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COMPILATION OF HEDGING SHARE PORTFOLIO BASED ON PCA ON INDONESIA'S LQ45 INDEX

Sunarto Wage[1], Nanda Harry Mardika[2], Suvianto Wangdra[3]

[1,2,3] Study Program Accounting, University Putera Batam
Email: sunarto@puterabatam.ac.id[1], mardikanandaharry@ymail.com[2] ,
suvianto@puterabatam.ac.id[3]

Abstract

Stock investing is a risky subject that requires hedging, but this is rarely questioned in the Indonesian stock index. The goal of this study is to create a stock portfolio using principal components to develop orthogonal components in the Indonesian LQ45 index for hedging purposes. The research method used time series over a five-year period from 2017 to 2021. From different cumulative returns, daily returns, and risk profiles, four components were created with total extracted variance of 84% and KMO of 90%. With a 95% confidence interval, the results are also statistically different. The hypothetical portfolio constructed from the four components produced an excellent hedge profile based on the sharpe ratio, with negative stock performance counterbalanced by positive stock performance.

Keywords: Investment, LQ45, Hedge

INTRODUCTION

Investment is an important activity in creating value where one can do it by relying on the performance of a particular company which is reflected in the stock price. An investor then has the potential to get a return from the increase in the share price which is accompanied by risk because the price also has the potential to fall.

In Indonesia, there is the LQ45 index which is a collection of stocks with the highest liquidity and can be categorized as having lower risk(IDX Stock Index Handbook v1.2 2021). In order to avoid unnecessary losses due to the economic situation(Fadly 2021), an investor can invest in low risk stocks by buying stocks from members of the index. However, risks still need to be minimized further in order to maximize investor returns or require hedging so that unnecessary losses are not incurred.

Hedging investment in stocks can be done by utilizing a portfolio where investors choose a collection of stocks that can maximize returns(Alam and Gupta 2018). This research was conducted with the aim of finding the hedging portfolio, especially in LQ45 index stocks which are categorized as lower risk.

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Previous studies have shown that hedging can occur in several ways, namely choosing uncorrelated stocks in the same direction so that one stock goes down, the other shares go up so that there is no total decline because it is supported by an increase in other stocks. Thus, returns are assessed from all combinations in the compiled portfolio(Singh and Yadav 2021).

The preparation of the portfolio then becomes important and one way that can be done is by grouping that can separate group members orthogonally and not directly related to the principal component analysis (PCA) technique.

PCA has been widely used for prediction(Zhong and Enke 2017)and more intense on developed country stocks(Zheng and He 2021). In Indonesia, previous studies have focused on individual stocks(Faurina, Winduratna, and Nugroho 2018)and on the grouping of macroeconomic factors(Darma 2021). In this study, the previous research gap was filled in terms of efforts to prepare a portfolio based on PCA which aims to provide further hedging of LQ45 index member stocks which basically already have a low risk profile and high performance. In addition, research will contribute to investors, especially in terms of finding potential stock members to be included in portfolios with tested hedging.

Shares are a form of ownership of a company that is already publicly traded and can go up or down depending on the market. The purpose of a company releasing ownership to the market is to raise funds and expand while the goal of an investor buying shares of a company is the hope that the price will rise in the future because the expansion is successful as well as dividends each year that the company gives(Ross et al. 2019).

Because stocks go up and down, hedging techniques are needed for investments that can be made with a portfolio or a combination of several stocks. Basically, portfolios are prepared by considering stocks with different return and risk profiles so that the combinations created can minimize risk or increase returns(Singh and Yadav 2021).

PCA is a data reduction technique in which a linear combination technique is performed to separate several variables into components that are fewer in number and mutually orthogonal / uncorrelated between components(Jollife and Cadima 2016). PCA is performed by maximizing the variance with the following formula

$$\max \; var(\alpha_1^T \mathrm{x}) = \alpha_1^T \Sigma \alpha_1$$

$$s.t. \quad \alpha^T \alpha = 1$$

Formula 1. Principal Component Analysis

By solving the formula using the Lagrange technique, several components will be formed based on the largest eigenvalues where the eigenvector is a component. Processing was continued with varimax rotation for better interpretation. Each component that is formed is a collection of stocks that have the potential to be arranged in a portfolio (Zhong and Enke 2017).

While the return is calculated from the closing price minus the opening price divided by the opening price of each share every day for 5 years which is then averaged.

Risk(Singh and Yadav 2021)measured from the standard deviation of the stock's daily return which can be calculated by formula 2 whereis the root of the daily return squared minus the average which is then divided by the number of observations in the calculation period.

$$Resiko = \sqrt{\frac{\Sigma(x_i - \bar{x})^2}{n}}$$

Formula 2. Stock Risk

The PCA results were hypothesized at first (H0) to produce no components with different returns or risks between components. Two alternative hypotheses formed to test the null hypothesis are

H1 : there are differences in returns between components separated by PCA
H2 : there are differences in risk between separate components of PCA

The hypothesis will be tested using the ANOVA technique with a 95% confidence level(Sekaran and Bougie 2016).

Meanwhile, to measure portfolio performance, the Sharpe Ratio is used which considers returns that have been adjusted for stock risk(Pav 2022). The Sharpe Ratio has the formula for the average return minus the risk free rate divided by the risk which can be seen in formula 3.

$$\zeta = \frac{\mu - r_o}{\sigma}$$

Formula 3. Sharpe Ratio

*Sharpe ratio*used as a benchmark for performance comparisons between portfolios, individual stocks and the main indicators of the composite stock price index / JCI.

METHODS

Studycarried out with the method of time series analysis(Sekaran and Bougie 2016)and processed in the following steps:

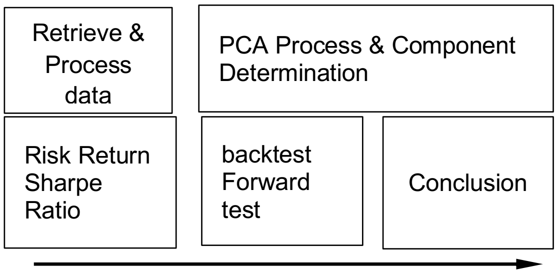

Figure 1 Research Flow

Data was retrieved with the help of Python 3 software based on Yahoo Finance data(Yahoo 2022)for 45 LQ45 stock members(Contact 2022)for 5 years (01-01-2017 to 31-12-2021). Data that does not contain is then removed and continued to be processed using the PCA technique using the pandas and numpy libraries. The number of components is determined by scree plot.

From the components that are formed, the sorting of component members is further processed by removing the members from the components. After the final components are formed, the hypotheses and the differences in returns and risks of the components are tested statistically with ANOVA. Portfolios are then compiled by selecting member stocks from each component and the Sharpe Ratio of the portfolio compared to individual stocks and the JCI.

RESULTS AND DISCUSSION

PCA testing was carried out by releasing data on 19-06-2019 because some stocks were not available. Total observations amounted to 58,006 data. In the results of the first test, the PCA that was carried out succeeded in separating 6 components. However, there are 2 components that do not have enough members and the loading factor is less than 0.7. The test was repeated with separation of only 4 components. The Kaiser Mayer Olkin indicator shows a value of 0.9 so it is sufficient to proceed with the separation of components. The separation was carried out satisfactorily with a steep total 4-component eigenvalue (figure 2) with a total explanatory variance of 82%.

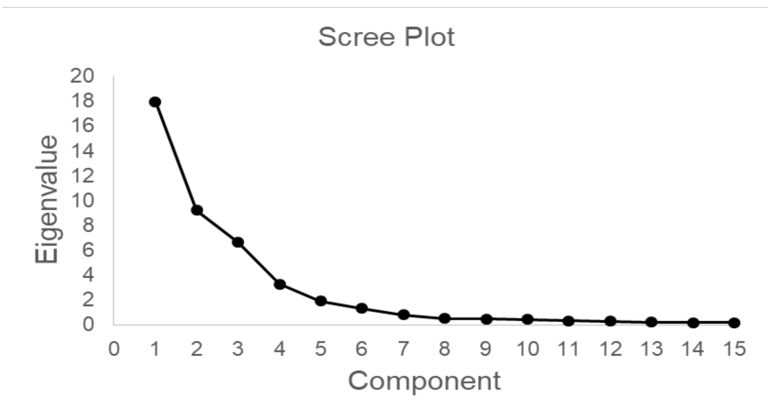

Figure 2 PCA Scree Plots

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The test was continued by eliminating several stocks that were strongly clustered on 2 components at once and had a loading factor > 0.6 on two components. The shares that were eliminated were SMRA, WIKA, MIKA, PWON, JSMR, and TBIG.

After the elimination was carried out, the final results were four components with the first component being AKRA, ASII, BSDE, ERAA, EXCL, INCO, INDF, INKP, JPFA, KLBF, MNCN, PTBA, PTPP, TKIM, TLKM, and TOWR. While the second component consists of ACES, BBCA, BBNI, BBRI, BMRI, BRPT, CPIN, GGRM, ICBP, INTP, MDKA, and SMGR.

In the third component, the shares that are members are ADRO, BBTN, HMSP, ITMG, MEDC, TPIA, UNTR, UNVR. Then the fourth component consists of ANTM, PGAS, and TINS.

From the formation of the four components it can be concluded that the fourth component is the majority of commodities, while the second component of the banking sector, the third component of mining, households and the first component varies.

Based on the PCA technique, the first component is the component that can absorb the largest variance so that it can be an indication of systematic risk because it will reflect the overall price fluctuations in the LQ45 index while the remaining components will have different characteristics.

In table 1 it can be seen that the first component has the second largest total risk compared to component 4. However, component 4 has the highest daily return with a value of 0.24%.

The second component has negative daily returns, even though many of the stocks in that component are stocks with high cumulative returns. Like BBCA with a cumulative return value (buy 1 Jan 2017 sell 31 Dec 2021) of 135 percent. Meanwhile, one of the stocks from component 1 such as ASII has a negative cumulative return of 30.5 percent. The results of the separation show the differences in each component which are quite contrasting.

Table 1. Total Daily Return / Risk

comp	Total Returns	Total Risk
1	0.05	2.41
2	(0.03)	1.94
3	0.07	2.15
4	0.24	2.58

The test is continued with the calculation of the daily return and risk of each stock which can be seen in table 2. The Sharpe Ratio (SR) is also calculated using the daily return data for 5 years divided by the standard deviation assuming a minimum risk free

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rate of 0%. The SR is then converted to a value per year (annual SR) which is assumed to be 252 days.

Table 2. Return and Risk

Code	Total Returns	Total Risk	comp SR	Daily SR	Annual SR
PTPP	0.32	2.50	1	0.13	2.02
TOWR	0.20	2.19	0.46	0.09	1.43
ASII	0.03	1.52		0.02	0.28
MDKA	0.05	2.41	2	0.02	0.35
BMRI	0.02	1.58	(0.24)	0.01	0.19
BBCA	(0.02)	1.20		(0.02)	(0.24)
ADRO	0.24	2.21	3	0.11	1.71
HMSP	0.09	1.72	0.48	0.05	0.84
MEDC	0.12	3.33		0.04	0.56
ANTM	0.28	2.28	4	0.12	1.98
TINS	0.24	2.65	1.53	0.09	1.45
PGAS	0.20	2.81		0.07	1.15

From the annual SR, it can be seen that each component also has an annual SR and an annual SR for different component members. From the annual SR per component, the fourth component is the component with a collection of stocks that provide daily returns based on the highest risk or 1.53 times. Meanwhile, the second component has a daily return that is no better than the daily risk, so it has a negative value of 0.24 times. Based on SR, each component also shows varying differences.

The difference between the returns and the risk of daily stock price movements is confirmed by statistical testing using ANOVA with an alpha of 5% where the results can be seen in table 3 with the ** sign meaning significant.

The results show that the PCA carried out succeeded in separating the stock groups at LQ45 where there were significant differences between returns and risks. Through ANOVA testing, the differences between the components were confirmed and the alternative hypotheses 1 and 2 were accepted.

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Table 3 shows that there are more differences in terms of return than risk because only components 2 and 4 have statistical differences in terms of risk. On the other hand, statistical differences occurred in almost every component group.

Table 3. ANOVA Testing

Component		return	risk
1	2	-	-
	3	-	-
	4	**	-
2	3	**	-
	4	**	**
3	4	**	-

The different characteristics of each component are further investigated by means of a visual daily cumulative return test where the rate of return is calculated daily from the first data entry (January 1 2017) to the last data (December 29 2021). The test is carried out by comparing the closing price of shares every day compared to the first data and is carried out on four stocks that are randomly selected from each component.

In Figure 3 it can be seen that each stock has a different pattern of return movement. The third component (MEDC) has high returns at the start and end, the second component (BBCA) increases from start to finish, the first component (ASII) is flat with returns decreasing in total, while component four (TINS) falls at baseline and increases on the final data. When compared with the annual SR in table 2, ASII is positive and BBCA is negative but cumulatively, BBCA is more profitable than ASII. These results can be related to SR returns and risks which are calculated per day while cumulative are calculated per total analysis period so that it can be interpreted that the second component stock is more suitable for long-term trading than short-term.

After testing was carried out on all stocks and on each component, the results showed that the PCA that was carried out was successful in separating groups of stocks where each member in the component has a pattern of daily cumulative returns that are similar in components but different from other components.

The research objective is for the potential of forming a hedging portfolio based on PCA results. With the components formed and the significance of the statistical test, the portfolio can be formed based on the stock members of each component. If the portfolio will be compiled, investors can choose members from each group and allocate funds.

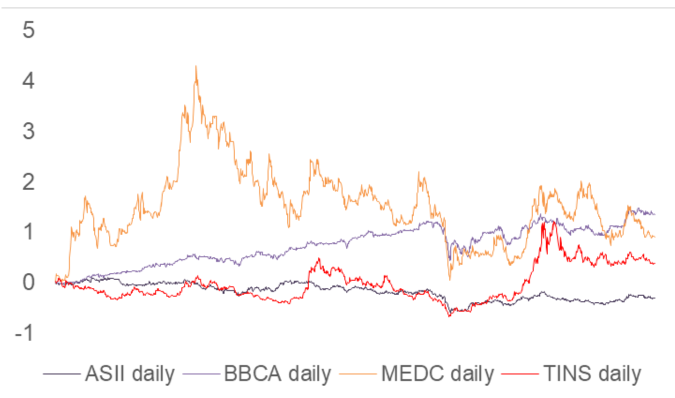

Figure 3. Component Differences

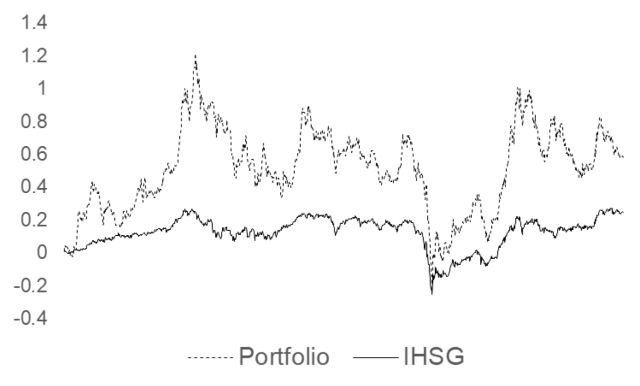

Figure 4 Portfolio and JCI

To test whether the portfolio provides a hedge, 4 stocks from 4 components are selected which are then compared visually with the Jakarta Composite Index (IHSG), which is a representation of the returns on all stocks in Indonesia.

Portfolios are formed using random stocks from each component, namely ASII, BBCA, MEDC, TINS. The portfolio is formed with an equal distribution of funds, namely 25% for each share. Cumulative daily return results that have been averaged per share and cumulative back test results(Arnott, Harvey, and Markowitz 2019)in figure 4.

From the figure it can be seen that the return performance of the portfolio (dash line / top) exceeds the JCI where at almost every data point, the return from the portfolio always exceeds the JCI return from 2017-2021.

Portfolio testing is continued by comparing individual stocks. Of the 2 stocks compared to the portfolio (figure 5) it can be seen that the portfolio provides a hedge by reducing the impact of losses on stocks whose prices are falling by taking profits on stocks whose prices are rising. The portfolio that is formed ultimately has a return that is halfway between the stocks that are performing well and the stocks that are performing poorly.

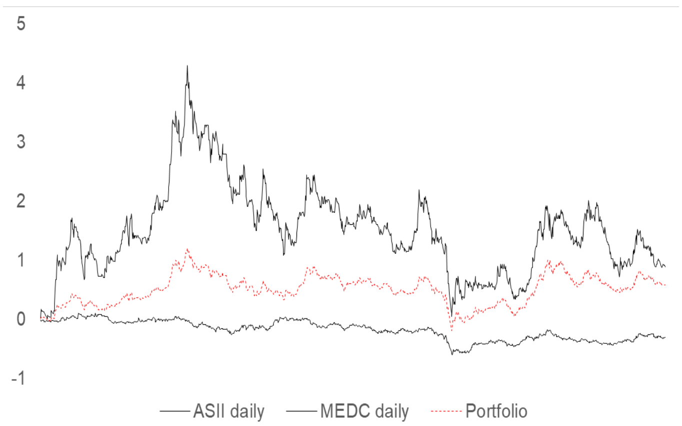

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Figure 5 Individual Shares and Portfolios

Table 3. Differences in Sharpe Ratio

	1	2	3	4
Annual Sr	0.46	-0.24	0.48	1.53
SR portfolio		0.51		
Delta (%)	10.86	312.5	6.25	(66.67)

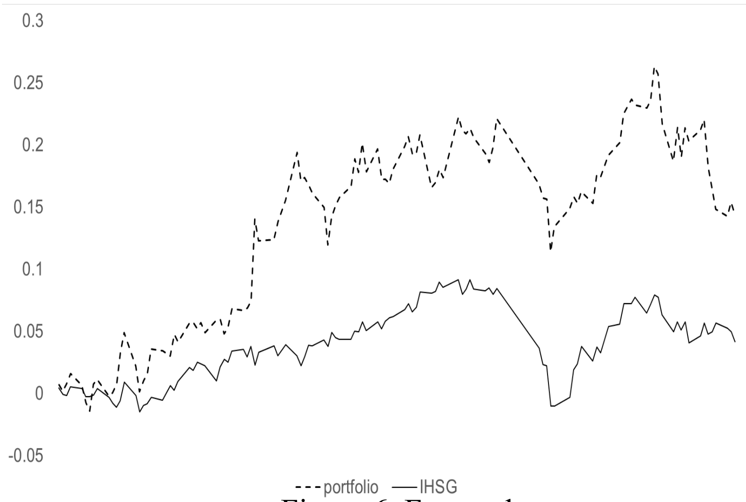

Figure 6. Forward test

After visual testing, the Sharpe Ratio of the portfolio is then compared to the Sharpe Ratio per component and the difference / delta is calculated in table 4.

Based on the Sharpe Ratio, the portfolio formed can reduce losses from components with a negative SR value of more than 3 times and take advantage of components that have a positive SR of 0.6 times. The results of forming a portfolio based on PCA provide evidence that hedging occurs with a combination of reductions in stock losses that are higher than reductions in individual stock profits.

The final test is carried out by testing forward or forward testing(Davidsson 2013)where the data used is future data from test data (January 1, 2022 to June 30, 2022). The results of the cumulative daily return test can be seen in Figure 6 and again provide evidence that the portfolio still provides a better return than the 2022 JCI.

Through a series of tests carried out, the results of research using PCA succeeded in further separating groups of stocks in LQ45 which basically already have a lower risk profile.

Hedging is achieved where the hypothetical portfolio formed can provide returns that have been adjusted for the risk of poor stock performance (table 4). With 2017-2021 data, the total cumulative return of the portfolio is 231.5 percent and the average return per share in the portfolio is 57.87 percent.

Table 4. Cumulative Return (%)

	2017-2021	2022
ASII	(30.51)	12.55
BBCA	135.48	(1.69)
MEDC	89.32	38.30
TINS	37.21	4.45
Total /	231.50 /	53.61 /
Average2	57.87	13.4

Whereas in 2022 which is the data forward test, the cumulative return is 53.61 percent and the average return per share is 13.4 percent. When compared to individual stocks that have negative performance (ASII) during 2017-2021, namely negative 30.51%, the average return per share in a portfolio that is worth 57.87 percent has a high hedge of 289.67% (difference minus 30.51% and 57.87%). This hedging occurs from reducing profits from one of the well-performing stocks / BBCA by 134.11% (the difference between 135.48% and 57.87%). These results also occur in data for 2022, for example at BBCA and MEDC.

The PCA technique succeeds in combining stocks by looking for groups that have similar price movement patterns. By incorporating an element of risk, PCA has also succeeded in providing the basis for forming a hedge portfolio by combining stocks with different return and risk profiles. Because it is based on price movements, it can be perceived more objectively because it avoids analysis bias.

While PCA can objectively classify stocks based on data without the more subjective and time-consuming fundamental analysis, the prices it analyzes can be said to be backwards due to past data. Based on past prices, PCA was successful in assisting the creation of a hedge portfolio with better returns and superior risk adjustment.

CONCLUSION

PCA succeeded in separating the stocks of LQ45 index members into 4 components which statistically provide different returns and risks. A portfolio made up of these 4 components provides a hedge whereby individual stocks that are underperforming can be supported by stocks that are performing well. The formation of the portfolio has succeeded in providing a hypothetical cumulative return of more than 200% from 2017 to 2022. Based on the Sharpe Ratio, the hedge that occurs is a 66% reduction in the stock component with good performance and a 312% increase in the stock component with poor performance.

The selection of stocks from component members is still carried out randomly so that further research can be developed by simulating and optimizing allocations. Even though it was tested with a forward test, the test results came from past data so that the possibility of future occurrence is still uncertain.

REFERENCE

Alam, Nafis, and Amit Gupta. 2018. "Does Hedging Enhance Firm Value in Good and Bad Times." *International Journal of Accounting and Information Management* 26(1):132–52.

Arnott, Rob, Campbell R. Harvey, and H. Markowitz. 2019. "A Backtesting Protocol in the Era of Machine Learning." *The Journal of Financial Data Science* 64–74.

Darma, Yuki Dwi. 2021. "Empirical Test of Apt Model to Predicting Portofolio's Stock Return Incorporated with Lq45 from 2014 until 2018 in Indonesia." *INCEESS 2020* 199–214.

Davidsson, Marcus. 2013. "Portfolio Theory Forward Testing." *Advances in Management & Applied Economics* 3(3):225–44.

Fadly, Syamsu Rizal. 2021. "Aktivitas Pasar Modal Indonesia Di Era Pandemi." *Kementrian Keuangan RI*. Retrieved July 1, 2022 (https://www.djkn.kemenkeu.go.id/kpknl-kupang/baca-artikel/13817/Aktivitas-Pasar-Modal-Indonesia-Di-Era-Pandemi.html).

Faurina, Ruvita, Bondhan Winduratna, and Prapto Nugroho. 2018. "Predicting Stock Movement Using Unidirectional LSTM and Feature Reduction: The Case of An Indonesia Stock." *2018 International Conference on Electrical Engineering and Computer Science (ICEECS)* 180–85.

IDX Stock Index Handbook v1.2, 2021. 2021. "IDX Stock Index Handbook V1.2." 52.

Jollife, Ian T., and Jorge Cadima. 2016. "Principal Component Analysis: A Review and Recent Developments." *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 374(2065).

Kontan. 2022. "Ini Daftar Lengkap Saham-Saham LQ45 Periode Agustus 2021-Januari 2022." Retrieved January 7, 2022 (https://investasi.kontan.co.id/news/ini-daftar-lengkap-saham-saham-lq45-periode-agustus-2021-januari-2022-1).

Pav, Steven E. 2022. *The Sharpe Ratio*. London: CRC Press.

Ross, Stephen A., Randolph W. Westerfiled, Jeffrey Jaffe, and Bradford D. Jordan. 2019. *Corporate Finance*. 12th ed. New York: McGraw-Hill.

Sekaran, Uma, and Roger Bougie. 2016. *Research Methods for Business*. 7th ed. West Sussex: Wiley.

Singh, Shveta, and Surendra S. Yadav. 2021. *Security Analysis and Portfolio Management a Primer*. Singapore: Springer.

Yahoo. 2022. "Yahoo Finance." Retrieved January 1, 2022 (https://finance.yahoo.com/).

Zheng, Linyu, and Hongmei He. 2021. "Share Price Prediction of Aerospace Relevant Companies with Recurrent Neural Networks Based on PCA." *Expert Systems with Applications* 183(December 2020):115384.

Zhong, Xiao, and David Enke. 2017. “Forecasting Daily Stock Market Return Using Dimensionality Reduction.” *Expert Systems with Applications* 67:126–39.