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There has been a growing interest in the application of data envelopment analysis (DEA) as a nonparametric approach in portfolio optimization due to its flexibility in overcoming the limitations of the conventional mean-variance portfolio (MVP) model. Therefore, this study aims to validate the allocative efficiency of the DEA cross-efficiency model using blue chip stocks in the Philippine Stock Exchange from 2010 to 2019. This study finds that the proposed model is able to distinguish a unique set of best-performing stocks across each holding period and outperforms the MVP more consistently. The results of this study suggest that the proposed DEA cross-efficiency model can encourage more Filipinos to invest because it can provide an allocatively-efficient manner of selecting optimal stocks and incorporate other factors that affect the return and risk of a portfolio. Finally, this study suggests that future studies can examine this model using the entire Philippine stock market with an alternative set of criteria that affect stock returns and, ultimately, the stock's performance.

1. INTRODUCTION

Investments in stocks can provide individuals with passive income in the form of capital gains and dividends. However, stocks provide risk as a result of continuously changing markets, uncertain market events, and other uncontrollable factors. Therefore, because of the risk associated with investing in stocks and the lack of knowledge in understanding which assets to invest in, individuals may stray away from investing in stocks within the Philippines.

Although the modern portfolio theory provides for existing portfolio selection processes, such as that of the mean-variance portfolio (MVP) model, the information utilized within existing models is limited to only the variance and return of stocks. Hence, this study was formed to form a portfolio that is more allocatively efficient than the MVP using the data envelopment analysis (DEA) cross-efficiency model as it can integrate fundamental analysis factors such as profitability ratios. The findings of this study should encourage more individuals to invest in the Philippine Stock Exchange (PSE) as they can use a reliable and convenient tool for portfolio optimization.

2. LITERATURE REVIEW

Factors Affecting Investor Behavior
An investment portfolio is a collection of financial assets held by an individual to make a profit. The individual's goal in creating such a portfolio is to benefit from the increase in the market value of the financial assets in his portfolio in the form of monetary returns after a certain period of time; however, the investor is not always assured of a positive rate of return due to surprises in the market. In fact, emerging markets like the Philippines have highly volatile, weak-form efficient stock markets due to their fast pace of growth and rapid response of investors to new market information (Bautista, 2003, 2005). Moreover, Janairo and Roleda (2012) found that the returns in the Philippine stock market do not follow a normal distribution; thus, to help investors understand the uncertainties behind erratic movements in stock prices, two disciplines of portfolio management are established—fundamental analysis and technical analysis.

Fundamental analysis assumes that current stock prices are lagged but will correct themselves in the long run; thus, investors use accounting information to gauge the profitability of firms and industries and to discover stock mispricing, which allows investors to profit from buying undervalued shares and selling overvalued shares (Suresh, 2013; Petrusheva & Jordanoski, 2016). Narrowing down the most significant profitability ratios, Anwaar (2016) found that stock returns had the highest positive correlation with return on assets (ROA), followed by net profit margin (NPM), and earnings per share (EPS) using panel data of the top 30 firms listed in the FTSE-100 Index from 2005 to 2014. On the other hand, technical analysis assumes that all fundamentals are already reflected in current stock prices; thus, investors simply look at historical price data to generate effective signals on when to buy and sell stocks to take advantage of the sluggish adjustment of stock prices (Adem, 2020; Frankel & Froot, 1990).

Notwithstanding the differences in both disciplines, Bettman et al. (2009) found that using a hybrid equity valuation model that considers both technical factors, in terms of lagged prices, and fundamental factors, in terms of book value per share, earnings per share (EPS), and forecast EPS, provided for a larger explanatory power compared to that of technical or fundamental models exclusively. This is supported by the findings of Petrusheva and Jordanoski (2016), which emphasizes that fundamental factors aid investors in deciding which stocks are promising to invest in, whereas technical factors aid investors in finding the right timing to invest in such stocks.

Mean-Variance Portfolio Framework
The concept of a risk-reward trade-off in investing was first introduced by Markowitz (1952). Using the framework of the minimum variance portfolio, or otherwise known as MVP, he

postulated that a rational investor selects the portfolio that maximizes his expected returns, measured by the mean return, for a given level of portfolio risk, measured by return dispersion. Markowitz (1991) further asserted the necessity for investors to diversify their portfolio allocation, not just by the number of stocks held, but across different industries to arrive at optimal portfolios with minimal risk. Based on this principle of diversification, investors are better off playing it safe rather than gambling for high returns when defined within the boundaries of their risk appetites. However, Statman (2004) found that investors prefer to hold portfolios following a pyramid-like structure, containing few stocks with upside potential and a majority of the stocks protecting downside potential. As observed, investors tend to construct undiversified portfolios that go against the rational behavior established by the MVP framework because investors are driven by aspirations rather than risk. Moreover, the MVP framework assumes that returns are normally distributed; thus, only the first two moments of distribution are considered. However, empirical evidence from 1993 to 2009, as reported by Janairo and Roleda (2012), showed that this assumption does not apply in the Philippine stock market. Similar circumstances also plague other emerging markets; thus, there has been a growing body of literature that aims to address the limitations of the MVP model.

Data Envelopment Analysis

DEA is a linear programming method used to evaluate the efficiency of a decision-making unit (DMU; Ramanathan, 2003). It utilizes a set of inputs a DMU wants to minimize and outputs a DMU wants to maximize to produce the efficiency rating of a DMU. It utilizes a nonparametric method that allows for an unlimited number of input-output variables without the requirement of uniform units of measurement (Charnes et al., 1978). The origins of this programming method started from the Charnes, Cooper, and Rhodes (CCR) model but have many disadvantages, such as the provision for unrealistic weighting schemes in determining the self-evaluation score of a DMU. In fact, the model may provide for an efficiency score greater than 100% (Ray, 2004). Thus, the cross-efficiency model, as introduced by Sexton et al. (1986), provides an approach that considers a peer-evaluation score such that unrealistic weighting schemes are rejected.

Furthermore, the use of the cross-efficiency approach allows for the determination of an efficiency score based on a peer evaluation–allowing for an improved discriminative power (Essid et al., 2018). Therefore, using the cross-efficiency approach in the context of portfolio investment selection is advantageous because it allows for the optimization of portfolio returns based on a specific set of criteria chosen by the investor while maintaining the objective of reducing risk. To elaborate, Amin and Hajjami (2020) utilized inputs of leverage and cash ratios, outputs of ROA and EPS. They applied the cross-efficiency approach using multiple alternative optimal solutions on the Tehran Stock Exchange in 2011 to obtain a portfolio that yields greater returns with lower risk compared to other DEA models when the risk-return trade-off parameter is set at 2%. The portfolio size is set at 10 stocks or approximately 30% of the publicly listed stocks in the Tehran stock market. Doyle and Green (1994) further elaborated on the advantages of the cross-efficiency approach as it introduces the concept of the maverick index, which is a measure of risk that captures a greater sense of environmental risk and change in the efficiency of varying elements (Essid et al., 2018).

3. FRAMEWORK

Modern Portfolio Theory

According to the modern portfolio theory (MPT), an investor constructs an investment portfolio by simultaneously maximizing the expected returns and minimizing the volatility of the portfolio. This is in line with the concept of risk and returns trade-off whereby investors must take greater risks to earn greater returns (Bradford & Miller, 2009). In this regard, MPT operates under the assumption that investors act rationally, which entails that behavioral biases of investors and non-financial factors do not take precedence over returns (Hodgson et al., 2000). Moreover, based on the premise that the returns on different securities are correlated, MPT reinforces the concept of diversification in reducing the risk factors in a portfolio to tackle the duality of the investor's problem.

Mean-Variance Portfolio

According to Markowitz (1952), individuals invest in financial assets to grow their money and lifetime consumption stream. However, depending on future circumstances, the investor may receive different possible future cash flow streams. As such, using mean-variance analysis, the optimal MVP is the portfolio that maximizes expected return or minimizes risk and is obtained by analyzing three parameters of the portfolio: (a) the expected return, (2) return standard deviation and variance, and (c) return covariance with other stocks. Given that the investor knows the degree and relationship across different alternative investments, the investor can form an effective risk reduction strategy to minimize the risk of the optimal portfolio without reducing his expected return by using Markowitz's diversification principle (Mangram, 2013).

Under this framework, combining securities with negatively correlated standard deviations minimizes the risk of the portfolio. Thus, diversification forms a portfolio that is less volatile than the sum of all its individual securities. The investor's objective is to select a combination of portfolio weights that minimizes the risk of the portfolio (Essid et al., 2018; Fahmy, 2019). The investor can determine the allocation of his wealth in each security of the optimal MVP using the constrained minimization problem defined by Equation (1).

$$\begin{aligned} & Min\ \sigma_\Omega^2 = Var(\Omega) = \textstyle\sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \sigma_{ij} \\ & s.t. \quad \textstyle\sum_{i=1}^{n} w_i = 1; w_i \geq 0, i = 1, \ldots, n \end{aligned} \tag{1}$$

where Ω is the portfolio with n securities, σ_{ij} is the covariance between R_i and R_j, R_i is the return of security, and w_i is the relative value of portfolio invested in security i.

Efficient Frontier

In the context of allocative efficiency, not all participating stocks in the stock market produce optimal returns. As such, investors endowed with a limited amount of wealth shall determine the optimal allocation of stock holdings in their portfolio to maximize portfolio returns subject to the rational investor's preference for risk. Using the MVP framework, portfolios yielding the highest expected return at a given amount of risk can be plotted graphically in a mean-standard deviation space to form the efficient frontier. Among the set of optimal portfolios forming the efficient frontier, there exists one optimal portfolio with the lowest risk regardless of expected return—this is called the global minimum variance portfolio. The global minimum variance portfolio dominates the other portfolios in terms of achieving the investor's goal of minimizing risk and maximizing returns; thus, the investor will prefer to hold the global minimum variance portfolio. In effect, the optimal MVP identified in this study is the portfolio that yields the lowest possible risk regardless of returns (Byrne & Lee, 1994; Mangram, 2013).

4. METHODOLOGY

This study uses secondary data from annual reports and daily stock price data of the blue-chip stock firms that form part of the Philippine Stock Exchange Composite Index (PSEi) provided by Thomson Reuters Eikon for a 10-year period from 2010 to 2019. It excludes entities that do not have complete data all throughout the sample period. These blue-chip stocks form the composite index to gauge the overall market performance as it is an empirical proxy to the index formed using all publicly-listed stocks and captures the impact economic variables have on the entire stock market (Annaert et al., 2011). Blue-chip stocks also provide a good source of passive income because they have a strong financial position, even during bearish markets (Chong et al., 2020; Mishra, 2018). Finally, the portfolios formed have a size of 10 stocks out of the 25, forming the sample as it is the minimum requirement for the effects of diversification to be positive (Evans & Archer, 1968). This study also utilizes a holding period of 1 year and 10 years.

It is important to note that the inputs to the DEA model are those that the investor wants to minimize, and the outputs are those that the investor wants to maximize. Therefore, this study will utilize the first four moments of the distribution of stock returns because the return is an indicator of expected gain, the variance is the measure of volatility and risk, the skewness approximates the probability of receiving massive negative returns, and the excess kurtosis measures the presence of great outliers (Crainich & Eeckhoudt, 2008; Markowitz, 1952; Menezes & Wang, 2005; Pratt, 1964). It will not consider higher-order moments because of the extreme complexity in its computation and lower partial moments because there are multiple methods to compute for these that result in inconsistent results for a singular portfolio (Essid et al., 2018). It will also use a firm's profitability ratios, namely, the Earnings per Share (EPS) and the Return on Assets (ROA), because they represent the efficiency of a firm in earning profits with respect to its assets (Titman et al., 2018). The list of inputs and outputs to the DEA cross-efficiency model is summarized in Table 1 in the appendix.

Using the inputs and outputs previously defined, the DEA cross-efficiency model first requires the self-appraisal score of the DMU, which is given by Equation (2).

$$\begin{aligned} &Max\ CCR_d = \textstyle\sum_{r=1}^{s} \mu_r y_{rd} \\ &s.t.\ \textstyle\sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} \omega_i x_{ij} \le 0, j = 1, 2, \dots n \\ &\textstyle\sum_{i=1}^{m} \omega_i x_{id} = 1 \\ &\omega_i, \mu_r \ge 0 \end{aligned} \tag{2}$$

where ω_i and μ_r are the set of input and output weights for *m* inputs and *s* outputs. The results obtained from the previous equation are the self-appraisal scores and set of optimal weights $\mu_{1d}^*, \dots, \mu_{sd}^*$ and $\omega_{1d}^*, \dots, \omega_{md}^*$ for each DMU_d which are utilized in Equation (3) to obtain the d-cross-efficiencies. The average of the d-cross-efficiencies, as calculated by Equation (4), is the cross-efficiency and represents the peer-appraisal score of each DMU. This approach uniquely distinguishes each individual firm in the sample separately from its peers, which are the other firms in the sample – in other words, the firm will maximize its own score regardless of what happens to the other firm (Essid et al., 2018).

$$E_{dj} = \frac{\sum_{r=1}^{s} \mu_{rd}^* y_{rj}}{\sum_{i=1}^{m} \omega_{id}^* x_{ij}} \quad d, j = 1,2, \dots, n \tag{3}$$

$$E_j = \frac{1}{n} \sum_{d=1}^{n} E_{dj} \quad d = 1,2, \dots, n \tag{4}$$

As for the maverick index, which, as defined by Doyle and Green (1994), is the deviation of stock's self-appraisal score and peer-evaluation score; it is defined by Equation (5). In the context of cross-efficiency, higher values are associated with the stock being a maverick or those that have high levels of risk (Essid et al., 2018).

$$M_j = \frac{CCR_j - E_j}{E_j} \tag{5}$$

Equation (6) defines the optimization problem of the DEA cross-efficiency model that provides the 10 best-performing stocks according to their maverick index, which are to be invested in equally by the investor for the holding period.

$$\begin{aligned} &\min_{w_j}\ I_\Omega = \tfrac{1}{K} \textstyle\sum_{j=1}^{n} w_j M_j \\ &s.t.\ \textstyle\sum_{j=1}^{n} w_j = K = 10 \\ &w_j \in \{0,1\}\ j = 1, 2, \dots, n \end{aligned} \tag{6}$$

where I_Ω is the risk degree indicator of the formed portfolio, and the constraints ensure only K =10 stocks enter the portfolio.

Upon forming the portfolio using the DEA cross-efficiency model, it is important that this is compared to the portfolio formed by the MVP model as well. This is defined by Equation (7), where the constraints ensure that only K =10 stocks enter the portfolio.

$$\begin{aligned} &Min\ \sigma_\Omega^2 = Var(\Omega) = \textstyle\sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \sigma_{ij} \\ &s.t.\ \textstyle\sum_{i=1}^{n} w_i = K = 10 \\ &w_i \in \{0,1\}\ i = 1, 2, \dots, n \end{aligned} \tag{7}$$

In order to compare these portfolios, the modified Sharpe ratio, as defined by Equation (8), is used as it assesses the reward-to-variability ratio of a given portfolio, whereby a greater value indicates greater returns over the risk-free asset per unit of risk incurred. This ratio evaluates portfolios using the portfolio's return and risk regardless of the number of stocks within a portfolio and the method by which the portfolio was chosen. However, when the Sharpe ratio is negative, there is little to no meaning provided by the ratio, which is why a modified Sharpe ratio must be used. According to Israelsen (2005), a modified Sharpe ratio may be formed simply by including an exponent, the excess return over its absolute value, by which the denominator is to be raised by.

$$S_{\Omega} = \frac{R_{\Omega} - R_f}{\sigma_{\Omega}^{\frac{R_{\Omega} - R_f}{|R_{\Omega} - R_f|}}} \quad (8)$$

where □□ is the return of the portfolio, □□ is the risk-free rate proxied by the yearly interest rates of the BSP 364-day Treasury Bills, and σ_{Ω} is the standard deviation of the portfolio.

Finally, to improve comparability with the MVP model, another iteration of the DEA cross-efficiency model is tested against the MVP model, where the inputs and outputs are given by the variance and returns.

5. RESULTS AND DISCUSSION

Portfolio Generation

The results of the portfolio generation under the DEA cross-efficiency approach are shown in Table 2 in the appendix, whereby a unique set of the best-performing stocks to be included in the optimal portfolio is identified for each holding period. Furthermore, because the most efficient stocks are defined as those stocks with the lowest maverick index score, the stocks are arranged from the most efficient to least efficient for the provided holding period (Doyle & Green, 1994). From the results, it can be observed that Universal Robina Corporation (URC) and AboitizPower (AP) performed the best during the 10-year period. The strong performance of URC and AP is attributable to their strong track records in their respective industries. More specifically, investors are highly confident in the global expansion of URC and the growing demand for AP's products, which drove their prices higher (AboitizPower, n.d.; URC, 2020). On the other hand, San Miguel Corporation performed the worst, followed by LT Group in the 10-year period due to high volatility of returns and lower-than-average return on assets, making them less desirable than other stocks in the sample. Overall, the results indicate that the DEA approach is able to successfully profile each stock according to its characteristics relative to the other stocks. Because DEA is able to pick out the most efficient stocks in the market for the investor, this approach allows investors to passively invest in portfolios that are allocatively efficient.

Comparative Tests

The results of the comparative tests for all portfolios are shown in Table 3 in the appendix. It is observed that the DEA portfolios outperformed the MVP 8 out of 11 times from 2010 to 2019. Therefore, the DEA cross-efficiency model provides investors with a more consistent portfolio selection tool that provides a superior risk-adjusted rate of return. This is mainly because it incorporates the use of both fundamental analyses, in the form of the financial ratios utilized, and technical analysis, in the form of the moments of distribution of the stock returns. In fact, previous studies have provided that those portfolio selection processes that incorporate the use of fundamental analysis outperform the benchmark portfolios more than 20 times over the past three decades (Graham & Dodd, 1934; Hughen & Strauss, 2017).

Portfolio Strategy Formulation

In terms of the strategies the investor is provided with, the strategy may either be to hold a short-term investment, as shown by the 1-year holding period or hold a long-term investment, as shown by the 10-year holding period.

For the short-term portfolio, it is suggested that the investor should use the DEA cross-efficiency model to form a portfolio as it has provided for a superior portfolio in terms of risk-adjusted rates of return 8 times out of 10, which may be further improved by incorporating other factors that may affect the portfolio risk and return. Included in these factors would be leverage and coverage ratios as inputs when a contractionary monetary policy is initiated in the holding period since its effect on interest paid on outstanding debt is felt in the same period (Kearney, 1996). On the other hand, the investor may focus on profitability ratios as outputs to be maximized during periods where an expansionary monetary policy has been initiated in the prior periods because its positive effects on the finance costs of the firm are gradually observed. The investor may also include a firm's dividend-yield ratio in the outputs because stock prices are affected by the short-run demand runs of a firm. In fact, Dasilas and Leventis (2011) found that there is a direct relationship between stock returns and dividends–that is, stock prices increase the more frequent, or the greater the amount, a firm distributes dividends. Of course, when a firm is more likely to distribute cash, property, or stock to its shareholders, investors will see this as a good investment opportunity as the eventual gains are not limited to capital gains, but also dividend income. The primary benefit of this strategy is the applicability of the most recent stock return data in predicting future stock returns (Atsalakis & Valavanis, 2009).

Assuming that all available information is reflected in the stock prices in the long run, the MVP model can already sufficiently provide for a higher risk-adjusted return based on the results of the generated portfolios (Poterba & Summers, 1988). However, it should be noted that the DEA model provided higher returns at the expense of higher risk. Thus, depending on the risk appetite of the investor, the DEA model likewise remains useful in identifying superior stocks that provide higher overall returns for the portfolio. Similar to the short-term strategy, the impact of monetary policy must also be considered in the formulation of the investor's long-term strategy. The investor can hedge on the announcements of an expansionary monetary policy upon its announcement because it will lead to an increase in stock prices from an eventual and sustained decrease in interest rates in the medium and long run (Kearney, 1996). Furthermore, the effects of the monetary policy in the long run may also impact long-run dividends and capital gains. For example, if an expansionary monetary policy is implemented, the capacity for a firm to earn higher profit and release dividends will increase gradually in the long run. Finally, it is important to note that MVP assumes that the risk associated with the portfolio is measured completely by the variance of the stock returns and the covariance between the stocks in the portfolio; thus, in the context of boom-bust cycles whereby forecast errors accumulate to sizable errors over time, the DEA model may provide for a more effective portfolio selection tool by incorporating relevant factors, such as leverage and coverage ratios (Jaeger & Schuknecht, 2007).

6. CONCLUSION

The results of this study show that the DEA cross-efficiency model was more consistent in providing for superior risk-adjusted returns throughout the short-run periods of one year. In other words, the DEA approach was able to generate portfolios that resulted in greater returns relative to the risk against those of the MVP approach for 8 out of the 10 portfolios under the short-term, one-year holding periods. The results, therefore, support this study's purpose of providing investors with optimal portfolios that are more allocatively efficient than those of the MVP approach. In the instances that the MVP model was observed to have a greater Sharpe ratio, the use of the DEA cross-efficiency model may, nevertheless, be justified because it has the unique capacity to allow the investor to utilize any sets of inputs and outputs, regardless of the unit of measure, that determine the eligibility of a stock to enter the optimal portfolio. Therefore, the use of the DEA model can include the use of other factors such as fundamental factors that reflect the impact of monetary policy or short-run demand runs. In fact, if the investor intends to calibrate the DEA cross-efficiency model to differentiate the criteria to determine an efficient portfolio, the investor can simply revise the inputs and outputs of the DEA cross-efficiency model to include specific measures that are believed to affect the portfolio's optimality. Overall, this study is able to demonstrate the flexibility of the DEA in capturing the effects of both technical and fundamental factors in determining the risk-adjusted returns of the optimal portfolio. Provided that the statistical tools needed to implement this methodology, namely R and Microsoft Excel, are readily available online, more investors will be able to hold portfolios with optimal returns.

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8. APPENDIX

Table 1

Inputs and Outputs of the Proposed Model

Inputs	Outputs
Variance $= \boldsymbol{\sigma_i^2 = \frac{1}{T}\sum_{t=1}^{T}(R_{it} - \overline{R_i})^2}$ Kurtosis $= \boldsymbol{\frac{1}{T}\sum_{t=1}^{T}\left(\frac{R_{it}-\overline{R_i}}{\sigma_i}\right)^4 - 3}$	Annual Return $= \left(\frac{P_{in}}{P_{i0}}\right)^{\frac{1}{n}}$ Skewness $= \frac{1}{T}\sum_{t=1}^{T}\left(\frac{R_{it}-\overline{R_i}}{\sigma_i}\right)^3$ Earnings Per Share $= \frac{\text{Net Income Before Extraordinary Items-Dividends on Preferred Stock}}{\text{Weighted Average Outstanding Shares}}$ Return on Assets $= \frac{\text{Net Income Before Extraordinary Items}}{\text{Total Assets}}$

Table 2

Top 10 Efficient Stocks (Least Maverick Scores)

Rank	2019		2018		2017		2016		2015		2014		2013		2012		2011		2010		2010-2019	
1	SM	0.06	MER	0.05	ALI	0.22	MER	0.14	JFC	0.16	URC	0.14	TEL	0.05	MBT	0.11	FGEN	0.15	SECB	0.13	URC	0.11
2	GLO	0.10	SMPH	0.21	BDO	0.25	MPI	0.20	AP	0.16	SCC	0.16	DMC	0.18	AGI	0.12	SMPH	0.22	AP	0.16	AP	0.12
3	FGEN	0.17	ALI	0.21	MER	0.28	SM	0.24	MEG	0.29	MPI	0.20	URC	0.21	SM	0.24	ICT	0.26	BDO	0.21	RLC	0.16
4	AGI	0.18	JFC	0.27	ICT	0.33	AEV	0.26	MBT	0.32	MER	0.23	MPI	0.27	TEL	0.24	AP	0.28	URC	0.21	SMPH	0.19
5	ALI	0.20	RLC	0.27	BPI	0.34	BDO	0.28	MPI	0.34	DMC	0.30	GLO	0.27	SECB	0.25	GLO	0.31	ICT	0.26	GLO	0.20
6	URC	0.20	MEG	0.30	DMC	0.34	SMPH	0.32	BDO	0.36	JFC	0.34	JGS	0.29	BPI	0.25	JFC	0.32	JGS	0.27	MPI	0.23
7	SMC	0.21	URC	0.34	SMPH	0.35	AP	0.34	ALI	0.37	AP	0.41	ICT	0.31	URC	0.26	ALI	0.32	SM	0.29	JFC	0.23
8	RLC	0.23	FGEN	0.35	AP	0.37	AGI	0.34	LTG	0.37	JGS	0.42	MBT	0.32	JGS	0.27	JGS	0.33	JFC	0.32	ICT	0.23
9	AP	0.23	ICT	0.46	MEG	0.39	URC	0.35	SM	0.37	RLC	0.42	JFC	0.33	SMPH	0.30	SCC	0.47	ALI	0.33	JGS	0.28
10	SMPH	0.28	DMC	0.52	AEV	0.41	SECB	0.42	BPI	0.39	ICT	0.43	MER	0.35	DMC	0.31	RLC	0.51	SCC	0.35	ALI	0.28

Table 3

Summary of Portfolio Performance

	2019	2018	2017	2016	2015	2014	2013	2012	2011	2010	2010-2019
Risk-free rate	0.0523	0.0482	0.0288	0.0176	0.0208	0.0179	0.0072	0.0198	0.0226	0.0426	0.0512
DEA Model (Variation 1)											
Return	0.0004	-0.0001	0.0010	0.0003	0.0000	0.0011	0.0006	0.0016	0.0003	0.0031	0.0006
Standard Deviation	0.0093	0.0108	0.0066	0.0100	0.0091	0.0071	0.0122	0.0077	0.0103	0.0103	0.0103
Modified Sharpe Ratio	-0.0005	-0.0005	-0.0002	-0.0002	-0.0002	-0.0001	-0.0001	-0.0001	-0.0002	-0.0004	-0.0005
MVP Model											
Return	0.0001	-0.0007	0.0006	0.0004	0.0000	0.0008	-0.0001	0.0198	0.0003	0.0019	0.0004
Standard Deviation	0.0096	0.0110	0.0074	0.0103	0.0089	0.0070	0.0115	0.0011	0.0098	0.0101	0.0094
Modified Sharpe Ratio	-0.0005	-0.0005	-0.0002	-0.0002	-0.0002	-0.0001	-0.0001	-0.0001	-0.0002	-0.0004	-0.0005
DEA Model (Variation 2)											
Return	0.0003	-0.0004	0.0007	0.0001	-0.0003	0.0009	0.0001	0.0014	0.0002	0.0026	0.0006
Standard Deviation	0.0102	0.0107	0.0075	0.0087	0.0085	0.0179	0.072	0.0198	0.0226	0.0094	0.0111
Modified Sharpe Ratio	-0.0005	-0.0005	-0.0002	-0.0002	-0.0002	-0.0001	-0.0001	-0.0002	-0.0003	-0.0004	-0.0006
Comparative Tests											
Test 1	DEA (Var. 1)	DEA (Var. 1)	DEA (Var. 1)	DEA (Var. 1)	DEA (Var. 1)	DEA (Var. 1)	DEA (Var. 1)	MVP	MVP	DEA (Var. 1)	MVP
Test 2	MVP	DEA (Var. 2)	MVP	MVP	DEA (Var. 2)	MVP	MVP	MVP	MVP	DEA (Var. 2)	MVP
Best Model	DEA (Var. 1)	DEA (Var. 2)	DEA (Var. 1)	DEA (Var. 1)	DEA (Var. 2)	DEA (Var. 1)	DEA (Var. 1)	MVP	MVP	DEA (Var. 2)	MVP