Arab Journal of Administrative Sciences

2011, Vol. 18, No. 3, 495 - 514

SELECTING PORTFOLIOS BASED ON SHARPE, TREYNOR AND GOAL PROGRAMMING METHODOLOGIES: APPLICATIONS TO MUTUAL FUNDS IN THE UK AND EGYPT

*Mehrdad Tamiz
**Rania A. Azmi
**Dylan Jones

* Kuwait University, Kuwait
** University of Portsmouth, UK

Key Words

Goal Programming; Investment Analysis; Portfolio Selection; Mutual Funds.

Abstract

This paper focuses on the portfolio selection problem facing an investor who is interested to hold a portfolio of mutual funds operating in the UK and Egypt. The article offers three techniques for setting up portfolios of mutual funds (Sharpe, Treynor and Goal Programming). The performance comparison of the selected portfolios reveals that the portfolios constructed based on Sharpe and Goal Programming methodologies have the minimum deviations with each other as well as compared to the relevant benchmarks. Although Sharpe and Treynor methodologies of ranking and selecting best mutual funds are well established, the paper finds Goal Programming methodology performing at least as well as both Sharpe and Treynor methodologies. The paper's results suggest also that the Goal Programming methodology is as practical in crises (the experiment in UK's market) as in regular time (the experiment in Egypt's market).

Introduction and Research Exposition

A prime task of portfolio management is to blend various assets together to provide a portfolio that is best suited to meet the longer term return goals of an investor or a fund at the least risk. By providing liquid, low-cost shares in a diversified portfolio of financial assets selected by professional managers, mutual funds have enabled an increasing number of households to enter financial markets. For example, from 1990 to 2000, total

Submitted November 2010, accepted May 2011.

mutual fund assets increased nearly sevenfold, and the assets of mutual funds that invest in stocks expanded nearly twentyfold (Engen and Lehnert, 2000).

The national association of U.S. investment companies emphasize that mutual funds are the most commonly held type of funds even after the onset of the current crisis. The US mutual fund market, with about $10 trillion in assets under management for 93 million US investors as of year-end 2008 (compared to $13 trillion at year-end 2007), remained the largest in the world, although their net assets fell reflecting the sharp drop in equity prices experienced worldwide in 2008. U.S. mutual funds account for 51% of the $19 trillion in mutual fund assets worldwide, while the European mutual funds account for 33% of the global mutual fund assets (ICI, 2009).

Portfolio Selection issues have been the subject for extensive research since the pioneer article of Markowitz on Portfolio Selection (1952). Markowitz (1991) was the first to quantify the link that exists between portfolio risk and portfolio return. By this, he founded modern portfolio theory. The Markowitz model was the starting point for numerous developments in finance. It contains, in particular, the fundamental elements of the Capital Asset Pricing Model which is the source of the first risk-adjusted performance measures (Treynor, 1965; and Sharpe, 1963, 1964). Treynor (1965), Sharpe (1966), and Jensen (1968) develop the standard indices to measure portfolios' performances, i.e. risk adjusted returns for portfolios.

Normally, performance measurement concentrates on how well a portfolio does both absolute and relative to a benchmark (usually market index). Numerous studies have tested the performance of portfolios, especially mutual funds, using Treynor (1965), Sharpe (1966), and Jensen (1968), performance measures (Raj, Forsyth and Tomini, 2003; Artikis, 2002; Cresson, Cudd and Lipscomb, 2002; Matallin and Nieto, 2002; Otten and Schweitzer, 2002; Zheng, 1999; Daniel *et al.,* 1997; Lehmann and Modest, 1987).

This paper, however, uses these standard performance measures, amongst others methodologies, for selecting portfolios of mutual funds.

In the portfolio selection literature and traditionally a well-respected Markowitz (1952) model and a less complex Sharpe (1967) model are used for portfolio selection problems. Both methods select portfolios either with highest expected return given a certain level of risk, or lowest risk given a certain level of return depending on whether return is maximised or risk is minimised. Using Goal Programming approach, however, return and risk can be optimised simultaneously.

Goal Programming (Charnes *et al.,* 1955) is perhaps the most widely used approach in the field of multiple criteria decision making that enables the decision maker to incorporate numerous variations of constraints and goals. Original Portfolio Selection problem, with risk and return optimisation can be viewed as a Goal Programming with two objectives. Additional objectives representing other factors can be introduced for a more realistic approach to portfolio selection problems.

Ignizio and Romero (2003) highlight that real world decision problems are usually changeable, complex and resist treatment with conventional approaches. Therefore, the optimisation of a single objective subject to a set of rigid constraints is in most cases unrealistic and that is why Goal Programming was introduced, in an attempt to eliminate or at least mitigate this shortcoming.

The two philosophical concepts that serve to best distinguish Goal Programming from conventional methods of optimisation (with single objective) are the incorporation of flexibility in constraint functions and the adherence to the philosophy of Satisficing as oppose to Optimisation. Satisficing is an old Scottish word that defines the desire to find a practical and real world solution to a problem, rather than an idealistic or optimal solution to a highly simplified model of that problem. In Goal Programming, the decision maker usually seeks a useful, practical, implementable and attainable solution rather than one satisfying the mathematician's desire.

This paper therefore, focuses on the portfolio selection problem facing an investor who is interested to hold a portfolio of mutual funds using three suggested methodologies, two of which are based on the traditional measurements of portfolio performance and the third is based on Goal Programming.

The experiments carried out are using data of mutual funds operating in UK, a developed country, or Egypt, an emerging market, assuming that mutual funds are efficient investments in terms of diversification and risk-adjusted returns.

This article is organised in several sections. Following a short overview of research data and time period utilized, a brief description of weighting algorithms for Portfolio Selection is provided as well. A section on constructing portfolios of British mutual funds is provided next, followed by a section on selecting the portfolios of

Egyptian mutual funds. The next section compares the constructed portfolios and the last section provides the main conclusions and future research.

Research Data and its Time Period

This article provides a methodology to select a portfolio of mutual funds in two consecutive time periods. The first period is used for constructing the portfolios and the second period is for performance testing. Two different markets are examined in two different time periods representing both stable and volatile times in relative terms.

In the UK, as well as in most countries (developed and emerging) the deterioration in financial markets began with the onset of the current financial crisis late 2007. The crisis phase of the mid-September to the end-October 2008 had the lion's share of the collapse with most market indices as well as mutual funds rate of returns falling 30% to 40% (Bartram and Bodnar, 2009).

Therefore, for the British mutual funds, 88 weeks of data from June 2007 to January 2009 is used to rank, select and construct portfolios. Subsequently, the period from February 2009 to June 2009 (20 weeks) is used to test and compare constructed portfolios (using FTSE 100 index as the benchmark).

The overall time period selected for the experiment in British mutual funds (from June 2007 to June 2009) includes different phases within the current financial and economic crisis. In particular, BIS (2009) mentions that the current crisis has developed in five distinct stages, starting with the subprime mortgage-related turmoil between June 2007 and mid-March 2008, in which the primary focus was on funding liquidity and bank losses. In the second stage, from March to mid-September 2008, funding problems morphed into concerns about solvency, giving rise to the risk of outright bank failures. One such failure, the demise of Lehman Brothers on 15 September 2008, triggered the third and most intense stage of the crisis, which is a global loss of confidence. Stage four, from late October 2008 to mid-March 2009, witnessed a gloomy global growth outlook amid uncertainties over the effects of ongoing government intervention in markets and the economy. Stage five, beginning in mid-March 2009 until now, has been marked by signs of optimism in the face of still negative macroeconomic and financial news.

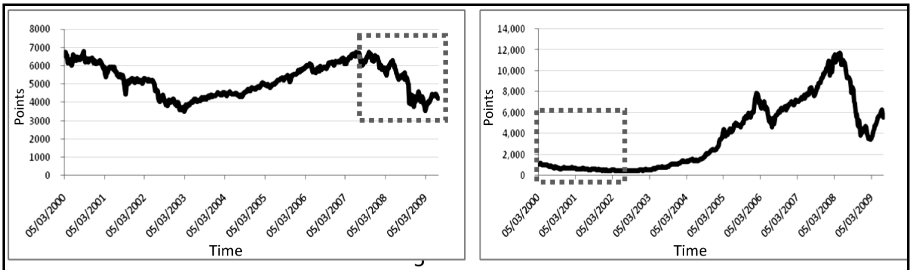
The paper also selects portfolios of Egyptian mutual funds (Tamiz and Azmi, 2009) in which the period from March 2000 to November 2001 is used on a weekly basis (83 weeks) in order to rank, select and construct portfolios, as detailed in the following sections. The subsequent 27-weeks period from December 2001 to June 2002 is then used to test the portfolios in terms of performance, comparison against each other and against the benchmark, EGX 30 index. These time periods were selected for the experimentation to ensure the consistency of the utilized data. In particular, the Central Bank of Egypt (CBE, 2003, 2009) mentions that during this period the activity of the emerging Egyptian financial market improved and the demand for mutual funds accelerated, as well as there was a continuity in trading rules adopted by the Egyptian stock exchange(Azmi, 2005).

The following exhibit illustrates the period covered by the study for both the British market (in a relatively volatile time) and the Egyptian market (in a relatively stable time).

The paper is using 880 observations for the UK's experiment and 1577 observations for Egypt's experiment in the constructing period, while it uses 200 observations in the testing period for the UK's experiments and 513 observations for Egypt's experiments. The specific time periods are used for their suitability and the availability of consistent data, especially for the emerging Egyptian market, where there is usually a lack of data.

Note that at the time of the experiment in Egypt, 19 mutual funds existed in the stock exchange, while 10 mutual funds were selected from the British financial market based on the highest net asset value of index tracking funds and the availability of recent data.

This paper uses the data of return and risk, utilizing various models, to select portfolios. The standard measure of return is applied. However, risk is more challenging and inherently a probabilistic or statistical concept. There are various, and sometimes conflicting, notions and measures of risk. As a result, it can be difficult to measure



The British Stock Exchange Index (FTSE100) | The Egyptian Stock Exchange Index (EGX 30)

Exhibit (1): The stock market performance from March 2000 through June 2009 in England and Egypt (the small boxes highlight this paper's study periods)

the risk of a portfolio and determine how various investments and asset allocations affect that risk (Travers, 2004; Pearson, 2002).

At least to an investor, the risk of historical portfolio is the uncertainty or degree of dispersion in the probability distribution of its future market value (Hymans and Mulligan, 1980).To be able to make decisions, it must be possible to quantify the degree of risk in a particular opportunity. The most common method is to use the standard deviation of the expected returns. This method measures spreads, and it is the possible returns of these spreads that provide the measure of risk.

This paper uses the standard deviation as a measure of risk due to its ease of use and the availability of the underlying data. However, many authors provide analysis of risk measures beyond the standard deviation, such as Artzner *et al.* (1999), Balbas, Balbas and Mayoral (2009) and Rockafellar, Uryasev and Zabarankin (2006):

- For example, Mansini, Ogryczak and Speranza (2007) study linear programs solvable portfolio optimisation models based on extensions of the Conditional Value at Risk (CVaR) measure. The models use multiple CVaR measures thus allowing for more detailed risk aversion modelling.
- Balbas, Balbas and Balbas (2009) discuss the portfolio choice problem and the classical APT and CAPM models when risk levels are given by risk measures beyond the variance.
- Balbas, Balbas and Mayoral (2009) emphasize that modern risk analysis must face two major drawbacks affecting most of the available securities and many investment strategies; namely: asymmetric returns and fat tails.

Weighting Algorithms for Portfolio Selection

Some portfolio selection methods, such as Sharpe and Treynor, identify the desired assets for the portfolio, but not their proportions. The weighting algorithms are therefore developed for finding the proportions of such portfolios' constituents. In these algorithms V_i represents the assigned value to the i^{th} asset and X_i represents its proportion.

Algorithm (1)

Weighting algorithm for values that are all positive is as follows:

$$V_i > 0 = 1, \ldots, n$$

$$X_i = \left[\frac{V_i}{\sum_{i=1}^{n} V_i}\right] \times i = 100\% = 1, \ldots, n$$

Algorithm (2)

Weighting algorithm for values that are all negative is as follows:

$V_i < 0 \qquad i = 1, ..., n$

$$V'_i = \frac{1}{|V_i|}$$

$$X_i = \left[\frac{V'_i}{\sum_{i=1}^{n} V'_i}\right] \times 100\% \qquad i = 1, ..., n$$

Note, this algorithm ensures that the order of importance is preserved (i.e. the larger the value, the higher the weight).

Algorithm (3)

If some of the values are positive while the rest are negative, the proportions can be obtained using either of the following algorithms:

Algorithm (3.1)

$V_i > 0 \qquad i = 1, ..., k$

$V_i < 0 \qquad i = k + 1, ..., n$

$V'_i = V_i i = 1, ..., k$

$V'_i = \frac{1}{|V_i|} i = k + 1, ..., n$

$$X_i = \left[\frac{V'_i}{\sum_{i=1}^{n} V'_i}\right] \times 100\% \quad i = 1, ..., n$$

Algorithm (3.2)

$V_i > 0 \quad i = 1, ..., k V_i < 0 \quad i = k + 1, ..., n$

$$X_i = \left[\frac{V_i + C}{nC + \sum_{i=1}^{n} V_i}\right] \times 100\% \quad i = 1, ..., n$$

Where:

C is a large enough scaling factor that is added to all the values to ensure that they are all positive.

The suggested algorithms are all useful in finding the relevant proportions from any assigned values to portfolio constituents. Such values can be assigned using any financial criteria of relevance to decision makers' aims in selecting their portfolios.

All algorithms are designed to ensure that each constituent's value is assigned a corresponding proportion that reflects its importance or ranking within a portfolio. This is the main advantage of using such weighting algorithms.

In particular, algorithm (1) is beneficial in assigning appropriate proportions in which it can preserve the relative importance of each constituent if their values are positive. If the constituents' values are negative, however, algorithm (1) is no longer useful (especially in preserving the relative importance) and that is why algorithm (2) is introduced. The main advantage of algorithm (2) is that it keeps the relevant constituent rank within a portfolio by assigning the corresponding proportion, even though the constituents' values are all negative. Algorithm (3.1) and (3.2) are both practical in deciding on the proportions form constituent values that include both positive and negative values.

Portfolios of British Mutual Funds

Sharpe: the 10 British mutual funds are ranked based on the Sharpe

Ratio (the higher the ratio, the better is the performance of the corresponding mutual fund).

Sharpe Ratio or the reward to variability ratio, developed by William Sharpe (1966), is the ratio of the realized fund return in excess of the risk-free rate to the variability of return as measured by the standard deviation of return.

The Sharpe Ratio is computed as follows:

$$S_j = \frac{R_j - R_f}{SD_j} \qquad (1)$$

where:

S_j = Sharpe Ratio for the jth Mutual Fund, J = 1,...,10.

R_j = Return on the jth Mutual Fund.

R_f Return on risk-free asset.

SD_j = Standard deviation of the jth Mutual Fund.

The best 5 mutual funds are selected to construct a portfolio of mutual funds, using Algorithm (3.2).

Treynor: the British mutual funds are ranked based on Treynor ratio.

Treynor ratio or the reward to volatility ratio, developed by Jack Treynor (1965), is the realized portfolio return in excess of the risk-free rate, to the volatility of return as measured by the portfolio beta.

The Treynor Ratio is computed as follows:

$$T_j = \frac{R_j - R_f}{\beta_j} \qquad (2)$$

where:

T_j = Treynor Ratio for the jth Mutual Fund, j = 1,...,10.

β_j = Beta Coefficient of the jth Mutual Fund, (measuring mutual fund's systematic risk (Milller, 2002)).

The best 5 mutual funds are selected with the proportions computed as in Algorithm (3.2).

Goal Programming: a multi-objective programming technique, first used in 1955 by Charnes et al., and developed further by Ignizio (1978), Romero (1991), Schniederjans (1995), and Jones and Tamiz(2010).

The original portfolio selection problem involving risk and return analysis can be modelled as a Goal Programming (GP) model with two objectives (Azmi and Tamiz, 2010). This makes GP helpful in achieving the competing goals in constructing funds with multiple objectives. More applications of GP to portfolio selection are provided by Lee and Lerro (1973); Kumar *et al.* (1978); Levaryand Avery (1984); Tamiz *et al.* (1996); Inuiguchiand Ramik (2000); Pendaraki *et al.* (2005); Gladish *et al.* (2007); and Wu *et al.* (2007).

The Goal Programming methodology based on the Mean-Absolute Deviation model as proposed by Konno and Yamazaki (1991) is used to select an index tracking portfolio of the available mutual funds as follows:

$$Min \sum_{t=1}^{88} (n_T + P_T) \qquad (3)$$

Subject to:

$$\sum_{j=1}^{10} (n_{jt} - I_T) X_j + n_t - p_t = 0 \quad t = 1, ..., 88 \qquad (4)$$

$$\sum_{j=1}^{10} X_j = 1 \qquad (5)$$

$X_j \geq 0 \quad j = 1, ..., 10 \quad n_t, p_t \geq 0 \quad t = 1, ..., 88$

where:

$R_{jt} =$ Return of the j^{th} mutual fund during period t.

$I_t =$ Return on FTSE 100 during period t.

$X_j =$ The proportion of the j^{th} mutual fund selected.

$n_t =$ The negative deviational variable for period t.

$p_t =$ The positive deviational variable for period t.

This model ensures that the sum of deviations from the benchmark (index) is minimised.

All positive and negative deviational variables are penalised in the achievement function (3) with equal weights. The model contains 88 objective functions (4) belonging to the 88 time periods. The target value of zero for each objective function indicates that the difference between the index's performance and the portfolio's performance for each period should be the same as an index tracking portfolio is sought. Constraint (5) ensures that the entire available fund is invested in the portfolio. Note that the normalization techniques described in Tamiz and Jones (1997) are not used for the GP model in this paper as all the objectives in (4) are measured with the same unit of measurement.

Note, in this GP model, the deviations from the portfolio returns for all the 88 periods are all given weight of 1 and hence treated the same. If, however, a decision maker wishes to give higher weights to more recent returns, then he/she can replace the achievement function (3) with the following one, say:

$$Min \sum_{t=1}^{88} \frac{t(n_t + p_t)}{88}$$

Where more recent returns have (relatively) higher weights indicating that the decision maker is more concerned with more recent data.

Exhibit (2): Sharpe's, Treynor's and GP's Constructed British Portfolios

Sharpe		Treynor		GP	
Portfolio constituents	Proportions	Portfolio constituents	Proportions	Portfolio constituents	Proportions
HE	21.1%	AR	27.1%	AR	35.0%
AR	20.4%	JP	28.3%	GA	35.0%
SU	19.8%	AN	22.1%	AI	15.4%
JP	19.5%	II	22.2%	JP	12.4%
AN	19.2%	SU	0.30%	FI	2.20%
Total	100%	Total	100%	Total	100%

The following exhibit shows the selected mutual funds in the three portfolios:

Portfolios of Egyptian Mutual Funds

19 mutual funds in the Egyptian stock exchange are ranked based on the Sharpe and Treynor ratios using (1) and (2).

A similar GP model (as in (3), (4) and (5)) is used to set up a portfolio of top 5 Egyptian mutual funds.

The following exhibit shows the selected mutual funds in the three portfolios:

Comparisons between the Selected Portfolios

The three portfolios of the British mutual funds are examined in terms of their returns during the testing period from February2009 to June 2009 (20 weeks).

The following exhibit depicts the returns on Sharpe, Treynor and GP portfolios:

The deviations between the constructed portfolios, the sum of the absolute return deviations, are calculated as follows:

Exhibit (3): Sharpe's, Treynor's and GP's Constructed Egyptian Portfolios

Sharpe		Treynor		GP	
Portfolio constituents	Proportions	Portfolio constituents	Proportions	Portfolio constituents	Proportions
MI	15.5%	MR	28.2%	EA	35.0%
EG	20.8%	ED	8.20%	AE	34.2%
N1	17.9%	N1	21.0%	BA	17.2%
AE	22.6%	MI	18.2%	ED	8.00%
BC	23.2%	EG	24.4%	S1	5.60%
Total	100%	Total	100%	Total	100%

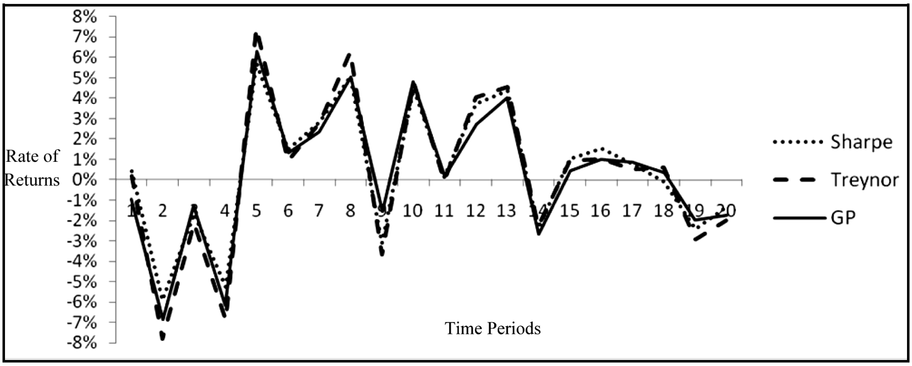


Exhibit (4): The returns of the constructed British portfolios

$$\sum_{t=1}^{20} |RS_t - RT_t| = 0.1214$$

$$\sum_{t=1}^{20} |RS_t - RGP_t| = 0.1094$$

$$\sum_{t=1}^{20} |RT_t - RGP_t| = 0.1381$$

where:

$RS_t =$ Return on Sharp's portfolio.

$RT_t =$ Return on Treynor's portfolio.

$RGP_t =$ Return on GP's portfolio.

Accordingly, the least deviation is between Sharpe's portfolio and GP's portfolio, whereas the maximum deviation is between Treynor's and GP's portfolios.

The three portfolios are further compared to the benchmark as follows:

The tracking error, which measures the deviation of the portfolio's return compared to the market return, is calculated for the constructed portfolios as follows:

$$\sum_{t=1}^{20} |RS_t - RBM_t| = 0.2177$$

$$\sum_{t=1}^{20} |RT_t - RBM_t| = 0.2308$$

$$\sum_{t=1}^{20} |RGP_t - RBM_t| = 0.1487$$

where:

$RBM_t =$ Return on the benchmark.

Accordingly, the best portfolio, relative to the benchmark, is the portfolio constructed based on GP methodology, followed by the portfolio constructed based on Sharpe's methodology.

Likewise, the three portfolios of the Egyptian mutual funds are examined in terms of their returns during the testing period from December 2001 to June 2002 (27 weekly returns).

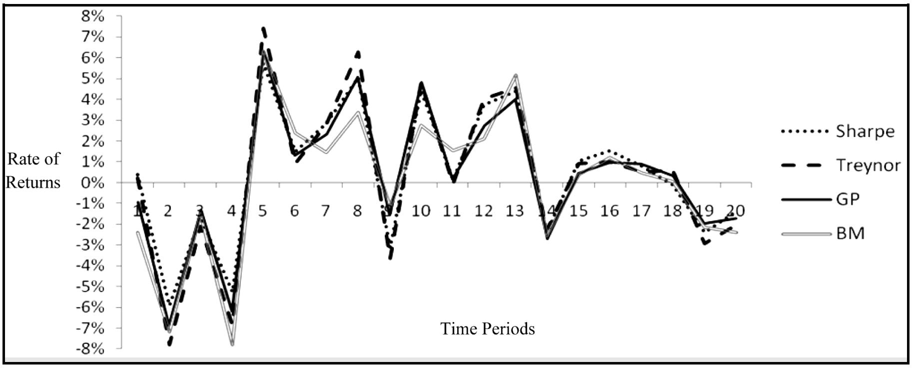


Exhibit (5): The returns of the constructed British portfolios vs. British financial market benchmark

The following exhibit depicts the returns on Sharpe, Treynor and GP portfolios:

The sum of the absolute return deviations between the constructed portfolios are calculated as follows:

$$\sum_{t=1}^{27} |RPS_t - RPT_t| = 0.0678$$

$$\sum_{t=1}^{27} |RPS_t - RPGP_t| = 0.0604$$

$$\sum_{t=1}^{27} |RPT_t - RPGP_t| = 0.0758$$

Accordingly, the least deviation is between Sharpe's portfolio and GP's portfolio, whereas the maximum deviation is between Treynor's and GP's portfolios.

The three portfolios are further compared to the benchmark as follows:

The tracking error is calculated as follows for the three portfolios each compared to the benchmark:

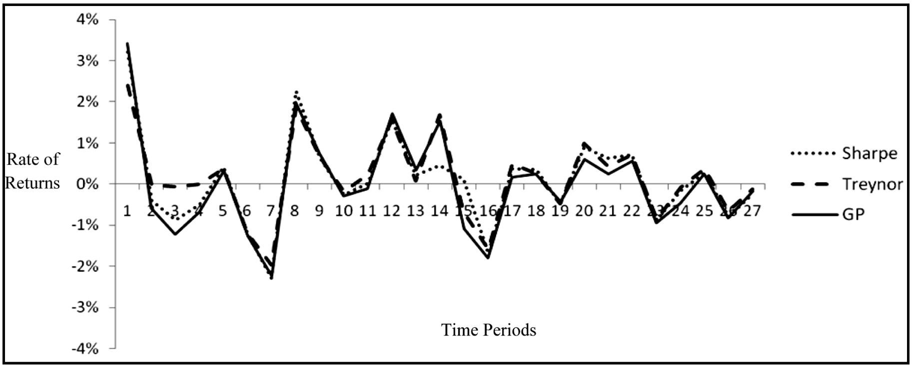


Exhibit (6): The returns of the constructed Egyptian portfolios

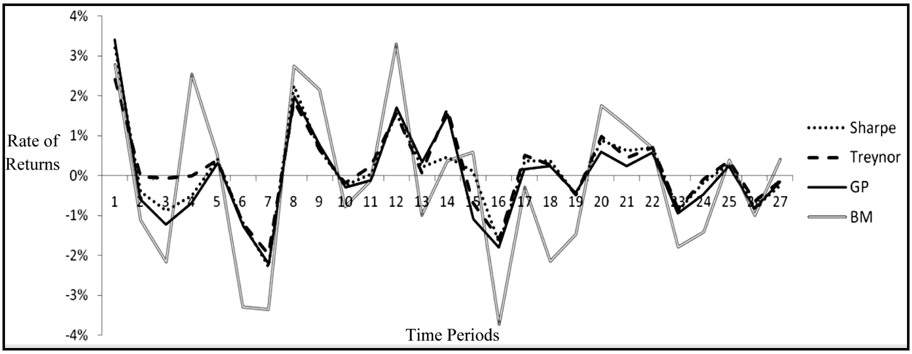


Exhibit (7): The returns of the constructed Egyptian portfolios vs. Egyptian financial market benchmark

$$\sum_{t=1}^{27} |RS_t - RBM_t| = 0.2579$$

$$\sum_{t=1}^{27} |RT_t - RBM_t| = 0.2956$$

$$\sum_{t=1}^{27} |RGP_t - RBM_t| = 0.2788$$

Accordingly, the best portfolio is the portfolio constructed based on Sharpe's ranking, followed by the portfolio constructed based on GP methodology.

Conclusions and Further Research

A selection of portfolios of mutual funds both in the UK, a developed market, and in Egypt, an emerging market, have shown interesting results. This paper offers three techniques for setting up portfolios of mutual funds. The performance comparison of the selected portfolios reveals that the portfolios constructed based on Sharpe and GP methodologies have the minimum deviations with each other as well as compared to the relevant benchmarks. Although Sharpe and Treynor methodologies of ranking and selecting best mutual funds are well established historically, the paper finds GP methodology performing at least as well as both Sharpe and Treynor methodologies.

The results from the paper also suggest that the GP methodology is as practical in crisis period (the experiment in UK's financial market recently) as in regular time (the experiment in Egypt's financial market nearly seven years ago). One of the reasons behind this success is the fact that GP has an underlying satisficing philosophy, which is intuitively more appealing to many portfolio selection problems. This result is critical as the spread of the credit crisis has challenged many of the key cornerstones of modern finance including the assumption of efficient markets and market allocations of risk.

There are two interesting results concerning the mutual funds studied and their benchmarks. First, the Egyptian benchmark (0.02) is less in variability (measured by the standard deviation) compared to the British benchmark (0.04). This is somewhat expected since the data gathered for the British experiment was during a volatile time. Second, the deviation of the portfolio of the British mutual funds from its benchmark is much less than the Egyptian mutual funds' portfolio deviation from its benchmark. In other words, the British mutual funds portfolio seems to perform better than the Egyptian mutual funds portfolio relative to their respective benchmarks. This in part is due to the fact that the British mutual funds are index-trackers, whereas, the Egyptian mutual funds are not clearly classified as index-trackers, or otherwise, in the Egyptian stock exchange.

In terms of further and future research, it would be interesting to use the same techniques in different markets as well as different time periods with extending the experiment to include not only mutual funds but also other market financial instruments such as stocks, bonds, moneymarkets funds, etc.

Furthermore, the GP model used in this paper contains the two traditional objectives of any portfolio, namely risk and return. Therefore, it would be interesting to explore other types of objectives or to add more objectives such as liquidity, sectors/regional preferences or turnover. The experiments can be repeated with the new GP model for same or different time periods and markets for mutual funds or any other investment instrument.

Acknowledgment

The authors would like to thank the anonymous referees for the insightful comments, which stimulated further useful discussions.

Appendix (A)
The complete list of the British and the Egyptian mutual funds used in the study

The British Mutual Funds				The Egyptian Mutual Funds			
No.	MF Abbreviation	Mutual Fund Name	Average Return	No.	MF Abbreviation	Mutual Fund Name	Average Return
1	AI	Aberdeen Income Fund ICVC- Alpha Income Fund	-0.005	1	AE	American Express Bank I MF	-0.005
2	AR	Allianz RCM UK Equity Fund	-0.004	2	AM	Arab Misr Insurance Group MF	-0.014
				3	BA	Bank of Alexandria MF	-0.006
3	AN	Aviva Investors UK Growth & Value Fund	-0.005	4	BC	Banque du Caire MF	-0.004
				5	B1	BanqueMisrI MF	-0.006
4	FC	F&C Investment Funds ICVC -UK Opportunities Fund	-0.006	6	B2	BanqueMisrII MF	-0.008
				7	DM	Delta Mutual Fund	-0.006
5	FI	Fidelity Investment Funds ICVC- Special Situations Fund	-0.004	8	EA	Egyptian American Bank MF	-0.006
				9	EG	Egyptian Gulf Bank MF	-0.005
6	GA	GAM Funds- UK Diversified Fund	-0.005	10	ED	Export Development Bank MF	-0.012
				11	ME	Misr Exterior Bank MF	0.138
7	HE	Henderson UK & Europe Funds- UK Opportunities Fund	-0.009	12	MI	Misr International Bank MF	-0.010
				13	MR	Misr Iran Development Bank MF	-0.006
8	II	Insight Investment Discretionary Funds ICVC- UK Equity Fund	-0.005	14	N1	National Bank of Egypt I MF	-0.008
				15	N2	National Bank of Egypt II MF	-0.009
9	JP	JPM Life Ltd- UK Disciplined (350) Equity Fund	-0.004	16	OT	Orient Trust Mutual Fund	0.002
				17	S1	Societe Arab Int'l BanqueI MF	-0.009
10	SU	Skandia UK Best Ideas Fund	-0.007	18	S2	Societe Arab Int'l BanqueII MF	-0.003
				19	SC	Suez Canal Bank MF	-0.005

References

Artzner, P.,Delbaen, F.,Eber, J-M. and Heath, D. 1999. Coherent Measures of Risk. *Mathematical Finance,* 9: 203-228.

Azmi,R.2005. *Analytical Study of the Egyptian Mutual Funds Performance and its Determinants*. Master's thesis, Alexandria University, Alexandria.

Azmi,R., Tamiz, M. 2010. A Review of Goal Programming for Portfolio Selection. In: D. Jones et al. (Eds). New Developments in Multiple Objective and Goal Programming, Lecture Notes in Economics and Mathematical Systems 638, Springer-Verlag Berlin Heidelberg: 15-33.

Balbas, A., Balbas, B., and Balbas, R. 2009. CAPM and APT Like Models with Risk Measures,Technical Report, 1 (09): 1-32.

Balbas, A., Balbas, R. and Mayoral, S. 2009. Portfolio Choice and Optimal Hedging with General Risk Functions: A Simplex-Like Algorithm, *European Journal of Operational Research,* 192: 603-620.

Bartram,S., Bodnar, G. 2009. No Place to Hide: The Global Crisis in Equity Markets in 2008/2009.*Journal of International Money and Finance,* 28: 1-69.

BIS. 2009. *The Global Financial Crisis.BIS 79th Annual Report*. Bank for International Settlements,June:16-36.

CBE. 2003. *Economic Review.Research, Development and Publishing Sector,* Central Bank of Egypt, 43:1-232.

CBE. 2009. *Economic Review. Research, Development and Publishing Sector,* Central Bank of Egypt,49:1-146.

Charnes, A., Cooper, W., Ferguson,R. 1955. Optimal Estimation of Executive Compensation by Linear Programming. *Journal of Management Science,*1:138-151.

Engen,E., Lehnert, A.2000. *Mutual Funds and the U.S. Equity Market*. Federal Reserve Bulletin,797-812.

Gladish, B., Jones,D., Tamiz, M. and Terol, B.2007. An Interactive Three-Stage Model for Mutual Funds Portfolio Selection.*The International Journal of Management Science,* OMEGA, 35: 75-88.

ICI. 2009. *Investment Company Fact Book: A Review of Trends and Activity in the Investment Company Industry*. Investment Company Institute, http://www.icifactbook.org, 49: 1- 208.

Ignizio, J. 1978.A Review of Goal Programming: A Tool for Multiobjective Analysis. *The Journal of the Operational Research Society,*29: 1109-1119.

Ignizio, J. and Romero, C. 2003. *Goal Programming. In: Bidgoli, H (Ed.), Encyclopedia of Information Systems,* Academic Press, San Diego, 2: 489-500.

Inuiguchi, M. and Ramik J. 2000. Possibilistic Linear Programming: A Brief Review of Fuzzy Mathematical Programming and a Comparison with Stochastic Programming in Portfolio Selection Problem. *Journal of Fuzzy Sets and Systems,* 111:3-28.

Jensen, M. 1968. The Performance of Mutual Funds in the Period 1945-1964. *The Journal of Finance,*23:389-416.

Jones, D. and Tamiz, M.2010. *Practical Goal Programming*. Springer Books.

Konno, H. and Yamazaki,H. 1991. Mean-Absolute Deviation Portfolio Optimization and its Applications to Tokyo Stock Market. *Management Science,* 37:519-531.

Kumar, P., Philippatos, G. and Ezzell, J. 1978. Goal Programming and Selection of Portfolio by Dual-Purpose Funds. The Journal of Finance, 33: 303-310.

Lee, S., and Lerro, A. 1973. Optimizing the Portfolio Selection for Mutual Funds. *Journal of Finance,* 28: 1086-1101.

Levary, R. and Avery, M. 1984. On the Practical Application of Weighting Equities in a Portfolio via Goal Programming. *Opserach,* 21: 246-261.

Markowitz,H.1952. Portfolio Selection. *The Journal of Finance,* 7:77-91.

Markowitz, H. 1991. Foundations of Portfolio Theory. *The Journal of Finance,* 46: 469-477.

Miller,E. 2002. Why the Low Returns to Beta and Other Forms of Risk. *The Journal of Portfolio Management, Institutional Investor,* Winter: 40-55.

Pendaraki. K, Zopounidis, C.and Doumpos, M. 2005. On the Construction of Mutual Fund Portfolios: A Multicriteria Methodology and an Application to the Greek Market of Equity Mutual Funds. *European Journal of Operational Research,*163:462-481.

Romero,C.1991. *Handbook of Critical Issues in Goal Programming*. Pergamon Press.

Schniederjans, M. 1995. *Goal Programming: Methodology and Applications*. Springer.

Sharpe, W. 1963. A Simplified Model for Portfolio Analysis". *Management Science,* January: 277-293.

Sharpe, W. 1964. Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk, *The Journal of finance,* 19: 425-442.

Sharpe,W. 1966. Mutual Fund Performance. *Journal of Business,* 39:119-138.

Sharpe,W.1967. Portfolio Analysis. *The Journal of Financial and Quantitative Analysis,* 2: 76-84.

Tamiz, M., Hasham, R. and Jones D. 1996. A *Two Staged Goal Programming Model for Portfolio Selection*. Lecture Notes in Economics & Mathematical Systems; Springer, 432:286-299.

Tamiz,M. and Jones,D. 1997. *An Example of Good Modelling Practice in Goal Programming: Means for Overcoming Incommensurability*. Lecture Notes in Economics and Mathematical Systems; Springer, 455:29-37.

Tamiz,M. and Azmi, R. 2009. *Mutual Funds Portfolio Selection for Emerging Market: The Case for Egypt,* paper presented at the 3rd International Workshop on Multi-Attribute Methods in Finance & Insurance, Madrid, April 23.

Treynor, J. 1965. How to Rate Management of Investment Funds. *Harvard Business Review,*43:63-73.

Wu, L-C., Chou,S-C., Yang, C-C. and Ong, C-S. 2007. Enhanced Index Investing Based on Goal Programming: Includes Passive Management of a Small Number of Stocks. *The Journal of Portfolio Management,* Spring:49-56.

الملخص

اختيار المحافظ الاستثمارية استناداً على منهجيات «شارب» و«ترينور» و«برمجة الأهداف» بالتطبيق على صناديق الاستثمار في المملكة المتحدة ومصر

ديلن جونز	رانية أحمد عزمي	مهرداد تميز
جامعة بورتسميث	جامعة بورتسميث	جامعة الكويت

يركز البحث على مسألة اختيار المحفظة الاستثمارية التي تواجه أي مستثمر معنيٍّ بالاستثمار في محفظة تتكون من صناديق استثمارية تعمل في كل من المملكة المتحدة ومصر. ويقوم البحث بتناول ثلاثة أساليب لتكوين محافظ الصناديق الاستثمارية (شارب وترينور وبرمجة الأهداف). وتوضح مقارنة الأداء للمحافظ الاستثمارية التي يتم اختيارها وفق تلك الأساليب أن المحافظ المعتمدة على أسلوبي شارب وبرمجة الأهداف لا تختلف كثيراً في أدائها عند مقارنة بعضها ببعض وكذلك عند مقارنتها بالمؤشر ذي الصلة بها. وبرغم أن منهجيتي شارب وترينور في تصنيف واختيار أفضل صناديق الاستثمار تعدان من المنهجيات الشهيرة في هذا المجال، فإن خلاصة هذا البحث تشير إلى أن أسلوب برمجة الأهداف يحقق أيضاً نتائج مفضلة. وترجح نتائج هذا البحث أيضاً أن منهجية برمجة الأهداف تعد منهجية عملية في كل من أوقات الأزمات (التجربة في سوق المملكة المتحدة) والأوقات العادية (التجربة في سوق مصر).

MehrdadTamiz has a Ph.D. from Brunel University (1986) in the UK. He is a Professor of Operational Research in the Department of Quantitative Methods and Information Systems, College of Business Administration, Kuwait University. His Research Interests include single and multi-objective analysis of real-life problems, portfolio selection and analysis, logistics and supply chain management.

Rania Azmi has a Ph.D. from University of Portsmouth. She is a member of the American Finance Association and the American Mathematical Society. In 2009, she was awarded the Google prize for the 'most interesting and creative work'. Her research interests include: portfolio selection, goal programming, multiple objectives optimization and investment decision making.

Dylan Jones has Ph.D. from University of Portsmouth (1995) in the UK. He is a Principal Lecturer in the Mathematics Department, University of Portsmouth. His research interests include linear programming, multi-objective and goal programming, compromise programming, modeling techniques for real world applications, multi-criteria decision analysis, preference modeling, genetic algorithms and heuristic techniques.