The Art of Goal Programming Model: A Tool for Rebuilding the 'Next Normal' in Outperforming the Philippine Stock Exchange Index

Arwin S. Layson
Bank of the Philippine Islands
arwinlayson@gmail.com

Abstract

This study focuses on a special type of portfolio management, called enhanced index tracking. In enhanced index tracking, a subset of stocks that comprise a benchmark index was reproduced in such a way that they generate excess mean returns over the index mean return at a minimum risk of loss without the need of buying all stocks in the equity market. In this study, results on the stock composition of the optimal portfolio were obtained using goal programming approach and compared against the benchmark index using portfolio performance measurement. Specifically, the output of this study is a model consisting of selected stocks that can outperform the benchmark index of the Philippines, namely, the Philippine Stock Exchange Index. Results of the model output showed positively that the creation of such an optimal portfolio was possible.

Key Words: benchmark index; enhanced index tracking; goal programming model; optimal portfolio; mean return tracking error

Introduction

Portfolio management can be more challenging especially in periods of heightened volatility and occurrence of extreme events. That is, performance of financial instruments is significantly affected by increased market uncertainty and multi-dimensional nature of risk. Performance of portfolio managers are routinely assessed or evaluated on their ability to maximize returns and mitigate against risk. Finding a balance between optimal returns and minimized risk, as well as taking a holistic view on portfolio risk becomes imperative.

One perception that has caught the interest of many finance enthusiasts in the area of portfolio management is the notion of building the optimal portfolio to outperform the index. This has led to various ways and developments that were explored by researchers. A common concept of portfolio management in equity market index was introduced by Beasley which is enhanced index tracking. Enhanced index tracking intends to reproduce higher portfolio mean return than the benchmark index mean return at a minimum tracking error without a need of buying all the stocks in the stock market (Beasley, 2003). A tracking error is a measurement of risk that is used to track how closely a portfolio trails an index (Roll, 1992).

Because of the dynamic nature of risk, more sophisticated analytical models are being developed and gaining wider interest nowadays. Specifically, optimization tools are one of the sophisticated analytical models that offer risk reduction strategies through diversification. Many variations of optimization models have been examined and developed by different group of academicians as a strategic decision-making tool in portfolio management (Canakgoz et al., 2008; Guastaroba et al., 2012; Lam et al., 2015; Meade et al., 2011).

In recent years, Wu et al. (2007) answered the twofold problem of enhanced index tracking in using goal programming model by formulating a dual-objective problem; that is, to maximize the mean return of the optimal portfolio and to minimize the tracking error. According to Taha (2011), goal programming can handle decision problems which include multiple goals.

Hence, this study sought to create an operations research model using the available Philippine data as inspired by the study conducted by Lam et al. (2016). This study applied goal programming approach to build an optimal portfolio that tracked the benchmark index – Philippine Stock Exchange Index (PSEi). Performance of the portfolio constructed using goal programming was then analyzed and compared against the benchmark index PSEi.

Despite the recent developments in the field of study regarding outperforming the market index, there are still many unresolved issues and other areas left unexplored. This study explored the concept of enhanced index tracking and applied it in the Philippine setting using the weighted goal programming approach. Specifically, this study presents a model based on the methodology used in "Strategic Decision Making in Portfolio Management with Goal Programming Model" by Lam et al. (2016), and sought to address the following questions:

- Which stocks from the basket of benchmark index constitutes the optimal portfolio?
- How does one determine whether the results obtained by the model are robust or not?
- Up to what extent will the optimal portfolio be able to outperform the benchmark index?

Related Literature

History bears record of how portfolio management has evolved over time since the father of Modern Portfolio Theory (MPT), Harry Markowitz started exploring this topic for his doctoral dissertation. The concept of modern portfolio theory was viewed by Markowitz (1952) as an efficient portfolio obtained from two measurements, the expected return and the standard deviation of the return. He explained that an optimal portfolio can be derived by maximizing the expected return for a given level of risk or minimizing the risk for a given level of expected return. He further clarified that it is not enough to look at the expected risk and return of one particular stock. An investor can gain the benefits of diversification or a reduction in the riskiness of the portfolio by investing in more than one stock. In other words, MPT accounts the benefits of diversification, or not putting all of your eggs in one basket. Portfolio diversification in MPT was further explored by Newbould and Poon (1994) and they have found out in their study that there is a minimum number of stocks needed for diversification. They have summarized all their findings from various references and tabulated each source recommending the minimum number of stocks in a portfolio. Eventually, they have come up a proposed recommendation that owning eight to twenty stocks achieves a risk-efficient portfolio. Wu and Olson (2009) noted that both returns and risks are considered objective functions in Markowitz's (1952) finance theory. The MPT strongly suggests that when investors and portfolio managers invest in high-yield financial assets or securities, it necessarily entails a high level of risk. Corollarily, investing in low-yield financial assets or securities carries with it a low amount of risk. It is in this context that this study bets on developing a model that not only maximizes returns and minimizes risk but outperforms the benchmark index Philippine Stock Exchange Index. This is consistent with the goals of many local equity portfolio managers, in addition to beating the inflation rate. There are several optimal approaches in solving a portfolio management problem as introduced by Taha (2011). This paper explored a specific optimization model as the solution to the equity portfolio managers' challenge of maximizing returns and minimizing risk. Although this model has been widely utilized for selecting financial portfolio based on several characteristics, there has been very limited to none that were applied in the Philippine context.

"Outperforming the benchmark index" has become a significant phrase for investors and fund managers. Beating and outperforming a benchmark index has long become a vital goal or objective among practitioners in the area of index investing (Beasley et al., 2003; Oh et al., 2005; Corielli & Marcellino, 2006; Maringer & Oyewumi, 2007). Beasley et al. (2003) highlighted that index tracking is a popular form of passive equity portfolio management strategy and described it as a process of trying to track or rather imitate the performance of an index. Corielli & Marcellino (2006) also explained that stock index tracking requires building a replica of pool of stocks whose behavior is as near as possible to that of a given stock index, noting that less stocks should constitute in the replica than in the index.

The Philippine Stock Exchange Index, otherwise known as the PSEi, is the benchmark index that was used in this study. This index is a basket comprising the common stocks of the top 30 companies listed in the Philippine Stock Exchange (PSE). The companies are carefully selected to represent the general movement and performance of the stock market in the Philippines. In a nutshell, PSEi is the benchmark index used to measure and scale the performance of the Philippine stock market together with its specific industry sectors and all shares index (PSE Academy, 2011). Some of the criteria used in deciding to include a company as part of the index consist of the following:

- Free Float – a stock should have a public float or minimum public ownership of at least 12%;
- Liquidity – a stock should belong to the top 25% by median daily value turnover per month for at least nine out of 12 months; and
- Full Market Capitalization – a stock must be one of the 30 companies with highest-ranked market capitalization, measured by the company's stock price multiplied by the number of shares being publicly traded.

The aforementioned criteria of PSEi composition is regularly reviewed by the Philippine Stock Exchange twice a year, one in March and the other in September. A stock may be included in the index if it escalates above the 25th position in terms of full market capitalization, substituting the company that ranks lower (Pinoy Money Talk, 2018).

A type of index tracking called enhanced index tracking was studied vastly in the last two decades and used to outperform the benchmark while sustaining a low tracking error (Ahmed &

Nanda, 2005; Bergstresser et al., 2009; Choi et al., 2010). Fabozzi, Gupta and Markowitz (2002) suggested that the optimal level of tracking error is between 1.75% to 3.00%. The major benefit in using this approach is that it provides the investor a return that is approximately equal to the market return. For example, almost 90% of all actively managed equity mutual funds from 1995 to 1998 was outperformed by the S&P 500 index. It is projected that investments worth more than USD 300 billion were managed in enhanced index portfolios in 2005 (Ahmed & Nanda, 2005) and the amount has sustained to grow (Adams et al., 2010).

Several optimization techniques are considered as the most fundamental tools in analyzing the portfolio selection processes. In a recent paper by Guastaroba et al. (2016) and Lam et al. (2017), a different optimization technique was utilized in modelling the enhanced index tracking. Guastaroba et al. (2016) made utilize of linear programming model in answering the enhanced index tracking problem based on the Omega ratio. On the other hand, Lam et al. (2017) made use of two-stage mixed integer programming model in outperforming the existing model that they used in their previous study.

This study utilized goal programming model. Goal programming model was first presented by Charnes, Cooper and Ferguson (1955) and Charnes and Cooper (1961). The main impression about this model is the grit of the aspiration levels of an objective function and minimization of any positive or negative aberrations from these levels. Through the years, goal programming model has become the most prevalent model in the field of multi-objective programming. According to Steuer and Na (2003), 69% of the published papers related to the application of multiple criteria decision-making techniques utilized the goal programming model and other multi-objective programming models while 29% dealt with portfolio selection problem. Variants of goal programming model have been studied by many scholars in the area of portfolio management throughout the years since Markowitz (1952) developed the portfolio selection problem. Aouni, Colapinto and La Torre (2014) tabulated and summarized the various variants of goal programming models that have been applied to the financial portfolio selection problem from the 1970s until 2013. Variants of goal programming model which were discussed in their paper vastly include weighted goal programming, lexicographic goal programming, polynomial goal programming, fuzzy goal programming and stochastic goal programming. Specifically, this study utilized the weighted goal programming model. Weighted goal programming was first illustrated by Callahan (1973) and Kvanli (1980) as an investment planning model with risk and profit. Sharma, Sharma and Adeyeye (1995) were the first academicians who dealed with portfolio selection problem. Then, Tamiz, Hasham, Jones, Hesni and Fargher (1996) adopted Lee's (1972) model and provided a weighted goal programming formulation for the Portfolio Selection Problem with two stages: (1) prediction of the sensitivity of the shares to specific economic indicators, and (2) selection of the best portfolio based on the FDM's preferences. Bravo, Pla Santamaria, and Garcia-Bernabeu (2010) examined a portfolio selection problem with multiple benchmarks. Cooper, Lelas, and Sueyoshi (1997) showed a weighted goal programming model for the evaluation of security portfolio and regression relations. Dominiak (1997) presented an application of interactive multiple goal programming on the Warsaw Stock Exchange. Pendaraki, Doumpos, and Zopounidis (2004, 2005) applied the weighted goal programming model to mutual funds selection and composition in the market of Greece. Other applications of the weighted goal programming to funds management can be obtained in Lee and Sevebeck (1971), Sharda and Musser (1986), Zaloom, Tolga, and Chu (1986), and O'Leary and O'Leary (1987). To cope with asset liability management, weighted goal programming was used by Kosmidou and Zopounidis (2004) and Tektas, Ozkan-Gunay, and Gunay (2005). Booth and Bessler (1989) developed two weighted goal programming models, namely, a forecast model and a duration model, to assist a bank in creating optimal strategies to manage the interest rate risk.

Wu et al. (2007) and Lam et al. (2016) explored, using goal programming model, an enhanced index tracking problem. They were the first two groups who applied the model across the ASEAN countries. Specifically, Wu et al. (2007) were able to examine the use of goal programming model in Taiwan stock market in different time periods. On the other hand, Lam et al. (2016) made use of goal programming model in technology sector of Malaysian stock market to obtain an optimal portfolio that was intended to outperform its technology index.

In summary, modern portfolio theory stems from Markowitz's insights in the mean-variance model, which states that an efficient portfolio can be derived from two measurements, the expected return and the standard deviation of the return. The classic mean-variance theory, proposed by Markowitz (1952), also addresses the tradeoff between the risk and the return dimensions. He suggested that an optimal portfolio can be derived by minimizing the risk for a given level of expected return or maximizing the expected return for a given level of risk. All portfolios on the efficient frontier have two properties. That is, they have the highest expected rate of return for each level of variance, and they have the minimum variance for each particular level of expected return.

The previous discussion and review of related literature have surfaced theoretical and practical gaps as regards to this topic. In particular, this study has identified the following theoretical gaps:

1. Portfolio management involves two concepts – return and risk. Generally, the primary goal of a portfolio manager is to minimize the risk and maximize the return. Notwithstanding its importance and relevance, the biased focus on this goal has inadvertently resulted to missing out on other relevant measures such as benchmarking against the stock market index.
2. The related literature had shown that there is a need to integrate in portfolio management an assessment on how to benchmark a market index and outperform that index.
3. Studies in the Philippines regarding optimal stock mix using specifically goal programming is practically unexplored.

The above-mentioned has motivated this study to adopt the model used by similar studies that focused on neighboring ASEAN countries like Malaysia, and also Taiwan.

Framework

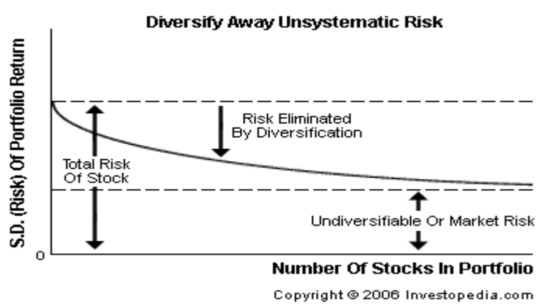
This study is based on the concept of Modern Portfolio Theory (MPT). This concept states that investors are risk averse and wealth maximizers. Investors seek to maximize expected portfolio return at a certain level of risk, or minimize portfolio risk for a given level of return. There is a positive relationship between expected return and risk of financial assets. When the risk of an asset increases, so does its expected return. An investor willing to take in more risk is likely to be compensated with a higher return. In a similar manner, an investor aiming to boost the expected return of an investment is expected to be prepared to take in more risk. This trade-off between return and risk is essential in constructing international portfolios.

By prudently allocating wealth across different stocks, portfolio risk can be collectively reduced without affecting return. As long as different stocks are not perfectly positively correlated, investors can reduce exposure to an individual asset by spreading the risk in other stocks. This notion of diversification is mathematically formulated in the mean-variance framework developed by Markowitz (1952). MPT states that the risk for individual stock returns have two components:

- Systematic Risk – These are defined as market risks that cannot be diversified away. Interest rates, wars and recessions are examples of systematic risks.
- Unsystematic Risk – Or "specific risk," which is specific to individual stocks, such as a decline in operations or a change in management. This kind of risk can be diversified away as the number of stocks in a portfolio increases (see Figure 1). It denotes a component of a stock's return that is not correlated with general market moves.

Figure 1

Average Portfolio Risk (Source: Investopedia)

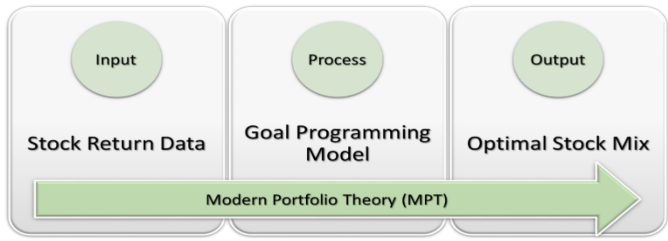


The risk or average deviation from the mean of each stock contributes little to portfolio risk for a well-diversified portfolio. Instead, it is the difference between individual stock's levels of risk that determines overall portfolio risk. As a result, investors benefit from holding diversified portfolios instead of individual stocks. It is in this framework to which the study written by Newbould and Poon (1994) is aligned, "further spreading of the portfolio's assets is superfluous diversification and should be avoided" and they eventually recommended a minimum number of stocks for a well-diversified portfolio.

The schematic diagram in Figure 2 explains that the model adopted for this study's operational framework is an Input-Process-Output (IPO) model. This framework is also anchored on Modern Portfolio Theory (MPT) defined above. Using the returns calculated from the closing prices of selected stocks as the input data, portfolio tracking error and portfolio mean return were obtained using goal programming method. The optimization model generated an output of optimal stock mix. Performance analysis of the generated optimal portfolio results were evaluated using the Information ratio to establish whether the estimates of the model were able to outperform the performance measurement of the benchmark index.

Figure 2

Schematic Diagram of Operational Framework



Methodology

The subject of the research included the top thirty (30) publicly listed companies of the Philippine stock market index. Listed below in Table 1 are the names of the companies and their corresponding ticker symbols as of February 18, 2019 (The Philippine Stock Exchange, Inc., n.d.).

Table 1

List of Top 30 Publicly Listed Company Tickers that Comprise the PSEi

1.	Ayala Corporation (AC)	16.	LT Group, Inc. (LTG)
2.	Aboitiz Equity Ventures, Inc. (AEV)	17.	Metropolitan Bank & Trust Company (MBT)
3.	Alliance Global Group, Inc. (AGI)	18.	Megaworld Corporation (MEG)
4.	Ayala Land Inc. (ALI)	19.	Manila Electric Company (MER)
5.	Aboitiz Power Corporation (AP)	20.	Metro Pacific Investments Corporation (MPI)
6.	Banco De Oro Unibank, Inc. (BDO)	21.	Puregold Price Club, Inc. (PGOLD)
7.	Bloomberry Resorts Corporation (BLOOM)	22.	Robinsons Land Corporation (RLC)
8.	Bank of the Philippine Islands (BPI)	23.	Robinsons Retail Holdings, Inc. (RRHI)
9.	DMCI Holdings, Inc. (DMC)	24.	Semirara Mining & Power Corporation (SCC)
10.	First Gen Corporation (FGEN)	25.	Security Bank Corporation (SECB)
11.	Globe Telecom, Inc. (GLO)	26.	SM Investments Corporation (SM)
12.	GT Capital Holdings, Inc. (GTCAP)	27.	San Miguel Corporation (SMC)
13.	Int'l Container Terminal Services, Inc. (ICT)	28.	SM Prime Holdings, Inc. (SMPH)
14.	Jollibee Foods Corporation (JFC)	29.	PLDT Inc. (TEL)
15.	JG Summit Holdings, Inc. (JGS)	30.	Universal Robina Corporation (URC)

This research study obtained data purely from secondary sources as stock price data were readily available and easily accessible. The stock price data used were adjusted closing prices, and taken from an external source which provided published industry statistical reports. A total of 7,998 observations of weekly stock prices of each of the stated companies, and also the Philippine Stock Exchange Composite Index were collected covering the period from January 2014 until December 2018. All stock price data were taken from the publications of the Wall Street Journal (The Wall Street Journal, n.d.). The 5-year stock price data was downloaded on a Microsoft Excel worksheet to facilitate data wrangling and data management. No variable was manipulated. No missing data was observed as any missing observation in the data set were filled in by using other database sources like the Thomson Reuters Eikon system.

The optimization model used in tracking the PSEi in order to construct an optimal portfolio mix from the dataset of the thirty (30) companies belonging to the index was the goal programming approach. In portfolio construction with the goal programming model, the decision variables represent the optimal portfolio composition that was determined by solving the model (Wu et al., 2007). The returns of the stocks were determined as below (Beasley et al., 2003).

$$Y_{st} = \ln ln \left(\frac{P_{s,t}}{P_{s,t-1}}\right) \quad (1)$$

Y_{st} is the return of stock s at time t,
$P_{s,t}$ is the closing price of stock s at time t,
$P_{s,t-1}$ is the closing price of stock s at time t-1.

The return of the benchmark index was determined as below (Canakgoz et al., 2008).

$$Y_{It} = \ln ln \left(\frac{I_t}{I_{t-1}}\right) \quad (2)$$

Y_{It} is the return of index at time t,
I_t is the index value at time t,
I_{t-1} is the index value at time t-1.

The mean return of the stock j was calculated as below (Gitman et al., 2011).

$$y_s = \frac{1}{N}\sum_{t=1}^{N} Y_{st} \quad (3)$$

y_s is the mean return of stock s,
Y_{st} is the return of stock s at time t,
N is the number of observations.

In this study, the optimization model with goal programming approach was performed using both Excel 2016 and its add-in Solver utilities.

Descriptive Statistics. The mean and standard deviation were used to describe the extent of the stock mix on each stock return. Test of normality was employed as well to validate if the distribution of the stock return data was normal through the measurement of skewness.

Goal Programming Model. In enhanced index tracking, there are two goals to be achieved, namely maximization of the mean return and minimization of the tracking error of the optimal portfolio. Wu et al. (2007) proposed the dual objective optimization model for enhanced index tracking problem which is expressed as follows.

Minimize

$$E = \sum_{s=1}^{N} E_s w_s \tag{4}$$

Maximize

$$Y = \sum_{s=1}^{N} y_s w_s \tag{5}$$

subject to

$$\sum_{s=1}^{N} w_s = 1 \tag{6}$$

$$w_s \geq 0 \tag{7}$$

y_s is the mean return of stock s in the optimal portfolio,
N is the number of stocks,
w_s is the weight of stock s in the optimal portfolio,
E_s is the tracking error of stock s,
E is the portfolio tracking error,
Y is the portfolio mean return,

Equation (4) is the first goal which minimizes the portfolio tracking error. Equation (5) is the second goal which maximizes the portfolio mean return. Constraint (6) ensures that the total weights of stocks invested equal to one. Constraint (7) ensures that the weight of each stock j in the optimal portfolio are positive.

The dual objective optimization model above is solved with goal programming approach (Wu et al., 2007). Goal programming is able to handle decision problems that involve multiple goals (Taha, 2011). The goal programming model is formulated as follows (Lam et al., 2016).

Minimize

$$z = d_1^+ + d_2^- \tag{8}$$

subject to

$$E + d_1^- - d_1^+ = u \tag{9}$$

$$Y + d_2^- - d_2^+ = v \tag{10}$$

$$\sum_{s=1}^{N} w_s = 1 \tag{11}$$

$$0\% \leq w_s \leq 15\% \tag{12}$$

d_1^- is the extent of underachievement for tracking error,
d_1^+ is the extent of overachievement for tracking error,
d_2^- is the extent of underachievement for portfolio mean return,
d_2^+ is the extent of overachievement for portfolio mean return,
E is the portfolio tracking error,
Y is the portfolio mean return,
u is target value for portfolio tracking error,
v is target value for portfolio mean return,
N is the number of stocks,
w_s is the weight of stock s in the optimal portfolio,

Equation (8) is the objective function of the model which minimizes the sum of deviations of all decision goals. Equation (9) is the first goal which minimizes the portfolio tracking error. In setting the target value for portfolio tracking error, optimal levels of between 1.75% and 3.00% were used. This is based on the study by Fabozzi, Gupta and Markowitz (2002), where they created a "tracking error budgeting" methodology. Equation (10) is the second goal which maximizes the portfolio mean return. In setting the target value for portfolio mean return, the maximum portfolio mean return of the solution was used. Constraint (11) ensures that the total weights of stocks invested equal to one. Constraint (12) was incorporated to ensure that the weight of each stock j in the optimal portfolio are nonnegative with lower bound set to 0.00% and upper bound set to 15.00%, as proposed by the Securities and Exchange Commission (SEC) its recent amendments in the Implementing Rules and Regulations of the Investment Company Act (ICA Rule 35-1) issued last June 2, 2017.

Sensitivity Analysis. A process of recalculating outcomes under alternative assumptions and scenarios (i.e., adjusting the target value for portfolio tracking error within and outside the range of the optimal level of 1.75% to 3.00%, and adjusting the target value for portfolio mean return greater than or equal to the benchmark index return) was conducted in order to determine the impact of a constraint variable to the optimal solution. The use of this process made possible a test for the robustness of the model. Bounds for each stock weights were further considered in the analysis and broke down into these following scenarios:

a. Scenario 1: Equally Weighted Stocks
b. Scenario 2: No Upper Bound Constraint
c. Scenario 3: Setting a Lower Bound Constraint
d. Scenario 4: Recalculation of Optimal Stock Mix

Portfolio Performance. Tracking error and mean return of the optimal portfolio are two elements in enhanced index tracking problem (Wu et al., 2012; Lam et al., 2015). Tracking error is the standard deviation of the difference between the returns of the portfolio and the returns of the benchmark index (Lam et al., 2014; Meade et al., 1990). The formula for tracking error is as follows.

$$E = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(Y_{P_t} - Y_{I_t})^2} \tag{13}$$

E is the tracking error,
N is the number of periods,
Y_{P_t} is the mean return of the optimal portfolio at time t,
Y_{I_t} is the mean return of the benchmark index at time t.

The mean return of the optimal portfolio is formulated as follows (Lam et al., 2015).

$$y_P = \sum_{s=1}^{N} w_s y_s \tag{14}$$

y_P is the mean return of the optimal portfolio,
w_s is the weight of stock s in the optimal portfolio,
y_s is the mean return of stocks in the optimal portfolio.

Excess return is defined as the difference between the portfolio mean return and benchmark index mean return which is formulated as follows (Wu et al., 2007, 2012).

$$\alpha = y_P - y_I \tag{15}$$

α is the excess return,
y_P is the mean return of the optimal portfolio,
y_I is the mean return of the benchmark index.

The performance of the optimal portfolio is measured with information ratio (Wu et al., 2012; Israelsen, 2005). The information ratio is defined as the ratio of portfolio's excess mean return to the portfolio's tracking error which is formulated as below.

$$IR = \frac{\alpha}{E} \tag{16}$$

IR is the information ratio,
α is the excess mean return of the optimal portfolio over the mean return of the benchmark index return,
E is the tracking error.

Higher information ratio indicates higher performance of the optimal portfolio (Reilly & Brown, 2012).

Discussion of Results

Descriptive Statistics. Table 2 displays the summary statistics of the stock returns in the data used for this study.

Table 2

Mean and Standard Deviation of the Stock Returns

	Stocks	Mean	Standard Deviation		Stocks	Mean	Standard Deviation
1.	**AC**	0.00213	0.03040	16.	LTG	0.00035	0.04630
2.	**AEV**	0.00011	0.03176	17.	MBT	0.00029	0.03106
3.	**AGI**	-0.00308	0.03855	18.	MEG	0.00141	0.04077
4.	**ALI**	0.00185	0.03386	19.	MER	0.00156	0.02472
5.	**AP**	0.00014	**0.02428**	**20.**	MPI	0.00025	0.03382
6.	**BDO**	0.00258	0.02849	21.	PGOLD	0.00036	0.03492
7.	**BLOOM**	0.00017	**0.06930**	**22.**	RLC	-0.00007	0.03576
8.	**BPI**	0.00035	0.02666	23.	RRHI	0.00124	0.03753
9.	**DMC**	0.00044	0.03588	24.	SCC	-0.00025	0.03863
10.	**FGEN**	0.00135	0.04020	25.	SECB	0.00106	0.03609
11.	**GLO**	0.00064	0.04425	26.	SM	0.00260	0.03057
12.	**GTCAP**	0.00060	0.03697	27.	SMC	0.00332	0.03858
13.	**ICT**	-0.00007	0.03403	28.	SMPH	**0.00344**	0.03341
14.	**JFC**	0.00206	0.03119	29.	TEL	**-0.00331**	0.04065
15.	**JGS**	0.00140	0.03888	30.	URC	0.00025	0.03479

As reported in Table 2, SMPH registered the highest mean return at 0.34% while TEL registered the lowest mean return at -0.33% whereas BLOOM registered the highest standard deviation at 6.93% and AP registered the lowest standard deviation at 2.43%, respectively. Skewness of the stock return data was also obtained which is 0.0649. This implied that the distribution of data is normal since the skewness obtained is between -0.5 and 0.5.

Table 3 was also obtained to see the trend of the annualized mean for each stock price. Compounded Annual Growth Rate (CAGR) was additionally incorporated in Table 3 to evaluate how well one stock performed against other stocks in a peer group.

Table 3

Annualized Mean of the Stock Prices

Stocks	2014	2015	2016	2017	2018	Trend	CAGR
1. SMPH	16.13	20.19	25.20	33.13	35.80		22.05%
2. SMC	73.98	60.81	77.60	104.34	148.89		19.10%
3. SM	508.69	590.73	637.62	808.79	933.50		16.39%
4. SECB	127.81	151.42	190.09	230.04	199.97		11.84%
5. JFC	180.81	205.04	230.20	223.10	278.50		11.40%
6. BDO	87.01	102.94	102.51	128.43	133.66		11.33%
7. AC	639.87	760.83	790.38	902.38	959.45		10.66%
8. MER	262.99	287.19	308.25	285.36	349.11		7.34%
9. ALI	31.17	36.87	35.64	40.03	41.28		7.27%
10. RRHI	66.42	76.82	75.11	87.07	84.93		6.34%
11. PGOLD	40.12	37.13	40.18	46.70	47.00		4.04%
12. LTG	15.89	14.06	15.24	16.39	18.39		3.72%
13. JGS	52.27	70.26	76.54	76.51	58.65		2.92%
14. AEV	54.79	57.03	70.10	73.84	60.20		2.38%
15. BPI	92.42	93.06	94.43	98.33	98.15		1.52%
16. MPI	4.86	4.96	6.39	6.63	5.14		1.45%
17. GLO	1720.94	2226.96	1958.55	1960.24	1818.00		1.38%
18. MEG	4.43	4.88	4.18	4.57	4.65		1.21%
19. GTCAP	904.80	1295.04	1381.45	1170.25	923.89		0.52%
20. MBT	81.06	88.13	82.42	83.04	79.34		-0.53%
21. SCC	31.21	36.05	31.05	39.07	30.23		-0.79%
22. AP	38.34	43.27	44.21	41.13	36.95		-0.92%
23. BLOOM	11.34	8.78	5.23	9.29	10.72		-1.38%
24. RLC	22.74	28.61	28.53	23.52	20.09		-3.05%
25. URC	158.17	200.37	191.25	156.72	139.64		-3.07%
26. ICT	109.14	99.38	68.24	96.05	94.48		-3.54%
27. DMC	14.59	13.85	12.56	14.21	12.30		-4.17%
28. FGEN	21.56	26.09	22.47	19.43	16.21		-6.89%
29. AGI	27.13	21.95	15.11	14.39	13.02		-16.76%
30. TEL	2933.50	2655.23	1809.91	1638.37	1375.67		-17.25%

As shown in Table 3, the annualized mean price of stocks SMPH, SMC and SM have increased significantly by a compounded growth rate of 22.05%, 19.10% and 16.39% over the five-year investment period, respectively. Whereas, the annualized mean price of stocks AGI and

TEL have decreased significantly by a compounded growth rate of 16.76% and 17.25% over the five-year investment period, respectively.

Goal Programming Model Formulation. Goal programming model is shown as follows and further set up in Excel worksheet and Solver add-in.

Minimize

$$z = d_1^+ + d_2^-$$

subject to

$$TE + d_1^- - d_1^+ = 2.3750\%$$
$$R + d_2^- - d_2^+ = 0.2353\%$$
$$\sum_{j=1}^{30} w_j = 1$$
$$0\% \le w_j \le 15\%$$

where

$$TE = \sum_{j=1}^{30} TE_j w_j$$
$$R = \sum_{j=1}^{30} r_j w_j$$

Optimal Stock Mix. From the model formulated above, Table 4 displays the stock selection in optimal portfolio which is constructed by solving the goal programming model. It is assumed in this study that the starting or base amount is Php 1,000,000.00 from hereon.

Table 4

Stock Selection in Optimal Portfolio

Stocks	Weights (%)	Amount (Php)
1. SMPH	15.00%	150,000.00
2. SM	15.00%	150,000.00
3. JFC	15.00%	150,000.00
4. BDO	15.00%	150,000.00
5. AC	15.00%	150,000.00
6. ALI	15.00%	150,000.00
7. MER	9.83%	98,300.00
8. BPI	0.15%	1,500.00
9. SMC	0.02%	200.00

As shown in Table 4, the list of stocks with positive weights indicate that those stocks are selected by the goal programming model in constructing the optimal portfolio to track the PSEi. The optimal portfolio consists of nine (9) stocks with different weights in tracking the Philippine Stock Exchange Index (PSEi). From Table 4 above, the optimal portfolio consists of AC (15.00%), ALI (15.00%), BDO (15.00%), BPI (0.15%), JFC (15.00%), MER (9.83%), SM (15.00%), SMC (0.02%) and SMPH (15.00%). This implies that the optimal portfolio composition are the optimal solutions of the goal programming model. AC, ALI, BDO, JFC, SM and SMPH are the most dominant stocks in the optimal portfolio with 15.00% of the allocated fund. On the other hand, SMC is the smallest stock in the optimal portfolio with 0.02% of the allocated fund.

Sensitivity Analysis. In order to test the robustness of the model derived from above, four different scenarios were plotted below. In each of these scenarios, stock weights were adjusted accordingly. Target value for portfolio tracking error was maintained at a level of 2.375%, which is the average of the optimal levels suggested by Fabozzi, Gupta and Markowitz (2002). Inclusion of the minimum (1.75%) and maximum (3%) tracking error levels were also tested but did not yield any optimal solutions. Similarly, tracking error levels below the minimum and maximum were also simulated and yielded no optimal solutions. Maximum portfolio mean return was targeted across all scenarios. These scenarios include the following:

a. Scenario 1: Equally Weighted Stocks
b. Scenario 2: No Upper Bound Constraint
c. Scenario 3: Setting a Lower Bound Constraint
d. Scenario 4: Recalculation of Optimal Stock Mix

<u>Scenario 1: Equally Weighted Stocks</u>

This type of scenario allots each stock with equal weights of 3.33% which is clearly shown in Table 5.

Table 5

Stock Selection for Portfolio with Equally Weighted Stocks

Stocks	Weights (%)	Amount (Php)	Stocks	Weights (%)	Amount (Php)
1. AC	3.33%	33,300.00	16. LTG	3.33%	33,300.00
2. AEV	3.33%	33,300.00	17. MBT	3.33%	33,300.00
3. AGI	3.33%	33,300.00	18. MEG	3.33%	33,300.00
4. ALI	3.33%	33,300.00	19. MER	3.33%	33,300.00
5. AP	3.33%	33,300.00	20. MPI	3.33%	33,300.00
6. BDO	3.33%	33,300.00	21. PGOLD	3.33%	33,300.00
7. BLOOM	3.33%	33,300.00	22. RLC	3.33%	33,300.00
8. BPI	3.33%	33,300.00	23. RRHI	3.33%	33,300.00
9. DMC	3.33%	33,300.00	24. SCC	3.33%	33,300.00
10. FGEN	3.33%	33,300.00	25. SECB	3.33%	33,300.00
11. GLO	3.33%	33,300.00	26. SM	3.33%	33,300.00
12. GTCAP	3.33%	33,300.00	27. SMC	3.33%	33,300.00
13. ICT	3.33%	33,300.00	28. SMPH	3.33%	33,300.00
14. JFC	3.33%	33,300.00	29. TEL	3.33%	33,300.00
15. JGS	3.33%	33,300.00	30. URC	3.33%	33,300.00

Table 6 displays the comparison of performance between the portfolio of equally weighted stocks and benchmark index PSEi.

Table 6

Performance of the Portfolio with Equally Weighted Stocks and PSEi

Portfolio	PSEi (Benchmark)	Goal Programming Model
Number of Stocks	30	30
Mean Return (%)	0.0885	0.0772
Excess Return (%)	-	-0.0112
Tracking Error (%)	-	3.1418

Information Ratio	-	-0.0036

As reported in Table 6, the performance of the portfolio with equally weighted stocks did not outperform the performance of the benchmark index since the portfolio mean return at 0.0772% did not exceed the benchmark index mean return at 0.0885% and the excess return reached a negative gap at about 0.0112%. Portfolio tracking error is at 3.1418%, which exceeded the optimal levels, and information ratio is equivalent to -0.0036, which indicates that the portfolio performed poorly. In this type of sensitivity analysis, the definition of enhanced index tracking was not only violated but also implies that this scenario is not acceptable in this study.

Scenario 2: No Upper Bound Constraint

This type of scenario does not set any upper limit in each weight of the stocks. Table 7 presents the stock selection of the portfolio produced in not setting any upper bound constraint.

Table 7

Stock Selection for Portfolio with No Upper Bound Constraint

Stocks	Weights (%)	Amount (Php)
1. SMPH	61.64%	616,400.00
2. SM	38.36%	383,600.00

Table 8 displays the comparison of performance between the portfolio with no upper bound constraint and benchmark index PSEi.

Table 8

Performance of the Portfolio with No Upper Bound Constraint and PSEi

Portfolio	PSEi (Benchmark)	Goal Programming Model
Number of Stocks	30	2
Mean Return (%)	0.0885	0.3115
Excess Return (%)	-	0.2230
Tracking Error (%)	-	2.3750
Information Ratio	-	0.0939

As shown in Table 8, the performance of the portfolio with no upper bound constraints outperformed the performance of the benchmark index since the portfolio mean return at 0.3115% exceeded the benchmark index mean return at 0.0885%. However, this portfolio comprises only of two (2) stocks. The model output contradicts the concept of diversification in MPT even though the portfolio tracking error is at optimal level and information ratio is high.

Scenario 3: Setting a Lower Bound Constraint

This type of scenario sets a lower limit in each weight of the stocks to about 1% or 2%. Unfortunately, the software used in this study did not generate a feasible solution since this scenario violated one of the conditions in the constraints – that is, it failed to generate an optimal solution where the sum of the weights was equal to 100%.

Scenario 4: Recalculation of Optimal Stock Mix

This type of scenario reruns the model using the generated optimal stock mix. Table 9 presents the stock selection of the portfolio produced in recalculation using optimal stock mix.

Table 9

Stock Selection for Portfolio with Recalculation of Optimal Stock Mix

Stocks	Weights (%)	Amount (Php)
1. SMPH	15.00%	150,000.00
2. SM	15.00%	150,000.00
3. BDO	15.00%	150,000.00
4. AC	15.00%	150,000.00
5. ALI	15.00%	150,000.00
6. JFC	14.88%	148,800.00
7. MER	10.04%	100,400.00
8. BPI	0.08%	800.00

Table 10 displays the comparison of performance between the portfolio with recalculation using optimal stock mix and benchmark index PSEi.

Table 10

Performance of the Portfolio with Recalculation of Optimal Stock Mix and PSEi

Portfolio	PSEi (Benchmark)	Goal Programming Model
Number of Stocks	30	8
Mean Return (%)	0.0885	0.2353
Excess Return (%)	-	0.1468
Tracking Error (%)	-	2.3750
Information Ratio	-	0.0618

Table 10 shows that the performance of the portfolio with recalculation using optimal stock mix outperformed the performance of the benchmark index since the portfolio mean return at 0.2353% exceeded the benchmark index mean return at 0.0885%. This scenario yielded the same results with the performance of the optimal portfolio. However, this portfolio comprises only of eight (8) stocks, and more stocks are preferred from the optimal portfolio than this scenario.

Portfolio Performance of the Optimal Portfolio. Table 11 displays the comparison of performance between the optimal portfolio of goal programming model, as derived from Section 5.2, and market index.

Table 11

Performance of the Optimal Portfolio of Goal Programming Model and PSEi

Portfolio	PSEi (Benchmark)	Goal Programming Model
Number of Stocks	30	9
Mean Return (%)	0.0885	0.2353
Excess Return (%)	-	0.1468
Tracking Error (%)	-	2.3750
Information Ratio	-	0.0618

As reported in Table 11, the optimal portfolio of goal programming model consists of nine (9) stocks to track the PSEi which comprises thirty (30) stocks. This implies that there is only 30% of PSEi components required to construct the optimal portfolio. The results that were obtained in this study are aligned with the framework presented in the previous chapter. That is, nine (9) stocks are within the recommended range of eight (8) to twenty (20) stocks by Newbould and Poon (1994). The weekly mean return for the PSEi is 0.0885% based on the study period. The weekly mean return for the optimal portfolio of goal programming model is 0.2353% which is higher than the weekly mean return for the PSEi. This implies that the optimal portfolio constructed by the goal programming model is able to outperform the benchmark index PSEi with weekly excess mean return 0.1468% at minimum tracking error of 2.3750%. Besides that, the information ratio 0.0618 indicates that the optimal portfolio can generate weekly excess mean return 0.0618% over the mean return of the PSEi at 1% tracking error. In summary, the optimal portfolio of goal programming model outperformed the benchmark index PSEi because of higher mean return with only 30% of PSEi components.

Conclusion

Goal programming model was used to solve the main objective of this paper, which was to construct a portfolio mix that is able to outperform the benchmark index PSEi. The results of the model output showed positively that the creation of such a portfolio was possible. The study made use of weekly stock price data starting January 2014 until December 2018, all of which were either sourced from the Wall Street Journal or Thomson Reuters Eikon. Goal programming, which has been shown to be a suitable method in portfolio analysis, was then utilized in capturing an optimal stock mix for the weekly stock returns of the specified period. Goal programming has the capability to generate models with multiple goals or objectives. This study focused on two objectives, namely, one is to maximize the portfolio mean return and the other is to minimize the portfolio tracking error. Optimization analysis was performed using the Solver add-in functionalities of Microsoft Excel software. Note that this study works only for small portfolio problems.

The mean-variance theory was used in the optimization process, limiting investor preferences to estimates of risk and return. Investor views on the market were not covered in this study. The constraints for goal programming optimization involved setting the target values for both tracking error and portfolio mean return to particular levels. The computed weights have reflected an optimal portfolio that outperformed the local market index. A sensitivity analysis was also conducted in order to test the robustness of the model. The generated optimal portfolio was then evaluated using the Information Ratio.

As to which stocks from the basket of the Philippine market index constitute the optimal portfolio as far as goal programming is concerned, the optimal stock mix constituted the following company stocks: Ayala Corporation (AC), Ayala Land, Inc. (ALI), Banco De Oro Unibank, Inc. (BDO), Bank of the Philippine Islands (BPI), Jollibee Foods Corporation (JFC), Meralco (MER), SM Investments Corporation (SM), San Miguel Corporation (SMC) and SM Prime Holdings, Inc. (SMPH).

As to the determination of the robustness of the model is concerned, sensitivity analyses were conducted for four (4) different scenarios. The first sensitivity analysis of equal weights comprising of all the stocks in the market index showed lesser excess mean returns than the index itself. The second sensitivity analysis, where no upper bound was imposed, generated an output of only two (2) stocks. The third sensitivity analysis imposed a lower bound constraint for the weights of the stock. This did not yield an optimal solution. The fourth sensitivity analysis involved recalculating of the optimal stock portfolio. It generated a portfolio quite similar to the optimal portfolio mix, but having one less stock in its mix. The results of the search for an optimal portfolio mix using goal programming model generated a portfolio that proved to be robust.

As regards the extent by which the optimal portfolio was able to outperform the benchmark index, the optimal portfolio generated a weekly excess return of 0.1468% at a minimum tracking error of 2.3750% with Information Ratio of 0.0618, consisting of only nine (9) stocks.

Limitations and Recommendations for future research

Note that the basis of this research model stemmed from using previous price data and used the data to find the optimal portfolio as part of its distinctive feature or limitation, and definitely a new optimal portfolio will emerge in the next years. However, the practical usage of the model (or goal programming model) is that researchers can set a target (or forecasted) value of portfolio mean return greater than the index mean return using the most recent historical stock price data available in order to project which stocks investors can possibly put more weights and invest in.

This paper has derived implications on the findings and conclusions to come up with the necessary recommendations about the study. With consideration of the preliminary conclusions, the following recommendations are presented:

- The significance of this study was able to identify and apply the goal programming model as a strategic decision-making tool for the fund managers to effectively track the benchmark index PSEi in the Philippines. Banks or portfolio managers may as well do portfolio rebalancing using the optimal stock mix obtained in this study for further analyses. They may also consider adding a goal or objective function in beating the inflation rate.
- This study will serve as an initial framework and reference for the government and other regulatory bodies, such as GSIS, SSS, Philippine Stock Exchange, etc., in effectively tracking the PSEi and to which company stocks they should allocate more in investing.
- In the papers that were studied, results mainly focused on the application of goal programming models in enhanced index tracking. To those who wish to pursue further

studies on the topic of portfolio optimization, the following problems are recommended to be explored:

a. The study made use of a weighted goal programming approach in addressing the statement of the problem. Consider the problem of making use of other variants of goal programming approach as well.
b. Consider adapting other optimization techniques that can be used to an enhanced index tracking problem.
c. To date, there is no published result yet on adding a goal or objective function to beat the inflation rate. Investigate the use of goal programming approach by adding another objective function or setting another constraint, if any.

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