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EFFECTIVENESS OF THE EXTENDED MEAN-VARIANCE MODEL USING FUZZY APPROACH FOR PORTFOLIO SELECTION IN MALAYSIAN STOCK MARKET

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Abstract

Purpose of the study is to investigate the effectiveness of the extended mean-variance model using fuzzy approach in maximizing portfolio diversification benefit in the Malaysian stock market. 10 types of portfolios involving 300 listed companies in Bursa Malaysia from 1998 to 2009 were used as a sample for the extended model testing. Linear programming optimization tool was used to derive efficient portfolios. Portfolio superiority then been measured by using the efficient frontier index (EFI). Empirical evidence revealed that the extended mean-variance model is able to maximize portfolio's diversification benefit in the Malaysian stock market compared to the conventional mean-variance and the VBS fuzzy models. The result provides on how the Malaysian investors could improve on their investment strategy. This study is perhaps one of the first to address portfolio diversification benefit using the extended mean-variance model in the Malaysian stock market.

Keywords: portfolio, mean-variance, efficient frontier, fuzzy, Malaysia.

Introduction

Fluctuation in stock market is unpredictable and it is random in nature. Therefore investors need to be very cautious in monitoring stock market movement. The past Asean economic crisis in 1997-1998 and the resent sub-prime problem in the USA and Europe in 2008-2009 have caused great loss to the public investors. One of the strategies to overcome the uncertainty in investment is by investing in form of portfolio. By having a right combination of asset and correct asset allocation, investors can diversify away the element of unsystematic risk in the investment. Therefore, unit trust investments become one of good alternatives for investment due to satisfied diversification offered.

Unfortunately, many of previous studies have shown that the unit trust performance is not as good as expected. Many of them are unable to outperform market benchmarks. Zulkifli and Roslim (2004) Fauziah and Mansor (2007) in their study in 1998-2006 found that, generally the Malaysian unit trust performance is underperformed the market benchmark. Studies in other countries also show the same trends. Pioneer paper by Sharpe (1966) found that in the USA market, only 32% of the mutual funds outperformed the DJIA, he also conclude that the past performance of the funds was not the best predictor of future performance. Other finding by Jensen (1968) has strengthen about the funds performance over time when he concluded that after taken into consideration the operating expenses of a mutual fund, on average the mutual funds could not beat a buy-and-hold strategy. As a result, the portfolio selection strategy and model should be improved further.

Therefore, fund managers and public investors are really needed for a robust model that is able to overcome the uncertainty in investing and maximize the portfolio's diversification benefit.

Previous literatures show that the fuzzy mathematic approach is a best tool to model the uncertainty data. The approach has been widely applied in engineering, computing, biology engineering and management sciences. Studies by Zhang, Zhang and Nie (2003), , Wang, Lee and Tzeng (2005), Bilbao-Terol, Perez-Gladish and Antomil-Ibias (2006), Vercher, Bermudez and Segura (2007), Lin and Liu (2008), Zulkifli, Daud and Omar (2008) and Li and Xu (2009) shows that the fuzzy approach also applicable in portfolio selection.

Scholars in previous literature had introduced and discussed various type of fuzzy portfolio selection models and approaches, every of them have its own advantages and weaknesses, but none of them have discussed about the model effectiveness in deriving portfolio diversification benefit. Therefore, the paper objective is to investigate the effectiveness of the fuzzy mathematical approach in deriving portfolio diversification benefit especially in the Malaysian stock market. As conformity, the portfolio performances were compared to the conventional mean-variance and the Vercher, Bermudex and Segura (2007) fuzzy model (VBS fuzzy model). The finding was supported by empirical evidence.

Literature Review

Portfolio selection issue continuously gaining an interest among scholars. H. Markowitz (1952) has initiated significant contribution to the finance body of knowledge when he introduced the mean-variance model which is become foundation to the modern portfolio theory (MPT). Markowitz idea on the mean-variance approach then being expended by Sharpe (1966), Mossin (1966) and Lintner (1965). The modern portfolio theory then evolved to Capital Asset Pricing Theory when risk free rate asset was included into the portfolio and then evolved to Arbitrage Pricing Theory as discussed by Reilly and Brown (2000).

General objectives of portfolio management are to diversify away the investment diversifiable portfolio risk and to maximize the portfolio return. By having the right combination of assets, these objectives can be achieved. Markowitz's mean-variance model has incorporated the asset return and co-variance factors as main contributors to the portfolio risk. Variance measures the volatility of asset return form the average of rate of return for both negative and positive return. By using H. M. Markowitz (1991) model, it revealed that the portfolio variance can be minimized by having weak or negative assets correlation in the portfolio. Since then, the model was well accepted by investors and fund managers that aimed to construct an efficient portfolio with the highest diversification benefit.

Portfolio diversification was influenced by many factors that govern the portfolio selection criteria such as the firm sizes, financial ratios, stock markets and investor's judgment. All these factors will be discussed below. Reinganum (1981) has conducted a study on abnormal return in small firm portfolio in the New York Stock Exchange (NYSE) and American Stock Exchange (AMEX). He had ranked the firm's market value and divided it into 10 equally weighted portfolios. The risk-adjusted returns for extended periods of 10 to 15 years have indicated that the small firms consistently superior than the larger firm. He has claimed that the firm size is more dominance than PE ratio in influencing the portfolio performance as reported by Basu (1977). Subsequently, Basu (1983) reexamined Reinganum (1981) works for different study period and different portfolio construction methods and found that the small and low PE ratio portfolios have highest risk-adjusted returns. In Malaysian case, Sazali et.al (2004) has evidenced that for long term, the Malaysian domestic-small firm's portfolio provided the highest diversification benefit compared to other portfolio classification such as domestic-large firms, international-developed and developing countries portfolio. The results suggested that in the long term, there are smaller stocks on the Bursa Malaysia which are correlated at the low values with each other as compared to assets of international portfolios or a portfolio of larger stocks on the exchange.Besides the assessment of portfolio's efficiency, diversification also can be achieved by having appropriate number of asset. According to Tang (2004) portfolio diversification also can be achieved by having sufficient number of assets in the portfolio. Previous studies show that the numbers of required asset are varied. It ranged from 10 to 40 assets. Statman (1987) and Evans and Archer (1968) have proposed that the appropriate numbers of assets in a portfolio are between 10 to 15 or less than 40 respectively. Additionally, finding by Solnik (1974) showed that the asset number is around 20 assets for the US stocks and international portfolios. In Malaysian stock market, Zulkifli, Basarudin, Norzaidi and Siong (2008) revealed that 15 stocks are sufficient to diversify away the diversifiable risk in the Malaysian stock market.

A study by Solnik (1974) noted that international diversification is more dominant than inter-industry diversification. To encounter this view, Cavaglia, Brightman and Aked (2000) had investigated the importance of industry diversification beside of inter country diversification. 21 developed equity markets and various industries covered the period December 1985 through November 1999. They presented evidence that industry factors have been growing in relative importance and may now dominate country factors. Furthermore, their evidence suggests that, diversification across global industries has provided greater risk reduction than diversification by countries. They concluded that industry allocation is an increasingly important consideration for active managers of global equity portfolios and those investors may wish to reconsider home-biased equity allocation policies.

In the context of globalization, international markets have turn out to be more open, leading to a common perception that global capital markets have grow to be more integrated. This integration resulting higher correlation would imply about the diversification potential across countries. Therefore, international diversification becomes more common to investors. Previous studies show that there are diversification benefits in international markets as well as in domestic market. Solnik (1974), Santis and Gerard (1997), Lewis (2006), Driessen and Laeven (2007) had confirmed this matter.

Study on the fuzzy mathematic modeling in portfolio selection was conducted by Ehrgott, Klamroth and Schwehm (2004) who has proposed a Multi Criteria Decision Making (MCDM) approach to solve portfolio selection problem. They had adopted 5 criteria's for stock selection purpose namely a 12 month LIBOR performance, 3 month t-bill rate performance, annual fund revenue, SandP fund ranking and return volatility. Genetic algorithm approach was used to solve the portfolio optimization process. They revealed that the model was able to provide portfolio selection in relevant size quickly. Huang (2007) has proposed two fuzzy mean-semivariance models in maximizing investment return and minimizing risk. Asset return was defined as a fuzzy number in triangular membership form. He has adopted genetic algorithm as a tool for portfolio optimization. As a result the model also successfully derived efficient portfolio with appropriate asset allocation. Both studies lucratively introduced a new model and deliver appropriate asset selection, unfortunately none of it provides model effectiveness in deriving portfolio diversification benefit.

In conclusion, asset selection and asset allocation are very important in constructing a portfolio. Regardless either the portfolio is having different asset criteria, market or industry. A rigorous portfolio model not only able to do asset selection and asset allocation, but also must be efficient in maximizing portfolio diversification benefit. To fill the gap, therefore, in the study we have investigated the effectiveness of the fuzzy mathematic modeling in maximizing portfolio diversification benefit.

Research Method

Fuzzy portfolio model derivation can be based on many factors depends on the scope of the study. For example, Vercher et.al(2007) has defined asset return data as a fuzzy number, otherwise Bilbao, Arenas, Rodriguez and Antomil (2007) have defined asset beta value as a fuzzy number and Fatma and Mehmet (2005) had used asset financial ratios data as a fuzzy number that being used in analysis. All the approaches have it own strength and weaknesses.

The paper focused on the portfolio selections based on the extended mean-variance model using fuzzy mathematic approach. As a controlling measure, we have compared the extended model performance to the conventional mean-variance (Markowitz, 1952) and the VBS fuzzy models (Vercher et.al, 2007) performance.

Initial model on portfolio selection was introduced by H. Markowitz (1952). In his model, Markowitz has incorporated the covariance into the model which explained that the pairs of asset correlation are very important in determining the portfolio risk. The Markowitz MV model also assumed that the asset return is normally distributed and investors are trying to maximize their return and minimize the risk as they are risk averse. The MV model is presented as below.

$$\begin{aligned} &Minimize : \sigma_P^2 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_i . w_j . Cov_{i,j} \\ &Subject\ to : R_P \geq \sum_{i=1}^{n} w_i . r_i \\ &\sum_{i=1}^{n} w_i = 1, \quad w_i \geq 0 \end{aligned} \tag{1}$$

where R_P is a portfolio return.
σ^2_P is a portfolio risk.
w_i is investment weighted in each asset i.
r_i is asset i average rate of return.
$Cov_{i,j}$ is a co-variance between asset i and j.
n is a number of asset in the portfolio.

The mean-variance model is well accepted in the industry due to it pioneer and simplicity in application even though it has several weaknesses such as limitation of variance and normality assumption. Vercher et al. (2007) has introduced a new version of the portfolio selection model (VBS fuzzy model) when they replace the variance with semi-variance as a risk measure. The asset return was defined as a fuzzy number since it changes is unpredictable and uncertain in nature. The VBS fuzzy model is has fulfilled all the fuzzy mathematical lemmas and propositions. The utilization of semi-variance as a risk measure in fuzzy number environment has created a new dimension for investor since it is able to represent investor's real situation in investing. The VBS fuzzy model is as below:

$$\begin{aligned} &Min\ \sigma_{FP}^2 = \sum_{i=1}^{n}\left(a_{u,i} - a_{l,i} + \tfrac{1}{2}(c_i - d_i)\right).w_i \\ &Subject\ to : Max\ R_{FP} = \sum_{i=1}^{n}[(\tfrac{1}{2})(a_{u,i} + a_{l,i}) + (\tfrac{1}{4})(d_i - c_i)].w_i \\ &\sum_{i=1}^{n} w_i = 1, \quad \forall w_i \geq 0. \end{aligned} \tag{2}$$

Where $a_{u,i}$ is asset *i*th return at 60th percentile.
$a_{l,i}$ is asset *i*th return at 40th percentile.
c_i is asset *i*th return spread between 40th percentile and 5th percentile.
d_i is asset *i*th return spread between 95th percentile and 60th percentile.
w_i is an investment weight imposed in asset *i*th.
σ^2_P is a fuzzy portfolio risk.
R_{FP} is a fuzzy portfolio return.
n is number of asset in the fuzzy portfolio.

In the model, the asset return set, ($a_{u,i}$ $a_{l,i}$ c_i d_i) was defined as a fuzzy number. The asset return set data were derived based on the percentile of the asset return in the asset return data distribution. The $a_{u,i}$ is an asset *i*th return at 60th percentile, $a_{l,i}$ is an asset *i*th return at 40th percentile. While the c_i is an asset *i*th return spread between 40th percentile and 5th percentile and lastly the d_i is asset *i*th return spread between 95th percentile and 60th percentile.

Adopting this approach, the expected asset returns were correctly determined based on the actual data distribution. As a result, Vercher et.al model is able to solve normality problem in the conventional mean-variance model and used semi-variance as a risk measure. The extended mean-variance model (extended MV) is developed by extending the Markowith (1952) model using fuzzy mathematic approach in defining asset rate of return. In the paper, we had adapted the idea of expected fuzzy return in the Vercher et.al (2007) model into the mean-variance model. In Vercher et.al (2007), the asset return was defined as a fuzzy number. They had used the asset rate of return distribution at 5th, 40th, 60th and 95th percentile as source of information for the fuzzy number as discussed above. Originally, in the mean-variance model, the expected asset return was derived by using the average rate of return of the asset and the asset return was assumed normally distributed. When we used the fuzzy return as a source of information to determine the expected asset return, actually it has adopted the actual asset return distribution. Therefore, this adaptation is able to solve part of the normality problem in the mean-variance model and maintained the important of asset co-variance in portfolio selection. The extended mean-variance model is as below:

$$\begin{aligned} & Minimize: \sigma_P^2 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_i.w_j.Cov_{i,j} \\ & Subject\ to: R_P \geq \sum w_i.[\tfrac{1}{2}.(a_{ui}+a_{li})+\tfrac{1}{4}.(d_i-c_i)] \qquad (3) \\ & \sum_{i=1}^{n} w_i = 1, \quad w_i \geq 0 \end{aligned}$$

where R_P is a portfolio return.
σ^2_P is a portfolio risk.
w_i is investment weighted in each asset i.
r_i is asset i rate of return.
$Cov_{i,j}$ is a co-variance between asset i and j.
n is a number of asset in the portfolio.
$a_{u,i}$ is asset *i*th return at 60th percentile.
$a_{l,i}$ is asset *i*th return at 40th percentile.
c_i is asset *i*th return spread between 40th percentile and 5th percentile.
d_i is asset *i*th return spread between 95th percentile and 60th percentile.

In the paper we have investigated the effectiveness of the model and comparing to the conventional mean-variance and the VBS fuzzy model.

Diversification Benefit Measures

There are several diversification benefit measures can be applied in assessing portfolio performance. Among others are Sharpe Index, Treynors Index, risk adjusted return, abnormal return and efficient frontier curve. But the most dominance measurement is efficient frontier due to it rigorous in providing risk and return information in portfolio analysis study. Efficient frontier is a set of feasible portfolio return and risk level that offers the highest profit at any level of risk or lowest risk at any level of return. The area under the efficient frontier curve is a potential feasible portfolio event not at the highest preferences compared to the one on the efficient frontier curve. Since efficient frontier is a set of optimum portfolios at different risk and return levels, the information was simplified into efficient frontier index (EFI) as discussed below.

Efficient Frontier Index (EFI)

In order to identify the superiority of the portfolio model, Sazali, Mohamed, Annuar and Shamsher (2004) noted that the efficient frontier index (EFI) can be used as a good indicator. The EFI index is able to identify the superiority of the efficient frontier in maximizing a portfolio diversification benefit. The highest index value shows that the portfolio is having highest return for every unit of risk. Therefore, the higher EFI is preferable. The EFI formula is as below:

$$EFI = \left(\sum_{i=1}^{n} \frac{R_i}{\sigma_i} \right) \cdot \left(\sum_{i=1}^{n} \frac{R_i - R_{Lowest}}{\sigma_i - \sigma_{Lowest}} \right) \tag{4}$$

where *EFI* is Efficient Frontier Index
R_i is portfolio i return on efficient frontier
σ_i is portfolio i standard deviation on efficient frontier
R_{Lowest} is portfolio i lowest return on efficient frontier
σ_{Lowest} is portfolio i lowest standard deviation on efficient frontier

EFI is resourceful to identify the most 'North-West' efficient frontier curve which indicates the highest return at every level of risk.

Portfolio Optimization

Portfolio selection problems can be solved by using quadratic, linear programming, genetic algorithm, fuzzy mathematical programming or neural network programming approach and ect. Previous studies have one similarity that is to construct efficient portfolios that are able to maximize portfolio return and minimize portfolio risk. They are different in optimization tools and several minor aspects. In the study we are choosing a linear programming approach as a tool to solve the optimization problem in the entire portfolio selection models due to it practicality and friendly to users.Portfolios optimizations were achieved by using the Solver function in the MS Excel. In the function, the entire models must be set into the system correctly. The Solver function will run a simulation to seek for the solution. Once the system converge the objective and the constraints, it will derive an appropriate asset selection, asset allocation, portfolio risk and return level. The process was repeated several times until efficient frontiers were obtained. The portfolio performances then were presented in form of efficient frontier curves and index (EFI).

Portfolio Sample and Descriptive Analysis

In the paper, the effectiveness of the extended mean-variance model, the VBS fuzzy model and the conventional mean-variance model were being tested in 10 types of portfolio. The portfolio sample was chosen from the listed companies in Bursa Malaysia for eleven and half years of period starting from January 1998 to June 2009. The sample was selected based on various criteria. Each portfolio consists of 30 assets due to many literatures noted that the appropriate number of asset for portfolio diversification are between 10 to 30 assets such as Evans and Archer (1968) and Zulkifli, Basarudin Shah, Norzaidi and Chong (2008).

Table 1: Portfolio Sample Descriptive Statistic

Type of Portfolio	No. of Asset	Mean	Std Dev	Skewness	Kurtosis
Large MV	30	1.20%	11.6%	0.931	10.144
Small MV	30	0.91%	20.6%	2.196	9.909
High EPS	30	0.86%	11.8%	1.140	10.947
Low EPS	30	1.24%	21.3%	2.349	11.440
High DPS	30	0.88%	10.8%	0.846	9.508
Low DPS	30	1.24%	21.9%	2.054	9.097
High PE	30	1.35%	18.0%	2.250	11.578
Low PE	30	1.29%	20.3%	2.495	12.700
Domestic	30	0.95%	15.5%	1.917	9.149
International	30	0.71%	7.7%	0.099	3.375

The descriptive statistics of portfolio samples are as below. The statistics show that the monthly portfolio mean rate of return is only ranging from [0.71%, 1.35%], but it standard deviation is ranging from [7.7%, 21.9%]. This shows that all the portfolios are very volatile. The highest and the lowest volatile are in the low DPS and in the international portfolio. Skew ness measure shows that all portfolios are positively skewed. This shows that in the long term investment, portfolio return distribution is positively skewed except for the international portfolio where it skewness measure is 0.099 which is very small and it is normally distributed. The entire portfolios also have a high Kurtosis value, which shows that the portfolios are highly centered at it median. These scenarios have exposed stock market investing to highly uncertain. The portfolio samples then were tested in the whole period of study for the models under investigation. The empirical evidence and it application were discussed below.

Empirical Evidence and Practical Application

In the section, for brevity purpose we have presented the example of efficient frontier curve and efficient frontier index calculation. To seek for portfolio superiority, the EF curves of different portfolios were compared to each other. Moreover, detail discussions on the portfolio diversification benefit are based on the efficient frontier index values.

Efficient Frontier Curve

Portfolio superiority can be seen in it efficient frontier curve. The more 'North-West' EF curve is preferable due to higher diversification benefit offered by the portfolio. Presented in figure 1 below is the example of efficient frontier curve of low EPS portfolios were constructed via the extended mean-variance model using fuzzy approach, the mean-variance and the VBS fuzzy model. In figure 1, virtually, the extended mean-variance curve is more superior to the conventional mean-variance and the VBS fuzzy portfolio. In the study, the models were tested in the all type of portfolios under observation.

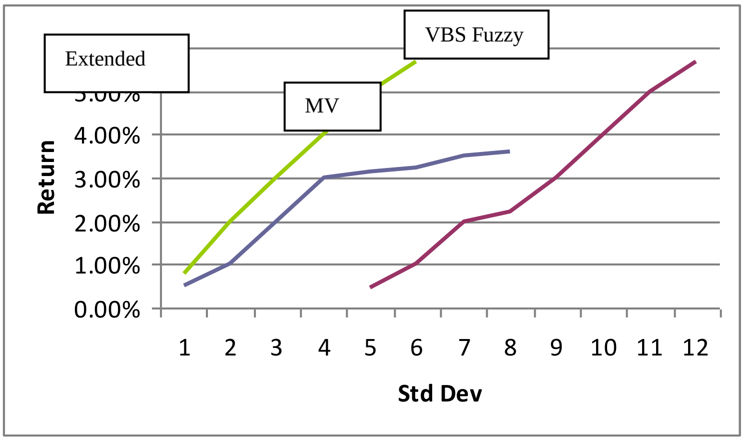

Figure 1: Efficient Frontier Curve of Low EPS Portfolios via VBS Fuzzy, MV and Extended Model

Portfolio superiority can be spot clearly in the curve, where the more 'North-West' portfolio EF curve is belongs to the extended mean-variance model. In many cases, the efficient frontier curve are overlapping each other and quite difficult to visually differentiate the superior portfolio. In this case, efficient frontier index (EFI) can be used to identify the portfolio superiority. The higher value of EFI shows that the portfolio is more superior. This measurement was introduced by Sazali et al. (2004). In table 2 below, presented an example of the EFI calculation for the low EPS portfolio via extended mean-variance model. In the example, the extended mean-variance model efficient frontier curve has EFI of 4.23. It has a positive value which means that the portfolio is able to generate higher return for every unit of risk. While, the negative value of EFI shows that the portfolio is in loss. To make it informative, the EFI value needs to be compared and from there we can see it superiority.

Table 2: EFI of Low EPS Portfolios via Extended Mean-Variance Models.

SDi	Ri	Ri/SDi	(Ri-Rl)/(SDi-SDl)	EFI=A.B
10.24%	0.80%	0.078	0	
11.36%	2.00%	0.176	1.069	
13.27%	3.00%	0.226	0.726	
14.37%	4.00%	0.278	0.774	
18.24%	5.00%	0.274	0.525	
26.54%	5.70%	0.215	0.300	
Total		A=1.25	B=3.39	4.23

Efficient Frontier Index (EFI)

As an index, comparison is an appropriate approach to explain the EFI result. In the study the calculated portfolios EFI then been compared accordingly in order to identify it superiority. The EFI values for all portfolios were summarized in table 3. The EFI value is very helpful especially in evaluating many and more complicated efficient frontiers. We fully utilized the EFI in the following section.

Table 3: EFI of Portfolios Constructed Via Extended Mean-Variance, VBS Fuzzy and Mean-Variance Models from 1998-2009.

Type of Portfolio	Portfolio Selection Model		
	Mean-Variance	VBS Fuzzy	Extended Mean-Variance
Large MV	1.99	0.87	7.67
Small MV	1.26	1.76	229.72 *
High EPS	0.70	0.31	2.59
Low EPS	1.64	2.10	4.23
High DPS	2.12	1.38	1.37
Low DPS	1.23	5.13	1.95
High PE	1.46	0.25	16.78
Low PE	1.62	1.09	2.68
Domestic	0.07	0.06	1.65
International	1.13	0.33	2.44
Average	1.32	1.33	4.60

* Significant at 95% confidence level.

In overall performance, all the portfolios have a positive value of the EFI. This shows that in the long term investment, regardless the portfolio selection model used, portfolio investing has offering a positive investment return at the various risk and return level, depend on the portfolio criteria. The highest EFI value of 229.72 is belongs to the small capitalization extended mean-variance portfolio and the lowest EFI value of 0.25 is belongs to the high PE VBS fuzzy portfolio. Basu (1977) revealed that using risk-adjusted performance measures indicated that the low PE stocks portfolio experienced superior result relative to market, whereas high PE ratio stocks portfolio had significantly inferior result. The finding is consistent with this study when we analyzed the PE ratio portfolios under mean-variance model. The EFI of low PE and high PE portfolios are 1.62 and 1.46 respectively, which shows that the low PE portfolio is more superior.

Size based portfolios revealed that under the mean-variance model, the small capitalization portfolio has higher EFI compared to the large capitalization portfolio where its EFI are 1.26 and 1.99 respectively. This shows that the large capitalization portfolio is superior. The result is contradict to Reinganum (1981) and Basu (1983) where using risk-adjusted return the small capitalization portfolio is superior. They do not compare the result with other model. But using the VBS fuzzy and the extended mean-variance approach, the result are the same where the small capitalization portfolio is superior.

The average of the EFI value for the entire portfolio shows that the extended mean-variance model has the highest average value of 4.60, followed by VBS fuzzy and the conventional mean-variance model at 1.33 and 1.32 respectively. This revealed that the EFI ranking shows the advantage of the extended mean-variance model in maximizing portfolio diversification benefit. The mixed EFI results are consistent with the finding by Sazali et.al (2004) when they comprehensively analyzed various types of portfolio performance under various economic events sub-periods from 1998 to 2003 in Malaysian stock market. The difference is Sazali et.al (2004) study was based on the conventional mean-variance model and no comparison to the other model. We mutually agreed that the portfolio with higher EFI is more superior in providing investment diversification benefit.

Kruskal Wallis test on the three models for each portfolio shows that there are no significant different in the portfolios rate of return except for the small capitalization portfolio. This means that, regardless the model used, 90% of the portfolios are no different in its rate of return. Only small capitalization portfolio has significant different in it portfolio rate of return where the extended mean-variance model is superior to other models under investigation. The Kruskal Wallis test method also applied by Blocka, French and Maberlyc (2000).

Investment performance ranking based on the different type of portfolio exposed that 80% of the EFI value of the extended mean-variance portfolios have higher value compared to the mean-variance and the VBS fuzzy portfolio which are only at 10% respectively. The market size, earning, price earning, domestic and international portfolio via the extended mean-variance have the highest EFI value in each respective groups. Only dividend based portfolio have a priority to the mean-variance and to the VBS fuzzy models. This shows that the extended mean-variance model is applicable in the all types of portfolio except in the dividend based portfolio. Otherwise, it shows that the portfolio performance is influence by the stocks size, earnings and PE ratios. The result is supported by Basu (1983) and Fama and French (1992) who conducted a relationship study between leverage, beta, size and return for stock return in the NYSE, AMEX and NASDAQ. They found that the relationship do exist between the variable under investigated even though they do not comparing any model.

Practically, Malaysian investors cannot longer rely on the naïve portfolio selection strategy. With computer technology optimization and new portfolio model derivation, investment performance can be improved. The study discovered that by using the extended mean-variance model it is able to maximize portfolio diversification benefit compared to the conventional mean-variance and the VBS fuzzy model. The model is superior in many types of portfolio such as market size, earning, price earning, domestic and international portfolio.

Summary

In this paper we have examined the performance of the extended mean-variance model, the VBS fuzzy model and the conventional mean-variance model in constructing a portfolio in long term period. The models were tested on the portfolio selection of various types of portfolio in Bursa Malaysia; namely large and small market capitalization portfolios, high and small earning portfolios, high and small PE ratio portfolios, domestic and international portfolios. In deriving the extended mean-variance model, we have defined asset return as a fuzzy number due to it uncertainty, vague and volatility. Purpose of the study is to investigate the effectiveness of the fuzzy mathematical modeling in portfolio selection. The fuzzy return modeling has taken into consideration the element of return data skew ness. The advantages of the modeling are it able to solve part of the normality problem in the conventional mean-variance model. The result revealed that the newly extended mean-variance model is able to maximize the portfolio diversification benefit in the long term and it has outperformed the mean-variance and the VBS fuzzy model. For further research, we would like to recommend that the model can be tested on more specific market trends such as in recession period and in the booming economics. Therefore the robustness of the model can be verified further. In the model derivation, at this stage we only fuzzify the element of the asset return. It is recommended that in the future research could extend it to fuzzify the other part of the model such as in it asset covariance or in asset correlation. We expect interesting finding is waiting in deriving a robust model that is efficient to maximize portfolio diversification benefit.

References

Basu, S. (1977). Investment Performance of Common Stocks in Relation To Their Price-Earning Ratios: A Test of the Efficient Market Hypothesis. *The Journal of Finance, 32*(3), 663-682.

Basu, S. (1983). The Relationship between Earnngs, Yield, MArket Value and Return for NYSE Common Stocks. *Jounal of Financial Economics, 12*(1), 129-156.

Bilbao-Terol, A., Perez-Gladish, B., and Antomil-Ibias, J. (2006). Selecting the Optimum Portfolio Using Fuzzy Compromise Programming and Sharpe's Single-Index Model. *Applied Mathematics and Computation, 182*, 644--664.

Bilbao, A., Arenas, M., Rodriguez, M. V., and Antomil, J. (2007). On constructing expert betas for single-index model. *European Journal of Operational Research, 183*, 827-847.

Blocka, S. B., French, D. W., and Maberlyc, E. D. (2000). The Pattern of Intraday Portfolio Management Decisions: A Case Study of Intraday Security Return Patterns. *Journal of Business Research, 50*(3), 321-326.

Cavaglia, S., Brightman, C., and Aked, M. (2000). The Increasing Importance of Industry Factors. *Financial Analysts Journal, 56*(5), 41-54.

Driessen, J., and Laeven, L. (2007). International Portfolio Diversification Benefits: Cross-Country Evidence from a Local Perspective. *Journal of Banking and Finance, 31*, 1693-1712.

Ehrgott, M., Klamroth, K., and Schwehm, C. (2004). An MCDM approach to portfolio optimization. *European Journal of Operational Research, 155*, 752-770.

Evans, J., and Archer, S. (1968). Diversification and the reduction of dispersion. *Journal of Finance, 23*(5), 761-767.

Fama, E. F., and French, K. R. (1992). The cross-section of expected stock returns. *Journal of Finance, 47*(2), 427-465.

Fatma, T., and Mehmet, A. (2005). Fuzzy logic selection using a new ranking and weighting algorithm. *Applied Mathematics and Computation, 170*(1), 144-157.

Fauziah, M. T., and Mansor, I. (2007). Malaysian unit trust aggregate performance. *Managerial Finance, 33*(2), 102-121.

Huang, X. (2007). Mean-Semivariance Models for Fuzzy Portfolio Selection. *Journal of Computational and Applied Mathematics, doi:10.1016/j.cam.2007.06.009*.

Jensen, M. C. (1968). The Performance of Mutual Funds in the Period 1945-1964. *Journal of Finance, 23*(2), 389-416.

Lewis, K. K. (2006). *Is The International Diversification Potential Diminishing? Foreign Equity Inside and Outside the US*. Massachusetts Avenue: National Bureau of Economic Research.

Li, J., and Xu, J. (2009). A novel portfolio selection model in a hybrid uncertainty environment. *The International Journal of Management Science, Vol. 37*(Issue 2,), 439-449

Lin, C.-C., and Liu, Y.-T. (2008). Genetic algorithm for portfolio selection problems with minimum transaction lots. *European Journal of Operational Research, 185*, 393-404.

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolio and capital budgets. *Review of Economics and Statistics, 47*, 13-37.

Markowitz, H. (1952). Portfolio Selection. *Journal of Finance, 7*(1), 77-91.

Markowitz, H. M. (1991). *Portfolio Selection: Efficient Diversification of Investments* (2nd ed.): Blackwell, Cambridge MA and Oxford UK.

Mossin, J. (1966). Equilibrium in a capital asset market. *Econometrica, 34*(4), 768-783.

Reilly, F. K., and Brown, K. C. (2000). *Investment Analysis and Portfolio Management* (6th ed.): Dryden.

Reinganum, M. R. (1981). Abnormal Return in Small Firm Portfolios. *Financial Analysts Journal, 37*(2), 52-57.

Santis, G. D., and Gerard, B. (1997). International Asset Pricing and Portfolio Diversification with Time-Varying Risk *Journal of Finance Vol. 52*(No. 4).

Sazali, Z. A., Mohamed, A., Annuar, M. N., and Shamsher, M. (2004). International Portfolio Diversification: A Malaysian Perspective. *Investment Management and Financial Innovation, 3*, 51-68.

Sharpe, W. F. (1966). Mutual fund performance. *Journal of Business, 39*(1), 119-138.

Solnik, B. H. (1974). Why Not Diversify Internationally Rather Than Domestically? . *Financial Analysts Journal, 30*(4), 48-54.

Statman, M. (1987). How many stocks makes a diversified portfolio? . *Journal of Financial and Quantitative Analysis, 22*(3), 353-363.

Tang, G. Y. N. (2004). How Efficient is Naive Portfolio Diversification? An Educational Note. *Omega The International Journal of Management Science, 32*, 155-160.

Vercher, E., Bermudez, J. D., and Segura, J. V. (2007). Fuzzy portfolio optimization under downside risk measures. *Fuzzy Sets and Systems, 158*, 769-782.

Wang, S.-Y., Lee, C.-F., and Tzeng, G.-H. (2005). Fuzzy Multi-Criteria Decision-Making for Evaluating the Performance of Mutual Funds.

Zhang, W.-G., Zhang, Q.-M., and Nie, Z.-K. (2003, 2-5 November 2003). *A class of fuzzy portfolio selection problems.* Paper presented at the Second International Conference on Machine Learning and Cybernetics, Xi'an.

Zulkifli, M., Basarudin, S. B., Norzaidi, M. D., and Siong, S. C. (2008, 17-20 June 2008). *A Study on Diversification in Malaysian Stock Market.* Paper presented at the EABR and TLC Conference 2008, Rothenberg ob der Tauber, Germany.

Zulkifli, M., Basarudin Shah, B., Norzaidi, M. D., and Chong, S. C. (2008). Portfolio diversification: the role of information technology in future investment decision-making. *International Journal of Electronic Finance, 2*(4), 451-468.

Zulkifli, M., Daud, M., and Omar, S. (2008, 16 Dec 2008). *Fuzzy Application in Portfolio Selection.* Paper presented at the National Seminar on Fuzzy Theory and Application 2008, Al-Ghazali Hall, Faculty of Computer and Mathematical Sciences, UiTM, Shah Alam.

Zulkifli, M., and Roslim, M. (2004, 19-21 May 2004). *The analysis of Malaysian Income Fund Performance in 2001 and 2002.* Paper presented at the Conference on Social Science Research 2004, Crown Plaza Riverside Hotel, Kuching, Sarawak.