,87%	169,78%	187,93%

Tabel 4. Daily Average Portfolio Return & Risks

Attributes	Before Covid-19	After Covid-19
Portfolio Return	-0,01695927	0,407211
Portfolio Risk	0,2242359	0,414559
Sharpe Ratio	-0,07645389	1,050311

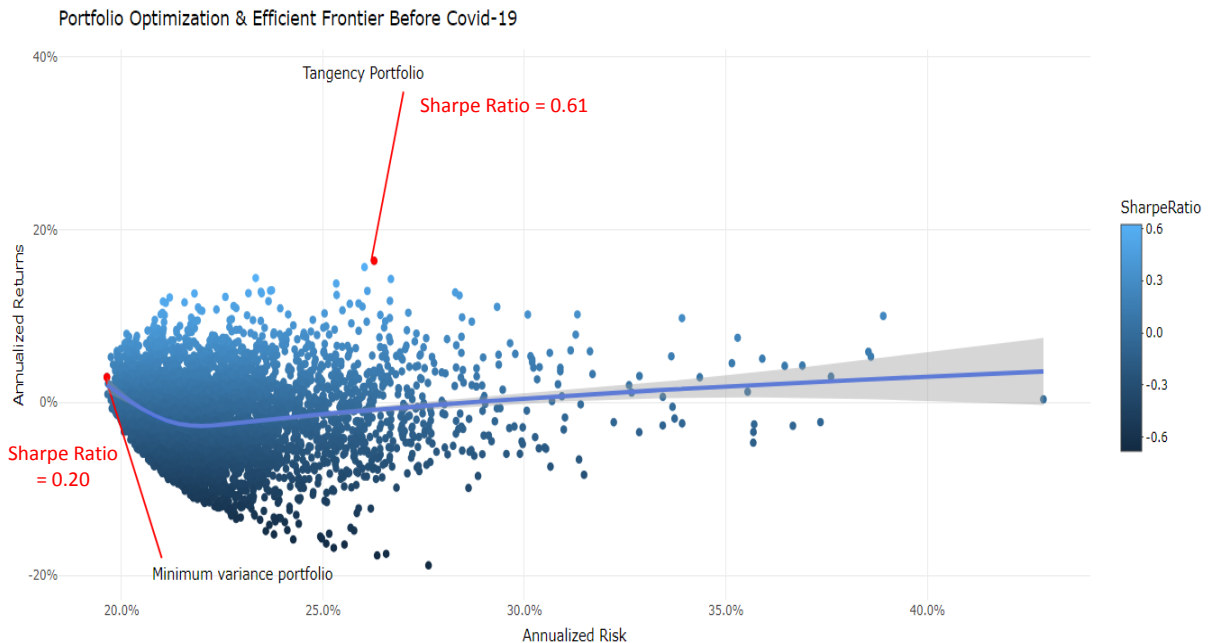
In the table above, we create a portfolio optimization model for the calculation of portfolio return and portfolio risk using random weights, followed by looping the portfolio sequentially for 5000 of the daily stock price portfolios of the five issuers that we selected so that the results can be seen in table 3 and table 4.

The tangency and minimum variance values for the rate of return before and after the Covid-19 pandemic increased from 14.83% to 54.80% and 4.01% to 45.04%. Meanwhile, the tangency and minimum variance values for the level of risk before and after the Covid-19 pandemic also increased from 24.37% to 29.16% and 19.63% to 26.53%.

The average daily share price for the portfolio of 5 issuers of shipping service companies before the Covid-19 pandemic fluctuated and experienced a downward trend from the beginning of the period January 1, 2018 to February 29, 2020 as seen from the minimum variance and tangency values which indicate the level of portfolio return, smaller than the level of portfolio risk. This is due to the fact that two large issuers of shipping services, namely FDX and UPS, experienced poor performance due to various business problems and in an effort to transform their organization and business.

After the Covid-19 pandemic, from March 1, 2020 to October 31, 2021, all share prices in the shipping service sector decreased, except for AMZN. However, this did not last long where after the new normal behavior adjustment occurred, business activity increased again until the end of the period as seen from the minimum variance and tangency values which showed the portfolio return level was greater than the portfolio risk level. This also applies to individual investments if assessed separately for the performance of each issuer's shares.

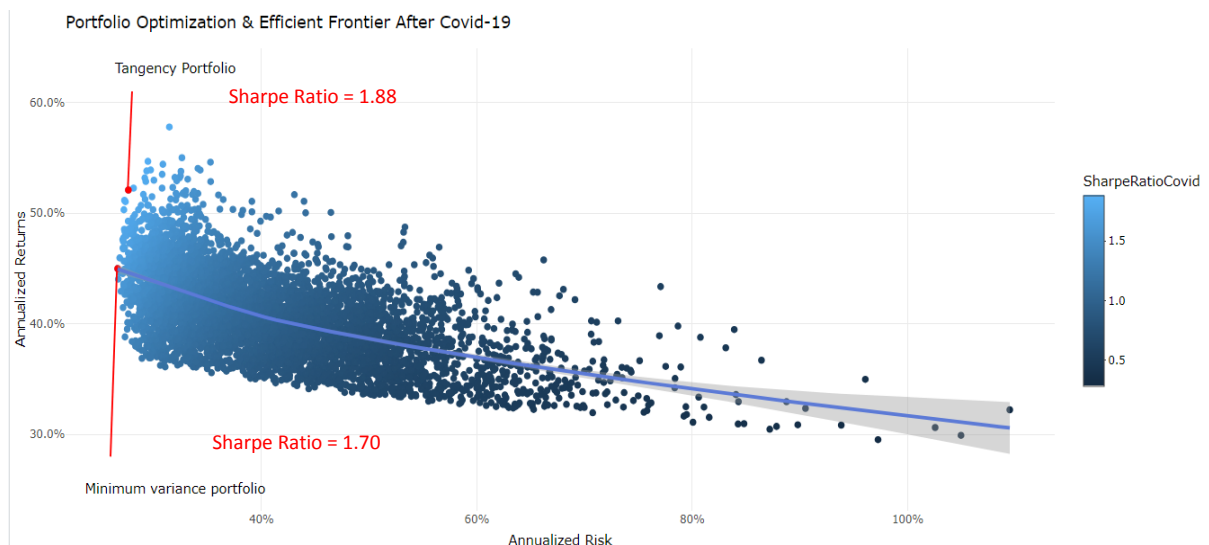
Picture 3. Portfolio Optimization Model Before Covid-19



The portfolio's sharpe ratio before the Covid-19 pandemic occurred at the optimum level, namely the return divided by the portfolio risk on the 5 shipping service companies that we randomly selected showed a positive number of 0.61, this means that this portfolio return has a return rate below the portfolio risk level.

While the minimum portfolio variance or indicator of the rate of return at the minimum risk level shows a positive Sharpe Ratio of 0.2. This shows that the rate of return on individual investment which is assessed separately for each issuer's stock is also still above the risk-free rate of return with a positive value.

Picture 4. Portfolio Optimization Model Before Covid-19



The sharpe ratio of the portfolio after the Covid-19 pandemic occurred at the optimum level, namely the return divided by the risk portfolio on the 5 shipping service companies that we randomly selected showed a positive number of 1.88, this means that the return of this portfolio has a return rate above the risk free rate of return, even higher than the portfolio risk level.

While the minimum portfolio variance or indicator of the rate of return at the minimum risk level shows a positive Sharpe Ratio of 1.70. This shows that the rate of return on individual investments which is assessed separately for each issuer's stock is also still above the risk-free rate of return with a positive value and is also greater than the variance of the risk level for each of these individual investments.

CONCLUSION

According the results of evaluation that has been carried out on 5 stock issuers of shipping companies by producing optimal portfolios using the Minimum Variance and Tangency models, we conclude that prior to the Covid-19 pandemic the performance of shipping service companies experienced a fluctuating and less stable trend caused by intense business competition and tight in that market.

After the Covid-19 pandemic, the portfolio performance of delivery service companies has seen a sharp increase because it is influenced by changes in consumer behavior who adjust to new normal conditions and prefer online transactions, it is estimated that this trend will increase in the future, supported by higher the role of information technology in the digital era.

AMZN made the most significant contribution to portfolio performance both before and after the Covid-19 pandemic, this is because AMZN has diversified its line of business and already has established e-commerce as its main business platform. Meanwhile, two other issuers, namely FDX and UPS, made a significant contribution to increasing portfolio performance where the two companies were able to carry out business transformations and seize opportunities from the increasing delivery service business as a result of the Covid-19 pandemic.

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