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Portfolio Diversification Strategy in the Malaysian Stock Market

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Abstract: Two opposed, widely known portfolio strategies – active and passive portfolio investment strategy – claim their superiority in competing for the excellence of risk adjusted portfolio performance. This study investigates the portfolio strategy that would sustain the risk adjusted performance from investing in the Malaysian stock market. The performance measures from the Sharpe, Treynor and Jensen Index are used to analyse and rank the portfolio performance. The GARCH model is adopted to analyse the Malaysian stock market volatility over the 16-year period (1998-2013) and the crisis years (1998 and 2008). The different diversification levels are compared relatively from the correlations and co-integration based portfolios. The overall outcomes show that the active portfolio strategy outperforms the passive portfolio strategy. The co-integration based portfolio outperforms the correlation based portfolio over the long run. As opposed to developed markets, the analysis of the results prove that adding more stocks to portfolios will not result in significant diversification benefits.

Keywords: Active and passive strategy, correlation, co-integration, GARCH.
JEL Classification: G10, G11, G17, G32

1. Introduction

The Modern Portfolio Theory and the mean-variance methodology, which were proposed originally by Markowitz (1952, 1959), quantify the benefits of diversification and explore how risk-averse investors construct portfolios to optimize expected returns against market risks, linking both the expected return (or mean) of a portfolio diversification return and the variance of portfolio returns as the investment risk. Most of the existing portfolio selection models are probability based (Zhang *et al.* 2007).

Diversification is a portfolio strategy that is designed to reduce the overall risk exposure by combining a variety of assets (stocks, bonds, mutual funds, etc.) into one basket of portfolio, with the rationale that a portfolio with different assets will yield higher returns and induce a lower risk than any individual investment (Drake and Fabozzi 2010). Diversification in stocks can be done easily by investing in companies across industries. Small capital stocks tend to produce a higher return since these stocks are far less accessible to international investors due to the high transaction costs associated with their limited liquidity, capital rationing and information availability. In this case, small-cap stocks are likely to be priced primarily according to their local or idiosyncratic risks (Wei 2007). Also, studies found that stocks with high positive momentum (high 52 weeks past return) are a

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better predictor of future returns than the price acquisition or macroeconomic risk factors (Liu *et al.* 2011). On the other hand, holding an industrial diversified portfolio over a long period will yield some risk reduction benefits (Mohamad *et al.* 2006). The prominent factors that affect portfolio diversification include the portfolio risk (Drake and Fabozzi 2010), the number of assets held in the portfolio (Sentana 2004; Tang 2004; Behr *et al.* 2013) and the correlation among the assets in the portfolio (Medo *et al.* 2009).

Correlation is intrinsically a short-run measure and persists with severe limitations as a dependency measure. Instead, co-integration based analysis has emerged as a powerful technique to investigate long-term dependency between asset prices and long-term equilibrium between the prices of financial assets (Alexander 1999, 2008a, 2008b).

Two opposing investment strategies, active investment, which gained active or speculative profits, and passive investment, which gained passive income, claim their superiority and risk-adjusted performance over the long-term (Miller 2006). Active portfolio investors utilize widely available information and forecasting techniques to acquire better portfolio performance rather than simply diversified broadly. Essential to all active strategists are the expectations about the factors that influence the performance of an asset class. These may include forecasts of dividends, future earnings and price-earnings ratios. An active portfolio strategy will outperform if financial or fund managers imposed appropriate active benchmarks in a multi-period context so that asset return predictability is properly accounted for. As such, the screening of managers and the delegation of work to talented managers will be useful in an active portfolio strategy (Lioui and Poncet 2013).

In contrast, passive portfolio strategy rely on diversification strategy with minimal inputs on the market performance. Passive strategy is an investment style in which a portfolio mirrors a market index or simply known as indexing the portfolio. Followers of the passive strategy tend to believe the efficient market hypothesis (EMH), which states that at all times markets will incorporate and reflect all information, rendering individual stock picking futile. It is nearly impossible to outperform the market, and, as such, the best investment strategy is to invest in index funds, or equally invest in every large capital stock.

The ongoing debate concerning an active versus passive strategy underlies the tests of the efficient market hypothesis and assertion of the possibility that markets may properly price the securities. Based on previous research, investors would expect the passive strategy to outperform the active strategy during the expansion period whereas the performance would reverse during market contraction (Prondzinski 2010). Prondzinski (2010) proved that an actively managed fund was outperformed by a passively managed fund from 1995 to 2004. As from 2000 to 2002, when the markets experienced three consecutive downturns, many believed that actively managed funds would be expected to outperform passive investments on a risk adjusted basis. However, the empirical results showed otherwise (Miller 2006).

By limiting the investment strategies to active and passive portfolio investment, this study aims to evaluate the long-term performance between active and passive diversification strategies across the Malaysian stock market using analyses of different scenarios. In acknowledging the consequences of market (systematic) risk and financial crisis on stock portfolio investment (Fiordelisi and Marques-Ibanez 2013; Melvin and Taylor 2009; Bartram and Bodnar 2009), using the Generalized Autoregressive Conditional Heteroscedasticity model (GARCH) estimation to measure and forecast the portfolio volatility, this study assesses whether market (systematic) risk could be significantly reduced by different diversification strategies during the financial crisis period. By comparing the level of diversification, this study examines both the correlation based portfolio and co-integration based portfolio. The portfolio with lowest correlation (correlation based portfolio) and the portfolio that is free from any co-integration (co-integration based portfolio) will be compared based on correlation and co-integration analysis of a number of stocks that are randomly selected ranging from 10 to a maximum of 100 stocks from 1998 to 2013, with the inclusion of the financial crisis period. In referring to the findings of Statman (1987), this study also attempts to examine whether the portfolio of 30 stocks can significantly reduce the portfolio diversifiable risk in the Malaysian stock market.

No doubt investors and fund managers may change or revise their portfolio investment strategy over time to suit the current market conditions and different risk profiles. This study aims to provide comprehensive insights and better risk management techniques for them based on the past, current and forthcoming situations.

Apart from enabling investors and fund managers to assess fundamental information on portfolio diversification strategy in the Malaysian stock market, the methodologies for evaluating the active or passive strategy provide valuable information that may influence their decisions concerning the allocation of funds, which may spur the economic growth of the country. The aftermath of the 2008 financial crisis encouraged many investors to evaluate portfolio returns under the extreme market conditions. Hence, this study guides them in terms of how to construct their portfolio investment efficiently. To date, there are still avenues to explore the asset risk management techniques that underlie the investor's portfolio diversification strategies. Aside from contributing to the literature, with all the practical econometric methodologies, this study encourages future researchers to embark on further studies concerning the portfolio diversification strategies in the Malaysian stock market.

2. Literature Review

In retrospect, the Sharpe ratio is the most frequently used performance measure. It indicates the reward to risk ratio, which measures the relationship between the mean and standard deviation (Sharpe 1964; Schuster and Auer 2012). In other words, using the Sharpe ratio, the risk can be adequately measured by standard deviation (Zakamouline and Koekebakker 2009). Econophysics contributions have been expanded and have enhanced the financial time series starting from the mid-1990s. The stochastic-optimization technique on active and passive fund performance has been carried out aggressively to determine optimal portfolio returns with minimal risks (Dose and Cincotti 2005). The Sharpe measure of portfolio performance is the key measure in financial physics in terms of the risk premium per volatility. The Sharpe ratio is consistent with Brownian motion as it has been proven technically by mathematical physics in terms of the risk premium definition (Frank 2006). The Jensen Index measures the proportion of market beta with the expected equity premium (excess return) in which the expected return on individual securities equals the risk-free rate plus the value of the market beta times the risk premium (Chen 2003). Practically, the 'beta' refers to the slope in a linear relationship fitted to data on an investment rate of return and the market rate of return or market index (Tofallis 2006). It is widely used in investment analysis with least squares regression. However, there is an ongoing debate concerning the accuracy of the beta coefficient when employing least squares regression (Fabozzi and Francis 1978). Research by Tofallis (2006) found that an alternative beta estimator is needed and is more appropriate in calculating the beta or market risks.

The factors affecting the portfolio diversification in the literature are the portfolio risk, number of assets in the portfolio, and the correlation among the assets in the portfolio. Sentana (2004) proved that many portfolios converge towards a greater reduction in the investment risk as the number of assets increases. Thus, the diversifiable risk of a portfolio can be effectively reduced by increasing the number of stocks held in the portfolio. In respect of the naive approach, investors should hold a portfolio of randomly selected stocks with equal investment in each (Tang 2004). The naive Portfolio Strategy is able to generate the best return and has outperformed other types of portfolio strategy, although its risk and turnover ratio are worse than other strategies (DeMiguel *et al.* 2009). Despite this, overall, the naive Portfolio Strategy provides a greater return with a low level of risk. According to Behr *et al.* (2013), to date, no single portfolio strategy from the existing portfolio selection literature outperforms the naively diversified portfolio.

Sharpe (1964) showed that a growing number of assets in a portfolio of 10–20 assets are sufficient for reward and for obtaining great diversification advantages. However, Statman (1987) indicated that these numbers have been underestimated. Statman (1987) argued that the optimal size is actually between 30 and 40 assets and that 400 stocks would fully drive out non-systematic risks. Portfolio size is increasingly playing a significant role that could result in the ability to estimate optimal portfolios (DeMiguel *et al.* 2013).

The research conducted by Surz and Price (2000) indicated an opposing view to the findings of Statman (1987), in that they measured the level of diversification using *R*-squared and argued that a portfolio of 30 stocks no longer provides full diversification, while 76% of the level of diversification can be achieved by holding only 15 stocks. A simulation test on performance concludes that optimal portfolio can be achieved by having more assets (Kan and Zhou 2007). With more assets, the Sharpe ratio of the tangency portfolio increases, which, in turn, leads to higher expected out-of-sample performance in the absence of risk estimation. This has been proven in the studies on active portfolio management whereby the funds of highest excess returns tend to have small and more concentrated portfolios, and do not have the highest turnover (Shukla 2004). Furthermore, the studies undertaken on cluster analysis indicate a significant linkage between the risk level and the portfolio size (Tola *et al.* 2008). Tola *et al*. (2008) argued that, in general, if the portfolio size N is significantly smaller than the correlation coefficient matrix portfolio, the portfolio, is more risky. The increase in risk is probably related to the diminished amount of diversification associated with the reduction in the size of the portfolio. Conversely, research done by DeMiguel *et al.* (2013) indicated that a large number for the portfolio selection base may result from a larger Sharpe ratio. They found that the minimum-variance portfolio formed from the shrinkage covariance matrix with condition numbering will outperform the portfolio for medium and large datasets. This is because the sample covariance matrix for medium and large datasets is more likely to be nearly singular, and, in turn, it is important to control the condition numbering when constructing optimal portfolios.

Diversification is essential in finance and portfolio analysis since the risk can be segregated into diversifiable risk and systematic risk (Sharpe 1964). Total portfolio risk, as measured by standard deviation, comprises both diversifiable risk and non-diversifiable risk. Diversifiable risk or better known as the firm-specific risk, company unique risk, non-systematic or residual risk, can be diversified away by increasing the number of stocks in a portfolio, leaving only the systematic risk as the relevant risk through diversification (Olibe *et al.* 2007). When the number of asset holdings increases, the level of non-systematic risk is almost completely eliminated or diversified away, leaving only the systematic risk. Thus, the relevant risk for decision-making purposes will be the systematic risk. Systematic risk is affected by the market beta, not the number of securities (Drake and Fabozzi 2010).

The remarkable ARCH (Autoregressive Conditional Heteroscedasticity) model serves as an alternative model of conditional CAPM, which includes the time observed series (Engle 1982). It is commonly employed in modelling financial time series that exhibit time-varying volatility clustering, and periods of swings followed by periods of relative calm. The ARCH model demonstrates how the volatility of returns is time-dependent and how its future can be predicted from the past (Chen and Li 2012). It was later extended to the generalized autoregressive heteroscedasticity (GARCH) model by Bollerslev in 1986, which was specifically designed to capture the volatility clustering of returns (Bollerslev 1986). One of the issues pertaining to ARCH, is that it fails to describe the height and shape of the implied autocorrelation function of the conditional variance as it is only a one parameter model. On the contrary, the GARCH model defines the current expected conditional variance as a linear function of the squared errors in previous periods (Bollerslev and Engle 1993). For post research on the ARCH model, many researchers have applied GARCH modelling strategies to describe time-series financial data. For instance, Lin and Fei (2013) investigated the long memory property of Chinese stock markets based on the conditional and actual volatility series using GARCH-class models. Their research showed that the asymmetric power GARCH model (APGARCH model) has superior forecasting ability and is able to capture the long memory property for different timescale intervals (Lin and Fei 2013).

There is an inverse relationship between the correlation and portfolio diversification. When the assets are positively correlated (increase in correlation), the benefits of investment diversification are greatly reduced. Therefore, an effective diversification will show that the assets in the portfolio should not be highly correlated (Medo *et al.* 2009).

In general, portfolio diversification with lower correlation tends to induce a lower portfolio risk. Past empirical research has shown that the correlation among each stock tends to be higher in bearish market conditions as opposed to calm and bullish periods (Butler and Joaquin 2001). Thus, during bearish market conditions, the overall risk would be higher and the portfolio return would be affected. It would be interesting to examine the impact of bearish market conditions on the Malaysian stock market, and determine which portfolio diversification strategy can provide reasonable return during the crisis period and over the long run.

In some scenarios, the spread between two asset prices can be stationary, and, in this case, the prices are said to be co-integrated. Co-integration was developed by Engle and Granger (1987), who empirically proved that two or more data series that are non-stationary may exist in a linear relationship that is stationary. Co-integration is a measure of long-term dependency between asset prices. Roll (1992) supported the traditional portfolio optimization models from stock returns. However, it would be hazardous to use linear regressions on non-stationary time series as it could produce a spurious correlation (Granger 1981). In a contrary view to correlation analysis, Alexander (1999) introduced optimization models based on co-integration analysis. The application of co-integration analysis was limited due to the pioneering empirical research work on correlation analysis introduced by Markowitz (1952, 1959). Alexander (1999) introduced optimization models with co-integration analysis. She argued that investment strategies that are only based on correlation analysis will not guarantee long-term performance, as this is intrinsically a short run measure, and that it would be misleading as a high negative correlation in a short period can constitute a low correlation to the overall portfolio (Alexander 1999). The co-integration technique has been used to investigate long-term dependence in multivariate time series. Indeed, one of the main advantages of co-integration analysis, is that it provides a sound statistical methodology for modelling both the long-term equilibrium and the short term dynamics (Alexander 2008b). Similarly, Grobys (2010) proved that the Sharpe ratios of the co-integration based optimal portfolios significantly outperform correlation based portfolios in respect of the Swedish stock market.

Inversely, Alexander and Dimitriu (2005) measured concurrently both the correlation and co-integration methodologies to analyse the S&P 500 stock market. Their studies indicated that there is no significant difference between the co-integration based model and the correlation based model. Such comparisons are limited in the Malaysian stock market.

In contrast, Lin *et al.* (2013) found that the emerging China stock markets of Shanghai and Shenzen are highly correlated and co-integrated but that the rate convergence to long-term equilibrium is not uniform. The co-integration results revealed that all the Asian Newly Industrializing Countries (NIC) – Hong Kong, Singapore, South Korea and Taiwan – share a long run relationship with the more developed markets in Japan, the US, UK and Germany (Masih and Masih 1997). In terms of the ASEAN region, Lim *et al.* (2003) showed that investors with long run horizons may not benefit and prove ineffective from an investment made across the countries in this region. However, according to Gupta and Guidi (2012), the use of correlations to measure the asset co-movements as input in portfolio optimization may contribute to the determination of asset allocation. If the asset data for certain markets are not integrated and have lower correlation, it is beneficial to consider these markets for possible inclusion in an international portfolio. Similarly, Ratanapakorn and Sharma (2002) investigated how short- and long-run relationships changed across five regional stock markets for the pre- and post-1997 Asian Financial crisis. Their results showed that no long-run relationships existed before the Asian crisis, whereas some evidence of integration was observed after the crisis. The concept of integrated markets has strong consequences for international investors as it implies the benefits of international portfolio diversification. As the world markets are integrated, the correlation between the returns of the developed markets increases. Investors target emerging markets to exploit the benefits of international diversification with the belief that correlations between developed markets and emerging markets will be lower (Driessen and Laeven 2007). There is an ongoing debate in stock markets between the application of co-integration in constructing a portfolio as opposed to the correlation analysis advocated by Markowitz (1952, 1959).

From the Malaysian perspective, Abidin *et al.* (2004) indicated that a local portfolio outperformed an international portfolio during the 1998 Asian Financial Crisis. Investors are advised to time their stock selection as it is an important element that affects the portfolio volatility and diversification benefit (Abidin *et al.* 2004). The study of Abidin *et al.* (2004) showed that domestic-based portfolios proved to be superior to internationally diversified portfolios after the 1998 Asian Financial Crisis, which is different to 1987 when international portfolio diversification was preferred. This is also supported by Kamaruzzaman and Isa (2013) who found that the Malaysian financial market volatility clustering on the financial returns yielded similar results. On the other hand, Abidin (2006), who studied Malaysian portfolio correlation with international diversification, indicated that stocks had lower correlation during the crisis period, hence the offsetting effect of a portfolio did perform well during crisis period. Conversely, Mohamad *et al.* (2006) concluded that correlation of returns was found to be unstable resulting from the differences in the economic sectors due to global integration. As the process of globalization continues, correlation between country specific fundamentals will increase and thus reduce the benefits of diversification. They further examined the issues concerning whether portfolio diversification across industries is more effective than portfolio investment based on the naive strategy. They discovered that diversification across industries can only be a supplementary strategy in combination with other diversification strategies (Mohamad *et al.* 2006).

3. Methodology

This study focuses on the Malaysian stock market given its relevancy and direct effects to most Malaysian investors, and takes into consideration the valuation and growth factors among all these companies. The data collection is based on a sample of 100 stocks of companies listed on the main market, Bursa Malaysia Stock Exchange, with the highest earnings at fiscal year-end 2013. The stocks' closing prices are collected based on a daily basis for a 16-year period, from 1998 to 2013.

As emphasized by Richard (2009), the valuation factors include the price-to-earnings ratio, price-to-book ratio and dividend yield, while the growth factors may include earnings improvement and the firm's long-term growth prospect. The valuation factors are determined by market demand, supply (price) and the company's dividend pay-out policy; it is inappropriate to only consider this in stock pick without considering the firm's long-term growth prospect. The fiscal year ending 2013 reported that most Malaysian firms recovered from the global financial crisis aftermath. In 2013, most firms possessed the ability to yield high earnings and sustain better growth opportunities. Hence, the top 100 companies listed on the Bursa Malaysia Stock Exchange with highest earnings in the fiscal year ending 2013 were selected as samples. All data were retrieved from DataStream by Thomson Reuters. This study examines the performance of active and passive portfolio investment strategies over the 16-year period from 1998 to 2013, inclusive of two crisis years in 1998 and 2008.

From the literature, the active portfolio strategy involves frequent reconstruction within the portfolio. The active portfolios in this study are constructed under five different scenarios based on the correlation coefficient of the stock prices. The active portfolio under scenario 1 consists of a combination of 15 stocks with the lowest correlation coefficient among each stock from the sample (the selected stocks are BOLTON, GTRONICS, INSAS, DBHD, SAPRES, ESSO, UAC, HLIND, CIHLDG, MISC, LEADER, GOPENG, FIMACOR, UAC and MAS). Next, the same method is used to form the active portfolio under scenario 2 with the remaining 85 stocks in the sample. Active portfolios under scenarios 3, 4 and 5 are constructed based on the same criteria. For the passive portfolio, 10 stocks with the highest market capitalization are selected from the sample, which mirrors a market index, or, simply put, the passive portfolio known as indexing the portfolio.

The daily stock prices for 16 years are gathered to calculate the portfolio return. The dividend yields of all the selected stocks are excluded from the portfolio return due to the inconsistency, different dates on dividend payments and policies, and missing data on daily dividend yields for certain stocks.

The portfolio return is analysed based on descriptive statistics using the mean return (arithmetic mean), and standard deviation of portfolio return. Three risk-adjusted indices – Sharpe ratio, Treynor and Jensen's index – are used to determine the portfolio that yields the highest performance over the long run as well as during the crisis periods.

Sharpe Ratio:	Treynor Ratio:	Jensen's Index:
$S_p = (\overline{r_p} - \overline{r_f}) / \sigma_p$	$T_p = (\overline{r_p} - \overline{r_f}) / \beta_p$	$\alpha_j = \overline{r_p} - [\overline{r_f} + \beta p(\overline{r_m} - \overline{r_f})]$

where $\overline{r_p}$ = Average return of the portfolio

$\overline{r_f}$ = Average risk-free rate of return (T-bill rate from Bank Negara Malaysia (BNM))

σ_p = Standard deviation of the portfolio

β_p = Portfolio beta

$\overline{r_m}$ = Average market return

A high Sharpe and Treynor ratio for a portfolio indicates that it has better risk-adjusted performance. A positive Jensen's index indicates that a portfolio is earning excess returns. Similar to the Sharpe, for both the Treynor and Jensen Index, there are three different average risk-free rates of return – long run from year 1998 to year 2013, and another two crisis periods from 1st January 1998 to 31st December 1999 and 1st January 2008 to 31st December 2009.

In addition, the market index is used to generate the market beta, which is determined from the SLOPE function in Excel. The slope function = SLOPE (range of % change of equity, range of % change of index). Since the result of the average return of portfolio is provided on a daily basis, this research needs to annualize the average return of the portfolio by a multiple of 365 days and annualize the standard deviation of the portfolio by the multiple $\sqrt{365}$, which is 19.1050.

Standard deviation is a measure of a set of data series from its mean, it is better known as historical volatility and is used by investors as a gauge for the amount of expected volatility. Standard deviation is calculated as the square root of variance. A low standard deviation indicates that the data points tend to be very close to the mean, whereas high standard deviation indicates that the data are spread out over a large range of values. The mean results (targeted portfolio returns) for the standard deviation will be used to obtain the results for the Sharpe, Treynor and Jensen ratios.

By utilizing the EViews software, the stock price volatility and forecasting for both active and passive portfolios are measured using the Generalized Autoregressive Conditionally Heteroscedastic (GARCH) model. The GARCH model is modified from the ARCH model. Four steps are required in the GARCH model, in which the first step involves the ARCH model estimation, with the purpose of testing the ARCH effect of all types of portfolio and examining whether all portfolios have the ARCH problem. This is followed by the estimation of the GARCH variance with the purpose of detecting the outliers or potential issues that might cause the model to be insignificant. If the portfolios do not show the ARCH effect, then a GARCH variance series graph is used to check the potential problem that causes an insignificant effect in the first step. Next, to estimate the GARCH model, the coefficient value will be examined in order to compare the volatility between portfolios, and to check which portfolio strategy provides the lowest volatility, and whether its volatility is caused by new information or its own lag effect (MA). Finally, in GARCH forecasting, the estimated model is used to forecast the future GARCH variance series, which aims to measure the market risk by investigating the portfolio beta of the 100 stocks.

The ARCH model is used to test whether the conditional variance is caused by its own lagged term, in which the model is:

$$h_t = \alpha_0 + \alpha_1 e^2_{t-1}, \qquad \alpha_0 > 0,\ 0 \leq \alpha_1 < 1 \tag{1}$$

The h_t is the time varying variance, which is a function of a constant term (α_0) plus lag one, the square of the error in the previous period ($\alpha_1 e^2_{t-1}$). To ensure the significance of the GARCH model, the ARCH model should be significant.

Both the α_0 and α_1 must be positive to ensure a positive variance. The coefficient α_1 must be less than 1, otherwise h_t will continue to increase over time, eventually exploding. In addition, the Obs*R-squared (LM - Lagrange multiplier statistic) and the F-statistic must be significant prior to estimating the GARCH model.

The GARCH model combines the MA (moving average) into ARCH model. Its final output of coefficient indicates whether its volatility is caused by new information (α) or its own MA (β) effect. The model is:

$$h_t = \delta + \alpha_1 e^2_{t-1} + \beta_1 h_{t-1} \tag{2}$$

This study includes one past lag time varying variance as the regressor. The coefficient of α represents the ARCH effect and is the level of volatility due to the new information, while the coefficient β represents the MA effect, which indicates the volatility caused by its own lag moving average effect. For the GARCH model to be valid, both coefficient α and β must be significant and have a positive value, and the sum of these values must be below 1. If the sum of these two values is above 1, it will be identified as the integrated GARCH process, or IGARCH. IGARCH can yield a very parsimonious representation of the distribution of an asset's return. The following hypotheses are formed prior to examining the ARCH and GARCH effect:

1. H_0: There is no significant ARCH effect between the past and current volatility (no ARCH errors).
   H_1: There is a significant ARCH effect between the past and current volatility.
2. H_0: There is no significant GARCH effect between the past and current volatility.
   H_1: There is a significant GARCH effect between the past and current volatility.

In forecasting, the one-step-ahead forecast of the conditional variance is:

$$E_t h_{t+1} = \alpha_0 + h_t \tag{3}$$

and the j-step-ahead forecast is:

$$E_t h_{t+j} = j_{\alpha 0} + h_t \tag{4}$$

Moreover, if the unconditional variance is clearly infinite, the IGARCH is not perfect.
The estimating of the 100 stocks with higher earnings refers to the mean of the series as described as:

$$r_t = \beta_0 \tag{5}$$

While the estimated variance is given as:

$$h_t = \alpha_0 + \alpha_1 e_{t-1}^2 \tag{6}$$

Once the model has been estimated, it can be used to forecast the next period's return r_{t+1} and the conditional volatility h_{t+1}. In share investment, the basis of mean returns and risk are considered. Therefore, the forecast return and the volatility are:

$$r_{t+1} = \beta_0 \tag{7}$$

$$h_{t+1} = \alpha_0 + \alpha_1 (r_t - \beta_0)^2 \tag{8}$$

In the return forecast, β_0 indicates that the higher the beta, the higher the risk due to the greater expectation of obtaining a higher return. In other words, low-beta portfolios are less responsive and less risky than high-beta portfolios.

R^2 is a measure of the squared correlation between a stock's performance. It measures how reliable the stock's beta is in judging its market sensitivity. R^2 is close to Beta, but it shows what proportion of a stock's risk is market-related. A completely diversified portfolio that diversifies all the firm-specific risk or unsystematic risk, would be perfectly correlated to the market; leaving only the market or systematic risk, which is indicative that R-Squared equals 1.0. Conversely, if R^2 equals 0, the beta measurement is irrelevant to its actual performance. To derive the R^2, various combinations of stocks are constructed with careful diversification, such as by selecting stocks from a variety of industries and balancing with respect to effects, such as style (e.g., value or growth) and size chosen, ranging from 10 stocks, 20 stocks, 30 stocks up to 100 stocks, in order to determine the level of diversification based on the increasing number of stocks. The R^2 in this study is used to determine the level of diversification for a portfolio consisting of randomly selected stocks, ranging from 10 to 100 stocks. The first 10 stocks are chosen to obtain the R^2 result, after that, an additional 10 stocks are added each time (20, 30, 40 stocks, etc.) until the portfolio reaches 100 stocks.

Subsequently, the diversification level achieved by correlation based and co-integration based portfolios is compared over the long run, with the inclusion of the crisis periods. To do this, the active portfolio constructed under scenario 1 serves as the correlation based portfolio, as it is a combination of the stocks with the lowest correlation in the sample. Thus, it is most suitable to represent the correlation based portfolio, as the lower the correlation the larger the diversification benefits. To construct a co-integration based portfolio, 15 stocks are randomly selected from the sample.

The Johansen and Juselius Co-integration Test is used to construct the co-integration based portfolio. Co-integration exists when the combination of the non-stationary data series exhibits a stationary linear combination. Hence, prior to using the Johansen and Juselius Co-integration Test, this study ensured that the data series (the stocks in the portfolio) is non-stationary (has a unit root). This is the prerequisite prior to conducting the co-integration test. Firstly, unit root tests based on the Augmented Dickey-Fuller test (ADF), Non-parametric Phillips-Perron test (PP) and Kwiatkowski *et al*. (1992) test (KPSS) are used to prove that the stock price series within the constructed portfolio is non-stationary. The combination of these three tests should give a consistent and reliable conclusion with regard to the non-stationarity of the data.

The ADF (Augmented Dickey-Fuller) test follows the τ critical values to determine the test result. The ADF test takes into account the possible serial correlation in the error terms by adding the lagged difference terms of the regression. The following hypotheses were formed prior to conducting the ADF test:

H_0: The data series has a unit root (non-stationary).
H_1: The data series does not have a unit root (stationary).

Rule of thumb for the ADF test: Reject the null hypothesis if the ADF test statistic < - τ critical value or ADF test statistic > τ critical value. The non-parametric Phillips-Perron test **(**PP) test follows the τ critical values to determine the test result. The PP test is a non-parametric statistical method that takes into account the serial correlation in the error terms without adding the lagged difference terms. The following hypotheses were formed prior to conducting the PP test:

H_0: The data series has a unit root (non-stationary).
H_1: The data series does not have a unit root (stationary).

Rule of thumb for the PP test: Reject the null hypothesis if the PP test statistic < - τ critical value or PP test statistic > τ critical value. The null hypothesis for the Kwiatkowski *et al*. (1992) test (KPSS) is stationary (does not have a unit root). KPSS is a semi-parametric procedure test for stationarity against the alternative of a unit root. It uses the LM (Lagrange multiplier) statistic to determine the test results. The following hypotheses were formed prior to conducting the KPSS test:

H_0: The data series is stationary.

H_1: The data series is non-stationary.

Rule of thumb for the KPSS test: Reject the null hypothesis if the KPSS test statistic > the LM (Lagrange multiplier) critical value. Next, after proving the non-stationarity of the data series, the Johansen and Juselius co-integration test with the determined optimal lag length is conducted. The VAR Lag Order Selection Criteria are based on Akaike's Information Criterion (AIC) and Schwarz's Information Criterion (SC). In other words, in order to generate a more comprehensive result, the optimal lag length is selected based on both the AIC and SC. Finally, the Johansen and Juselius Co-integration test is used to construct the co-integration based portfolio.

The stocks without any co-integration among the stock price movement are selected as the co-integration based portfolio, as a well-diversified portfolio should be free from co-integration. The Johansen and Juselius (JJ) multivariate co-integration technique uses the maximum likelihood procedure to determine the number of co-integrating vectors among a vector of time series.

Two likelihood ratio (LR) test statistics, namely, the trace and maximum eigenvalue statistics, are used to determine the number of co-integrating vectors. Critical values for both the trace and maximum eigenvalue tests are tabulated in Osterwald-Lenum (1992). The trace statistic is used to test the $H_0(r)$ against $H_1(p)$, and is written as:

$$\text{Trace} = -T \sum_{i=r+1}^{p} In(1-\hat{\lambda}_i) \tag{9}$$

On the other hand, the maximum eigenvalue statistic tests the $H_0(r)$ against $H_1(r+1)$, which is given by: Maximum eigenvalue = $-T\ In(1-\hat{\lambda}_{r+1})$. The following hypotheses were formed prior to conducting the JJ test:

H_0: There is no co-integration among the data series.
H_1: There is at least a co-integration among the data series.

Rule of Thumb: If the Trace statistic and Max-Eigen Statistic are larger than their 0.05 critical values, respectively, the null hypothesis is rejected.

4. Data Analysis

4.1 Risk-Adjusted Performance Indices (Sharpe, Treynor and Jensen's Index)

The outcome from Table 1 indicates that the active and passive portfolio in all five scenarios consistently outperformed the market return, resulting in significant positive values for both the Sharpe and Treynor ratios.

The overall risk-adjusted performance measures (Sharpe, Treynor and Jensen index) for the active portfolio in all five scenarios indicated a higher ratio as opposed to the passive portfolio and FBM KLCI market return. This implied that long run active portfolio management spurred higher performance than the passive strategy. The higher the ratio, the better the performance of the portfolio. For 16-year analysis, the active portfolio in scenario 1 (with the Sharpe ratio 0.5737) outperformed the FBM KLCI market return. The passive portfolio outperformed the market return based on the Treynor and Jensen index, but the Sharpe ratio showed otherwise. The Treynor ratios of all active portfolios consistently outperformed the Treynor ratio of the passive portfolio. As for the Jensen index, both active and passive portfolios showed positive ratios, which reflected that the portfolio performance was relatively superior compared to the market return. Again, the Jensen index of all active portfolios consistently outperformed the Jensen index of the passive portfolio; the higher the Jensen index, the better the risk-adjusted return resulting in a positive Alpha value.

The overall analysis during the crisis period of 1998 to 1999 showed that active portfolio management outperformed both the passive portfolio and FBM KLCI market return. In the overall comparison, the active portfolio constructed under scenario 2 showed the highest performance with all three ratios (1.1739 for Sharpe ratio, 0.8732 for Treynor ratio and 0.5879 for Jensen ratio) performing better than the passive portfolio. For the Jensen index, both portfolios showed positive ratios, which reflect that the portfolios performance is relatively good compared to the market return. Nevertheless, the active portfolios during the crisis period of 1998 to 1999 still outperformed the passive portfolio based on the Jensen index. However, for the passive portfolio, the Treynor ratio showed an equal ratio to the market return of 0.3327. Most active portfolios performed better than the market downturn, except for the active portfolio in scenario 5 for which the portfolio performance was low compared to the other ratios. Generalization on the active portfolio in scenario 5 showed that 8 out of 15 stocks were related to the palm oil plantation sector, with palm oil plantation exports experiencing the loss of a trade channel during the Asian Financial Crisis, most ASEAN countries and Asia trade partners were badly hurt by the severe economic and financial crisis. The active portfolio under scenario 2 consisting of five consumer stocks eventually proved to be the best performer during the crisis, which may imply that consumer stocks generally provide protection against downside risk as most of the products sold are necessities. Therefore, there was still a strong demand for consumer products throughout the crisis period, which also implied that these defensive stocks were crisis resistant and would sustain profits during a market downturn. These results generally showed that the performance of the portfolio could be attributed to the stocks relating to a particular industry.

The analysis during the crisis period from 2008 to 2009 showed that, once again, overall, active portfolio management outperformed both passive portfolio and FBM KLCI market return. For the Jensen ratio, both portfolios showed a positive ratio, which reflected that the performance of the portfolios was relatively good opposed to market return. However, the passive portfolio had a Jansen ratio of 0.0442 lower than the active portfolio with a ratio of 0.1430. All the active portfolios outperformed the market downturn during the crisis from 2008 to 2009. However, there was one exception with the active portfolio in scenario 4, which exhibited low performance during the crisis. This could be because this portfolio held a large proportion of property stocks, which consisted of 7 property stocks out of 15 stocks. The property sector in Malaysia was not heavily affected by the 2008 global financial crisis (the financial crisis in the United States erupted as a result of the collapse of the subprime mortgage market in 2007, for which the economic impact was more evident in developed countries of the Western hemisphere; the economic growth began to slow down in emerging markets). However, most local consumers responded negatively to the falling home prices from the cut in interest rates, and lost the desire to invest their money in the property sector. Most investors preferred to invest extra money into savings, shares and unit trusts. This is likely because people generally felt more secure holding their money in high liquidity investments for the period 2008 to 2009.

As opposed to the performance of the passive strategy, overall, active portfolios significantly outperformed the passive portfolio and the FBM KLCI market return in the long run and during the crisis periods, was indicative that diversification under passive portfolio strategy did not provide much risk reduction during the crisis period.

Table 1: Risk-adjusted performance indices

Portfolio Strategy	Sharpe Ratio	Treynor Ratio	Jensen Index
Active – Scenario 1			
16-year period	0.5738	0.2008	0.0832
Crisis (1998 – 1999)	1.0800	0.7592	0.3460
Crisis (2008 – 2009)	0.3042	0.1023	0.1430
Active – Scenario 2			
16-year period	0.6381	0.2368	0.1439
Crisis (1998 – 1999)	1.1739	0.8732	0.5879
Crisis (2008 – 2009)	0.6892	0.2569	0.2843
Active – Scenario 3			
16-year period	0.6459	0.2279	0.1312
Crisis (1998 – 1999)	0.9605	0.6171	0.3169
Crisis (2008 – 2009)	0.6941	0.2531	0.2935
Active – Scenario 4			
16-year period	0.7690	0.2360	0.1262
Crisis (1998 – 1999)	1.1224	0.7076	0.3519
Crisis (2008 – 2009)	0.0863	0.0245	0.1126
Active – Scenario 5			
16-year period	0.9395	0.2699	0.1235
Crisis (1998 – 1999)	0.8265	0.5019	0.1310
Crisis (2008 – 2009)	0.1060	0.0252	0.1179
Passive			
16-year period	0.2546	0.1425	0.0359
Crisis (1998 – 1999)	0.5681	0.3327	0.0136
Crisis (2008 – 2009)	-0.1893	-0.0437	0.0442
FBM KLCI Return			
16-year period	0.4032	0.1004	-0.0007
Crisis (1998 – 1999)	0.5911	0.3390	0.0219
Crisis (2008 – 2009)	-0.3270	-0.0870	0.0091

4.2 ARCH Outputs (Significance of Model)

Table 2 exhibits the ARCH outputs, which include coefficients, F-statistic, Probabilities of F-statistic, Obs*R-squared, and Probabilities of Obs*R-squared. "Obs*R-squared" is the LM (Lagrange Multiplier) test statistic for the null hypothesis of no serial correlation. The (effectively) zero probability value strongly indicates the presence of serial correlation in the residuals. The primary usage for these outputs is to check the validity of the models. From the results displayed in Table 2, as required by the ARCH model, both coefficient α_0 and α_1 must be positive, and α_1 must be less than 1. The FBM KLCI market return and all the portfolios fulfilled this requirement.

All the F-statistics and observed R^2 are significant at the level of 1%. As such, the results showed the presence of the ARCH effect for all the portfolios constructed over the 16-year time period. Hence, the null hypothesis of no significant ARCH effect (no ARCH errors) between current and past volatility was rejected.

As for the crisis period from 1998 to 1999, as required by the ARCH models, all the portfolios fulfilled this requirement and were significant at the 1% level with the F-statistic and Obs*R-squared, except for the active portfolio in scenario 4.

Table 2: ARCH coefficients, F-statistics, obs*R-squared

Portfolio Strategy	$\alpha 0$	$\alpha 1$	F-statistic	Prob.	Obs*R-squared	Prob.
Active – Scenario 1						
16-year period	0.00014	0.4236	1330.5210	0.0000	1009.1060	0.0000
Crisis (1998 – 1999)	0.00052	0.4074	168.8926	0.0000	127.7974	0.0000
Crisis (2008 – 2009)	0.00013	0.2012	21.9813	0.0000	21.1710	0.0000
Active – Scenario 2						
16-year period	0.00025	0.4121	887.1007	0.0000	731.8084	0.0000
Crisis (1998 – 1999)	0.00106	0.3858	95.9808	0.0000	81.2653	0.0000
Crisis (2008 – 2009)	0.00022	0.1207	7.7288	0.0056	7.6449	0.0057
Active – Scenario 3						
16-year period	0.00022	0.3947	845.8943	0.0000	703.5492	0.0000
Crisis (1998 – 1999)	0.00069	0.4842	187.2590	0.0000	137.9996	0.0000
Crisis (2008 – 2009)	0.00022	0.1487	11.8315	0.0006	11.6128	0.0007
Active – Scenario 4						
16-year period	0.00012	0.4708	1359.2250	0.0000	1025.5240	0.0000
Crisis (1998 – 1999)	0.00055	0.4618	166.1356	0.0000	126.2186	0.0000
Crisis (2008 – 2009)	0.00019	0.0112	0.0653	0.7984	0.0655	0.7980
Active – Scenario 5						
16-year period	0.00008	0.3586	629.4103	0.0000	547.1125	0.0000
Crisis (1998 – 1999)	0.00033	0.3472	73.0453	0.0000	64.2501	0.0000
Crisis (2008 – 2009)	0.00010	0.1054	5.8525	0.0159	5.8096	0.0159
Passive						
16-year period	0.00009	0.4544	1384.8430	0.0000	1040.0330	0.0000
Crisis (1998 – 1999)	0.00043	0.4304	153.8651	0.0000	119.0343	0.0000
Crisis (2008 – 2009)	0.00009	0.1154	7.0144	0.0083	6.9477	0.0084
FBM KLCI Return						
16-year period	0.00010	0.4115	1071.1980	0.0000	852.6334	0.0000
Crisis (1998 – 1999)	0.00058	0.3962	118.7988	0.0000	96.0817	0.0000
Crisis (2008 – 2009)	0.00011	0.1055	5.8526	0.0159	5.8097	0.0159

This could be due to the fact that one of the companies in active portfolio scenario 4, which is BDRB (Bandar Raya Development Berhad), stopped trading for some time and thus led to a stagnant price movement, and flattened the return of the overall portfolio. Overall, all the portfolios are significant.

4.3 GARCH Outputs

Table 3 shows the estimated GARCH outputs, which included the coefficient value, *z*-Statistic, and probabilities of the coefficients. The value of the coefficients represents the volatility due to new market information and its own MA (Moving Average) effect or its own lag effect.

The *z*-statistic and probabilities represent the significance level of the model. From table 3, all the β values for long run analysis and during the crisis periods were far higher than the α value, thereby indicating that the volatility of the market return for all the portfolios was caused more by the MA effect than new market information. This is aligned with Jing (1999) who found that when investors tend to be noise traders, the market is

Table 3: GARCH model coefficients

Portfolio Strategy	α	z	Prob.	β	z	Prob.
Active – Scenario 1						
16-year period	0.0948	22.7086	0.0000	0.8950	269.8597	0.0000
Crisis (1998 – 1999)	0.1934	7.7965	0.0000	0.7280	27.4237	0.0000
Crisis (2008 – 2009)	0.0857	5.1888	0.0000	0.8357	27.1492	0.0000
Active – Scenario 2						
16-year period	0.1243	23.2003	0.0000	0.8719	184.2341	0.0000
Crisis (1998 – 1999)	0.2442	11.7706	0.0000	0.7621	52.2899	0.0000
Crisis (2008 – 2009)	0.0769	3.5143	0.0000	0.8758	21.9971	0.0000
Active – Scenario 3						
16-year period	0.1378	24.2045	0.0000	0.8450	0.0059	0.0000
Crisis (1998 – 1999)	0.1756	8.7138	0.0000	0.8187	66.1207	0.0000
Crisis (2008 – 2009)	0.1652	3.9815	0.0000	0.7057	11.0712	0.0000
Active – Scenario 4						
16-year period	0.1255	23.3480	0.0000	0.8732	195.5926	0.0000
Crisis (1998 – 1999)	0.1550	8.7217	0.0000	0.8471	76.4066	0.0000
Crisis (2008 – 2009)	0.1284	5.9985	0.0000	0.8622	44.5821	0.0000
Active – Scenario 5						
16-year period	0.1205	20.8412	0.0000	0.8742	208.4470	0.0000
Crisis (1998 – 1999)	0.1532	7.6147	0.0000	0.8680	88.9955	0.0000
Crisis (2008 – 2009)	0.1692	7.2534	0.0000	0.7909	25.3878	0.0000
Passive						
16-year period	0.0763	20.7741	0.0000	0.9175	362.9944	0.0000
Crisis (1998 – 1999)	0.1001	8.0529	0.0000	8.0529	138.9727	0.0000
Crisis (2008 – 2009)	0.1445	4.8908	0.0000	0.7886	14.5389	0.0000
FBM KLCI Return						
16-year period	0.0972	22.2737	0.0000	0.9009	273.7739	0.0000
Crisis (1998 – 1999)	0.1560	8.4919	0.0000	0.8485	36.9553	0.0000
Crisis (2008 – 2009)	0.1433	3.8800	0.0000	0.5074	6.2550	0.0000

affected more by the noise factor than new information. Simply put, investors who invest in the Malaysian stock market may overreact to past information and underreact to new information. Hence, this implied that the Malaysian stock market is inefficient because the volatility (caused by share price movement) is not due to new information, but rather a pattern of movement caused by "noise traders" (Jing 1999).

All the coefficient values of the portfolios for the 16-year period are significant at the 1% level, accompanied by a high z-stat value, which implied that the GARCH model fits quite well with the data.

Hence, the null hypothesis that stated that there is no significant GARCH effect between current and past volatility was rejected. The sum of the coefficients for all portfolios was below 1 and not significant for an IGARCH appearance in the entire analysis.

In active portfolio scenario 1, the α value of 0.0948 was the lowest among the active portfolio scenarios. However, its β value of 0.8950 was the highest among all the portfolio scenarios, which might indicate that the stock returns in portfolio scenario 1 had a high risk and return profile. Similarly, the passive portfolio, with the β value of 0.9175, displayed the highest value among those constructed portfolios. Again, this showed that the performance of the passive portfolio exhibited the highest risk and return profile. As for the FBM KLCI market return, its α value of 0.0971 was lower than most active portfolios but close to the active portfolio of scenario 1. This indicated that the market reacts better than most constructed portfolios with regards to new information. However, consistent with other portfolios, its β value was similar to the active portfolio scenario 1 and passive portfolio, thereby indicating that the market had the highest MA effect. As discussed in the research methodology, all the active portfolios in this study were constructed under five different scenarios based on the correlation coefficient of the stock prices. The overall long run results (16-year period) exhibited that portfolios with lower correlation did not necessarily have lower volatility. As for the crisis periods, overall, the β values were found to be far above the α value in the market and for all constructed portfolios.

As reference to the crisis period from 1998 to 1999, all coefficient values for all portfolios were significant at the 1% level. However, the sum of both α and β exceeded 1 for all portfolios except for active portfolio scenarios 1 and 3 which showed otherwise. Therefore, an IGARCH (integrated GARCH process) appeared in the portfolio analysis, indicating that the constraint forces the conditional variance to act like a process with a unit-root. Hence, it is useful for step-ahead forecast. All the z values were also large enough to indicate that the GARCH fitted quite well with the data. Since all the portfolios during the crisis period from 1998 to 1999 had a significant ARCH effect in the GARCH model (as shown in Table 2), it implied that by combining the MA effect with the ARCH, ARCH is a significant coefficient to determine the output. There is a co-movement of the 2 series since both the coefficient values in the GARCH model were significant at the 1% level. For active portfolio scenario 1, the β value of 0.7280 showed the lowest value among all the portfolios. Active portfolio scenario 1 was constructed using the lowest correlation among the stocks, and is the core representative of the active portfolio. This implied that active portfolio scenario 1 performed the best during the crisis period. This finding is aligned with Abidin (2006) who found that Malaysian stocks tended to have low correlation during the crisis period, but had higher correlation during normal times, and that the portfolio constructed using correlation analysis performed well during the crisis period rather than in the long run. Conversely, the passive portfolio indicated the abnormally highest β value of 8.0582, which is the highest value among all the portfolios during the crisis period of 1998 to 1999. This exhibited the highest risk in the stock trading.

Similarly, for the second crisis period from 2008 to 2009, all the coefficient values for all portfolios were significant at the 1% level. The sum of both α and β for all portfolios was below 1 as required by the GARCH model, and the z values were also large enough thereby indicating that the GARCH fitted quite well with the data. As opposed to the ARCH outputs in Table 2, with the exception of active portfolio scenarios 4 and 5, and the market portfolio, the other portfolios during the crisis period from 2008 to 2009 had a significant ARCH effect in the GARCH model, which implied that by combining the MA effect with the ARCH, the ARCH is a significant coefficient for determining the output. Again, all the β values were far higher than the α value, which indicated that the volatility of the market return for all the portfolios was caused more by its MA effect, rather than new market information. For the passive portfolio, its β value of 0.7885 was lower than all the active portfolio scenarios, thereby indicating moderate stock return volatility, and a moderate risk and return profile for the passive portfolio. The β value of 0.5074 for FBM KLCI market return was the lowest value among all the constructed portfolios, thereby indicating that the market did not have the highest MA effect during the credit crisis.

In short, the comparison among the constructed portfolios and the market during the crisis periods provides clearer results. During the crisis periods, active portfolios produced a somewhat lower volatility compared to the long run analysis. This finding is consistent with

Abidin (2006) who found that Malaysian stocks tended to have low correlation during the crisis period. In contrast, the overall long run results (16-year period) exhibited that a portfolio with low correlation does not necessarily have lower volatility.

In addition, the results in Table 3 yield an argument that the Harry Markowitz modern portfolio theory (1952, 1959), which utilized correlation to construct the portfolio, should be categorized as an active portfolio strategy, as it only performs well in the short period, not over the long run. This is because the correlation may vary with different market situations and company conditions. Simply put, the correlation is not fixed by holding a constant portfolio. In the long run, active monitoring and frequent reconstruction are needed to sustain a low correlation in the portfolio.

4.4 Graphs on GARCH Model

Figures 1, 2 and 3 exhibit the estimated GARCH variance series. These graphs are useful to detect the outliers and potential problems that caused the model to be insignificant. In Figure 1, all the scenarios showed high volatility in the middle of year 1998 due to the Asian Financial Crisis. To be more precise, the KLCI hit its historical lowest at the point 262.7 on 1st September 1998. However, the market started to rebound after two days. Through all the scenarios, the graph analyses indicated that scenarios 2 and 3 had the highest volatility in the middle year of 1998. This can be explained in that most portfolios in scenarios 2 and 3 were involved in the manufacturing and plantation sectors. Most of the industrial outputs from plantation and manufacturing were facing an uncertain situation since most trade partners around the neighbouring countries within the same region had also fallen into deep recession.

The other high volatility was in the early stage of 2008, whereby all scenarios showed the same trend through all the graphs. This high volatility can be viewed in Figure 3, and the highest volatility is in scenario 4 at the year-end of 2008. Most of the stocks in scenario 4 were from the property sector, which is aligned with the credit crisis of 2008 when most of the property related stocks were adversely affected by the global crisis. As discussed earlier, although the housing market in Malaysia was not heavily affected by the 2008 global financial crisis, most local consumers responded negatively to the falling home prices and the cut in interest rates, and thus lost their desire to invest in the property sector.

4.5 GARCH Forecasting

Table 4 shows the GARCH forecast result with the coefficient values of β_0, α_0 and α_1 for 100 stocks of listed companies with the highest earnings at fiscal yearend 2013. Figures 4 and 5 show the GARCH forecast result for the return of 100 stocks with dynamic forecasting and static forecasting. The forecast for the portfolio consisting of 100 stocks (given its β value of 0.01, α_0 value of 0.00009 and α_1 value of 0.8714) exhibited much less exposure to market risk with its β value being less than 1 and approaching zero. Simply put, a portfolio of 100 stocks mirroring the market portfolio will have less exposure to market risk and its expected return is approximately equal and approaching the risk-free rate. Theoretically, a portfolio with no market risk should have an expected return equal to the risk-free rate (Drake and Fabozzi 2010). Practically, for individual investors, in reality, it is hard to form a portfolio with 100 stocks or construct a portfolio that is totally free from market risk.

Both graphs in Figures 4 and 5 display the forecast of variance from the estimated risk return. Figure 4 shows the dynamic forecasting with a variance of 0.0007, indicating good accuracy for the risk return estimate. In other words, this variance value is significant for the 100 stocks when estimating the market risk return. Whilst for the static forecasting shown in Figure 5, the variance in estimation varies for all the years and was most volatile

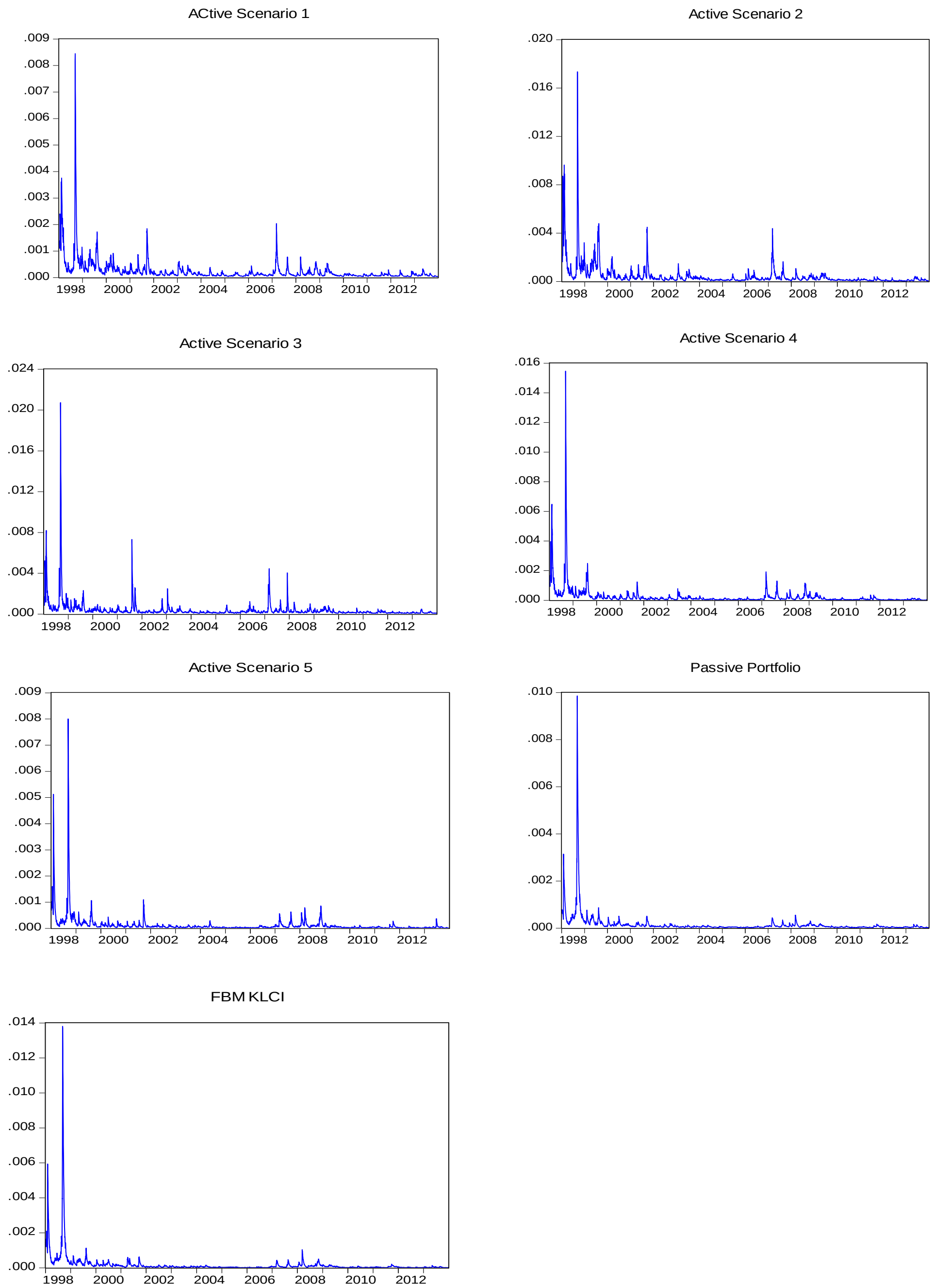

Figure 1: Estimated GARCH variance series for all portfolios (16 years period)

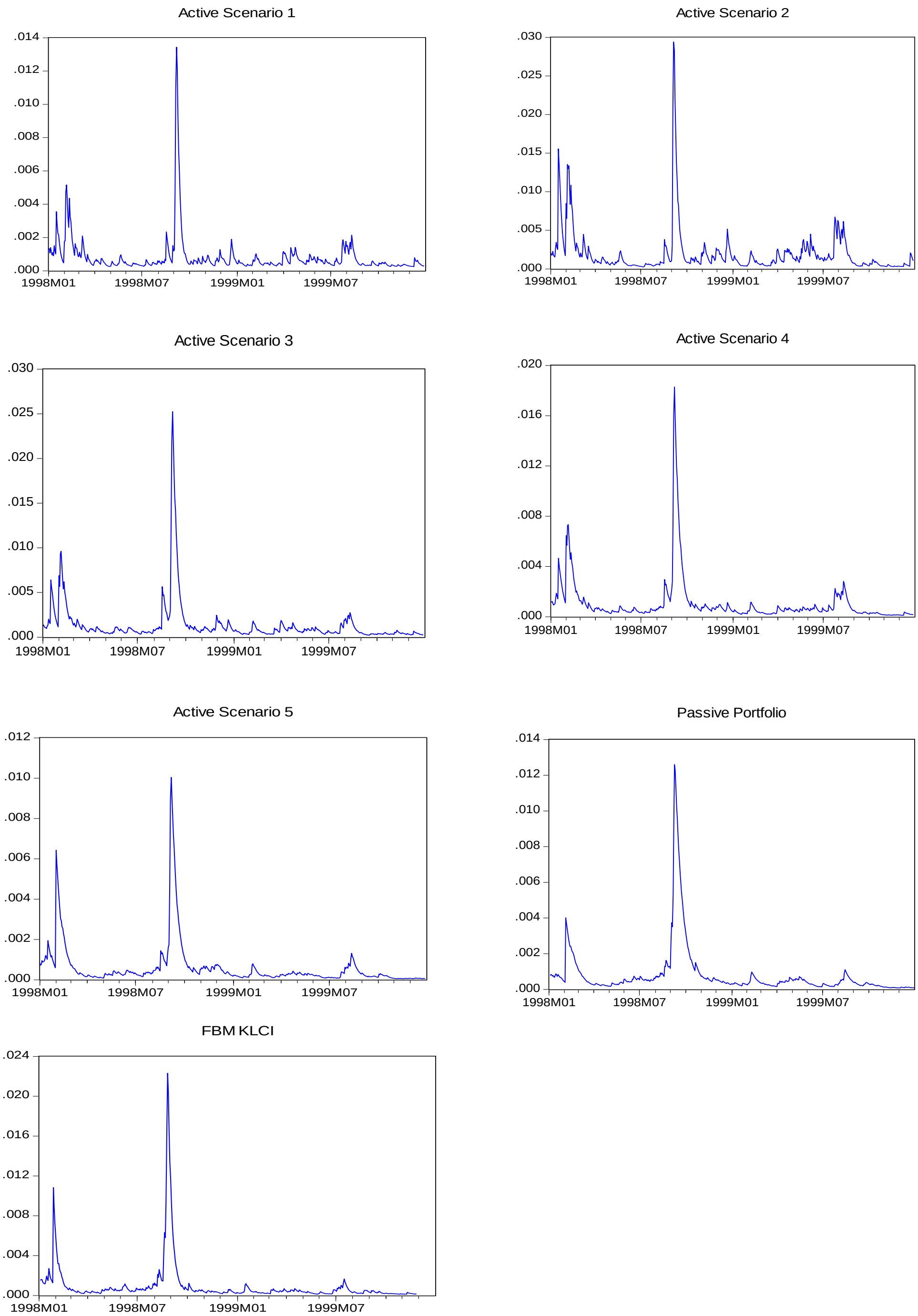

Figure 2: Estimated GARCH variance series for all portfolios (crisis period from 1998 to 1999)

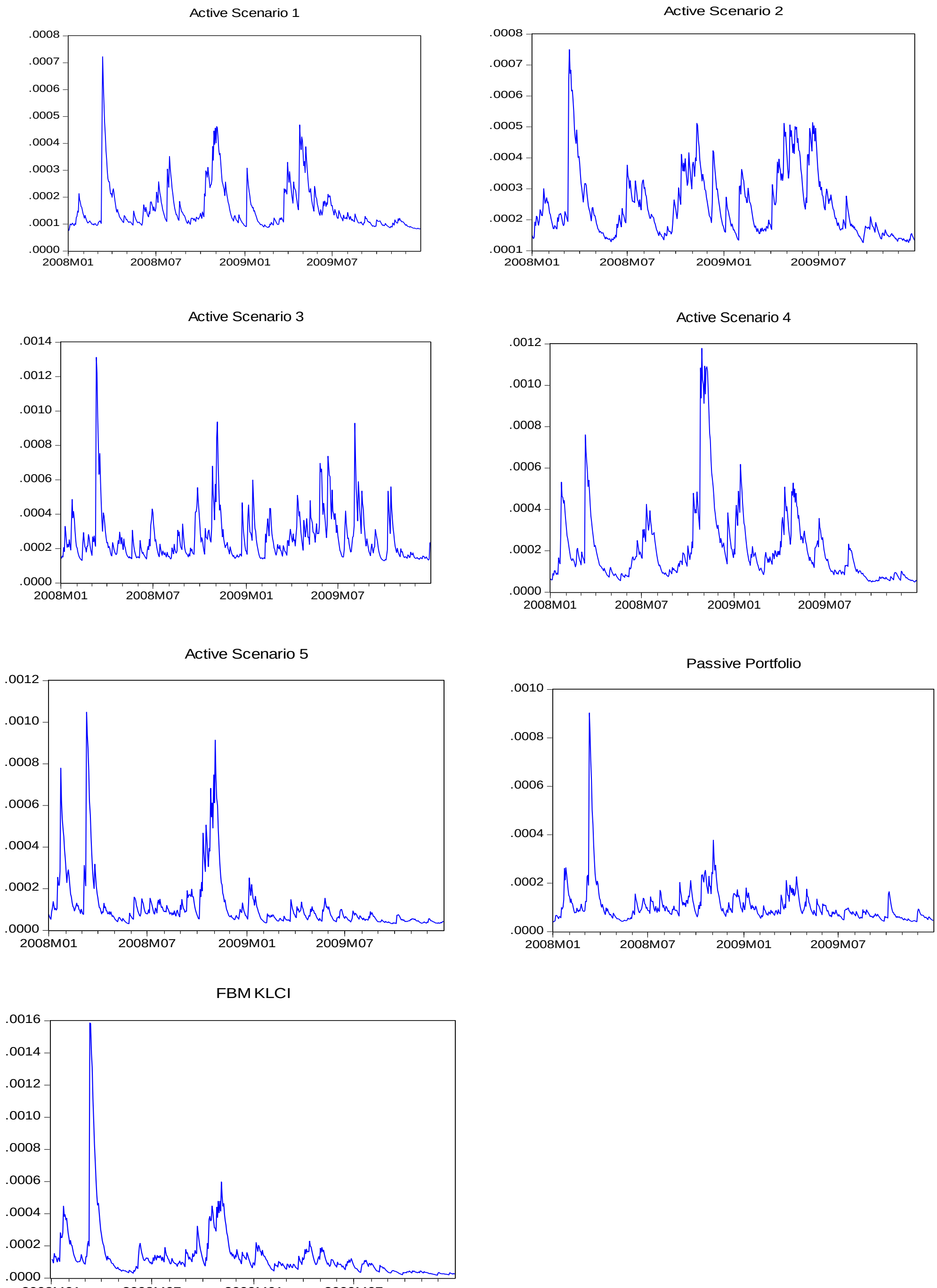

Figure 3: Estimated GARCH variance series for all portfolios (crisis period from 2008 to 2009)

in 1998 and 1999. Technically, dynamic forecasting performs a multi-step forecast of the portfolio return for 100 stocks; static forecasting on the other hand performs a series of one-step ahead forecasts for the portfolio return of 100 stocks. Both forecasting methods are applied together and useful in forecasting judgment (Christos 2005).

Table 4: GARCH forecast result (100 stocks portfolio)

Portfolio	β_0	α_0	α_1
100 stocks	0.010424	8.91E-05	0.871479

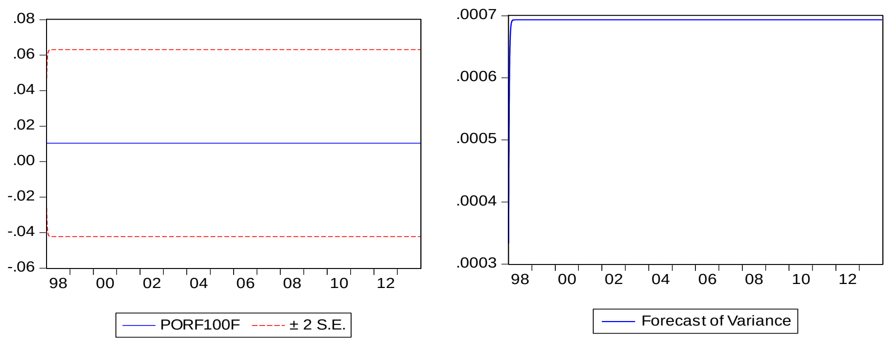

Figure 4: GARCH-Dynamic Forecasting for 100 Stocks Portfolio

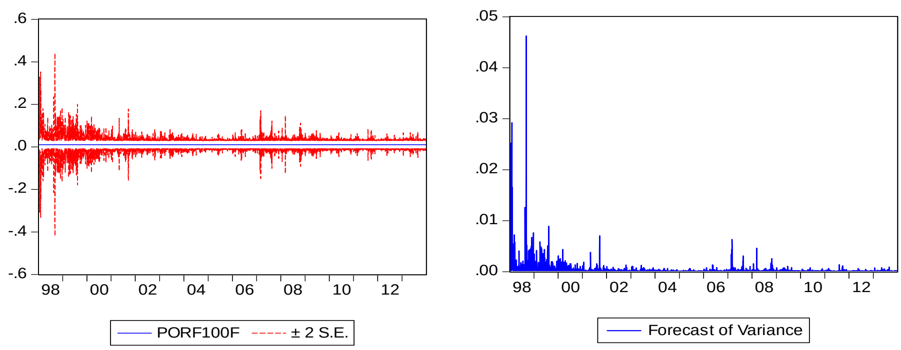

Figure 5: GARCH-Static Forecasting for 100 Stocks Portfolio

4.6 *R*-squared Diversification Measure

Table 5 indicates the *R*-squared (R^2) results for the portfolios of randomly selected stocks from the samples in order to determine the level of diversification. The randomly chosen 10 to 100 stocks with an assumption of equal weight for all stocks in a portfolio were used to determine the *R*-squared. According to Stevenson and Jennings (1984), 8 to 16 stocks would be sufficient to construct a well-diversified portfolio.

Conversely, Surz and Price (2000) argued that 15 stocks in a portfolio would only get 76% available diversification, which is also contradictory to Statman (1987) who found that 90% diversification would be achieved with 15 stocks or more. To testify the portfolio with an ideal number of stocks added in the case of Malaysia, *R*-squared was used to measure the squared correlation among the stock performances. The results from Table 5 indicate that ten stocks in a portfolio could achieve 56.03% of diversification benefits, and that this number will keep on increasing gradually when adding more stocks to the portfolio. When the number of stocks reached 90, a portfolio would achieve a total of 70.47% diversification benefits. In referring to Surz and Price (2000), a portfolio of 30 stocks would bring 86% of diversification benefits. However, investing in 30 stocks on the Malaysian stock market only brought about 62.3% of diversification benefits, which is less effective compared to the diversification benefit in developed markets. This is due to the significant differences in the market structure, market size and efficiency in well-developed countries (the United States for instance), which are far more established compared to the local context. Therefore, the lower efficiency of the Malaysian stock market may imply that the measures of risk in the Modern Portfolio Theory of Markowitz (1952, 1959), such as portfolio standard deviation and correlation, are somehow limited and do not reflect the reality of the market investment conditions.

Therefore, standard deviation may not be an appropriate measure to effectively assess the reality of risk in a portfolio due to market inefficiency. Instead, R^2 becomes a more essential measure to gauge the level of unsystematic risk.

Table 5: *R*-Squared for number of stocks added into portfolio

Diversification Measure	Number of Stocks added									
	10	20	30	40	50	60	70	80	90	100
R-squared (%)	56	60.8	62.3	65.8	65.9	68.4	69.8	69.7	70.5	49.5

4.7 Unit Root Tests

Prior to conducting the co-integration test, unit root tests based on the Augmented Dickey-Fuller test (ADF), Non-parametric Phillips-Perron test (PP), Kwiatkowski *et al.* (1992) test (KPSS) were used to prove that the stock price series within the constructed portfolio was non-stationary (has a unit root). Fifteen selected stocks without any co-integration among the stock price movement were formed as the co-integration based portfolio.

The selected stocks included AJI, BJTOTO, CARLSBG, CCB, GENTING, KIANJOO, KULIM, MAA, MFLOUR, MRCB, PBBANK, RVIEW, SHCHAN, SIME and UMCCA. The stationary test results for these 15 stocks (co-integration based portfolio) were based on the outcomes generated by the ADF, PP and KPSS tests, as shown in Table 6. Both the ADF and PP tests had the null hypothesis of data series being non-stationary. Conversely, KPSS had the null hypothesis that the data series is stationary. Table 6 indicates the critical values to determine the significance of the tests. The ADF and PP are judged based on the critical τ value, while the KPSS follows the LM- Stat critical value.

Based on the consistent outcomes from the ADF and PP tests for almost all stocks, the null hypothesis of non-stationary should not be rejected (fail to reject); with the exception for BJTOTO, which should be rejected at the 5% significance level, and CCB and MAA, which should be rejected at the 10% significance level. On the other hand, the KPSS test revealed the null hypothesis of stationary for every stock that was rejected at the 1% significance level. Thus, the 3-unit root tests consistently indicated that the selected stocks for the co-integration based portfolio were non-stationary. Aligned with the null hypothesis of co-integration, the outcomes displayed in Table 6 allowed the Johansen and Juselius (JJ) Co-integration Test to proceed and validate the co-integration based portfolio.

4.8 Johansen and Juselius Co-integration Test

Table 7 exhibited the VAR lag order selection criteria. AIC and SC will be the selected optimal lag length (chosen criteria) in this study. The lag period of 1 and 2 were chosen as they generated the highest SC and AIC figures respectively. In Johansen and Juselius (JJ)

Table 6: Unit root tests – test on non-stationary in data series

Name of Stock	ADF	PP	KPSS
AJI	-2.4253	-2.1236	1.1961***
BJTOTO	-3.6865**	-3.8254**	0.3623***
CARLSBG	-1.0338	-0.9952	1.2490***
CCB	-3.2517*	-3.2528*	0.6603***
GENTING	-2.8032	-2.5825	0.5789***
KIANJOO	-1.2694	-1.3083	1.2034***
KULIM	-2.1997	-2.2301	1.2724***
MAA	-3.3284*	-3.3064*	0.5602***
MFLOUR	-2.1152	-2.0819	0.8891***
MRCB	-2.6044	-2.9218	0.5319***
PBBANK	-0.8599	-1.0874	0.9932***
RVIEW	-2.5978	-2.2769	0.7835***
SHCHAN	-3.6173**	-3.3914*	0.7293***
SIME	-3.0537	-3.0343	0.3228***
UMCCA	-1.9887	-2.0584	1.5315***

	Critical τ value	LM-Stat critical value
	ADF PP	KPSS
1% significant level	-3.9609	0.2160
5% significant level	-3.4112	0.1460
10% significant level	-3.1274	0.1190

Notes: *(**)[***] denotes rejection of the hypothesis at 10%(5%)[1%] significance level.

tabulate test results, under the lag 1 and lag 2 periods, the null hypothesis of no co-integration equation was failed to be rejected at 5% significance level (for both Trace statistic and Max-Eigen statistic). It is proved that the portfolio constructed with the 15 stocks is free from any co-integration equation. Simply put, a co-integration free portfolio would fail to reject the entire null hypothesis listed.

Table 7: The VAR lag order selection criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-49356.36	NA	6.44e-09	23.7077	23.7306	23.7158
1	93470.01	284555.4	1.18e-38	-44.7683	-44.4033*	-44.6392*
2	93791.25	637.6974	1.12e-38*	-44.8145*	-44.1073	-44.5644
3	93988.78	390.7030	1.14e-38	-44.8013	-43.7519	-44.4301
4	94182.44	381.6394	1.15e-38	-44.7863	-43.3946	-44.2940
5	94361.87	352.3128	1.18e-38	-44.7644	-43.0306	-44.1511
6	94544.06	356.4109	1.20e-38	-44.7438	-42.6678	-44.0095
7	94723.20	349.1749*	1.23e-38	-44.7218	-42.3036	-43.8664
8	94851.74	249.6057	1.29e-38	-44.6755	-41.9151	-43.6990

Notes: * denotes the selected optimal lag length; LR = sequential modified LR test statistic; FPE = Final Prediction and Error; AIC = Akaike Information Criterion; SC = Schwarz information criterion; HQ = Hannan-Quinn information criterion.

4.9 Comparison between Correlation and Co-integration Based Portfolio

A well-diversified portfolio should be free from co-integration and generate the lowest correlation among the stocks. For a robust comparison, the 15 stocks with the lowest correlation (correlation based portfolio, as in active portfolio scenario 1) and 15 stocks that were free from co-integration (co-integration based portfolio from Table 6) were compared. *R*-squared is used to assess the level of diversification achieved by both portfolios. The higher *R*-squared proves, thus the higher level of diversification, vice versa. The comparison between the R^2 of correlation based portfolio and co-integration based portfolio are displayed in Table 8. In both cases, the latter outperformed the former.

This outcome validates that the level of diversification in the co-integration based portfolio outperformed the correlation based portfolio over the long run and throughout the crisis periods. This is aligned with the findings from Philips *et al.* (2012), which indicated that using correlation as a method of portfolio construction does not necessarily yield the best result.

Table 8: *R*-Squared (level of diversification) for correlation and co-integration based portfolio

	Long Run		Crisis Period (1998 – 1999)		Crisis Period (2008 – 2009)	
	Correlation Based Portfolio	Co-integration Based Portfolio	Correlation Based Portfolio	Co-integration Based Portfolio	Correlation Based Portfolio	Co-integration Based Portfolio
R2	0.5063	0.6955	0.6336	0.8078	0.3899	0.5804

5. Conclusion and Discussion

The performance of the active and passive portfolios were assessed and ranked based on the risk-adjusted performance measure (Sharpe, Treynor and Jensen index). Overall, the active portfolios significantly outperformed the passive portfolio and FBM KLCI market return based on these measures. The active portfolio strategy, which was constructed using five different scenarios produced higher returns over the long run and crisis periods. The outcome demonstrated that diversification under passive portfolio strategy did not provide effective risk reduction, particularly during the economic downturn periods.

The performance of both portfolios were further explored by analysing the GARCH model and its ARCH effect. The analysis of the results from the GARCH models were consistent with the risk-adjusted performance measure for both crisis periods. The volatility of the active portfolio was significantly reduced throughout the crisis periods. This was consistent with Abidin (2006) who ascertained that correlation among the Malaysian stocks tended to have low correlation during the crisis period. The coefficients of the β values were far higher than the α value from the GARCH output, which indicated that the Malaysian stock market is inefficient and that the stock price volatility was affected more by its own lagged effect (noise factor) than the new information. Simply put, the imperfect Malaysian stock market condition was attributed to the investor's behaviour and psychological biasness. The investors who invest in the Malaysian stock market might overreact to past information or underreact to new information. However, in general, equilibrium and anomalies are raised from asymmetric information, rational investors can hold different portfolios with access to different information (Clarke *et al.* 2004). Aligned with the risk-adjusted performance measure (Sharpe, Treynor and Jensen index), the analysis of the results indicated that abnormal profits (or excess return) can be obtained with the active portfolio strategy in imperfect market conditions. From the overall analyses, it can be concluded that the active portfolio performed the best; its superiority as opposed to the passive portfolio is more obvious, particularly in the crisis periods. It is best to implement the active portfolio strategy in the Malaysian stock market in the long run and during the crisis periods.

In GARCH model forecasting, the 100 stocks with the highest earnings exhibited a low β value, indicating that the 100 stocks that mirrored the market portfolio will have less exposure to market risk. In other words, the forecast on the targeted high earning stocks in Malaysia were perceived to be less risky for risk adverse investors. In addition, the GARCH results showed that the correlation may vary with the new market situation and company condition over the long run. Thus, a portfolio with low correlation does not necessarily have low volatility. It can be concluded that the correlation among the stocks is not fixed by holding a constant portfolio. This finding is consistent with Alexander (1999), who found that a correlation based portfolio is relatively better in the short period. In other words, the Harry Markowitz Modern Portfolio Theory (1952, 1959), which is based on correlation analysis, is more suitable to construct an actively managed portfolio in the short run. Undoubtedly, the Markowitz diversification strategy has led the modern finance from the discovery of optimal portfolio diversification strategy, with primary concern about the degree of covariance between asset returns in a portfolio.

This contributes to the formulation of an asset risk in a portfolio of assets rather than in isolation, and seeks to combine assets in a portfolio with returns that are less perfectly positively correlated, which is in line with an effort to lower portfolio risk (variance) without sacrificing return.

The imperfect Malaysian stock market condition may portray certain diversification effects in the local perspective, which may also imply that applying the Modern Portfolio Theory of Markowitz (1952, 1959) is not appropriate in the local context. In the Modern Portfolio Theory, the measures of risk using portfolio standard deviation and correlation do not reflect the realities of the market's investment condition. Due to market inefficiency, standard deviation may not be an appropriate measure to effectively assess the realities of portfolio risk. Instead, R-squared (R^2) is a more robust measure to appraise the level of unsystematic risk in the local perspective. By utilizing the measure from R-squared, diversification in the Malaysian stock market seems to be less effective compared to in developed markets. The results from R-squared indicated that a portfolio with 90 stocks in the Malaysian stock market could only achieve 70.47% of the diversification level. Conversely, Surz and Price (2000) discovered that a portfolio with 30 stocks was able to achieve 86% of the diversification level. The 15-stock portfolio in the active investment strategy with the lowest correlation, could only achieve about 60% of the available diversification, which contradicts the 90% of available diversification found by Statman (1987). In the local situation, a portfolio consisting of 60 stocks achieved less than 90% of full diversification. As such, the relationship between the number of stocks held in a portfolio and the diversification level have been verified for the local context.

Therefore, local investors can no longer rely on a simple rule of thumb in the traditional approach to decide the number of stocks to be included in the portfolio. Diversification is more complex in reality due to the significant differences in the market structure, market size and efficiency in different economies, and thus it is different from that suggested by the traditional diversification methods. Hence, this study concluded that there are limited diversification benefits by investing in the Malaysian stock market. In the long run, however, frequent reconstruction of the portfolio is needed to achieve the desired diversification effect. Such reconstruction should utilize the correlation measure and the GARCH model given its accuracy in forecasting future volatility.

By comparing the performance between the co-integration based and correlation based portfolios, the risk reduction benefits of the co-integration based portfolio were superior to the correlation based portfolio over the long run and throughout the crisis periods. Again, this is aligned with the discovery of Alexander (1999). However, co-integration analysis is explicitly robust for long run analysis. The underlying reason being that a combination of two stocks with low correlation does not imply that they will diverge in opposite directions over the long run. A large opposite movement in the short period will yield a low correlation between the two stocks. However, in the long run, the desired diversification level between the two stocks may fail to achieve as they may still be co-integrated. This means that a price series fails to wander off (get lost) in opposite directions for long without coming back to its mean distance eventually. Hence, a convincing argument is that constructing a portfolio that is free from co-integration is far more realistic than forming a portfolio with low or negative correlation. This finding is aligned with Alexander and Dimitriu (2005), and Grobys (2010) who discovered that under the buy and hold strategy, the co-integration based portfolio outperformed the correlation based portfolio. The GARCH volatility also verified that correlation is not fixed for the long-term. Instead, the correlation may vary with different market situations and company conditions. In other words, the correlation is not fixed by holding a constant portfolio, active monitoring and frequent reconstruction is needed to sustain a low correlation in the portfolio.

Finally, this study concluded that particular related stocks across different sectors do matter and should be considered by value investors when constructing a portfolio. The large proportion of consumer stocks in the active portfolio eventually proved to be the best performer during the crisis period (1998 – 1999). This may imply that consumer stocks were generally defensive and crisis resistant throughout the recession period as most of the products sold were necessities.

In addition, holding a large proportion of property stocks may have been indirectly affected by the 2008 global financial crisis (subprime mortgage crisis). Although the property sector in Malaysia was not heavily affected by this crisis, most local consumers responded negatively to the falling home prices from the cut in interest rates, and lost the desire to invest their money in long-term property, instead investing their money in high liquidity investments during 2008 to 2009. Hence, investors might target consumer stock investment strategies more during the economic downturn due to their crisis resistant nature.

5.1 Limitations and Recommendations

The top 100 companies listed on the Bursa Malaysian Stock Exchange with the highest earnings in the fiscal year ended 2013 were selected as samples. As for accounting-based measures, however, earnings can be easily manipulated and failed to reflect the true cash receipts in the firms. As such, more appropriate company selection criteria should be based on a firm’s market capitalization or its free cash flow level. The return of the portfolios was only calculated based on the daily changes of stock prices in this study. Indeed, when assessing the return of the portfolio, both the daily price changes and dividend returns should be considered. The arithmetic mean was used to calculate the mean return in this study, this method failed to take into account the compounding effect and carried the effect from outliers.

Conversely, the average or mean calculation from the geometric mean takes into account the impact of compounding, and thus provides a more robust average figure. Hence, future research should consider the inclusion of dividend yields in the total portfolio return and apply the geometric return in the mean calculation. Furthermore, when comparing the active and passive portfolio, it is important to clarify that such a comparison was done without considering the transaction costs. In reality, the transaction costs incurred in the active portfolio strategy would exceed those of passive portfolio investment due to the frequent margin trading. Practically, transaction costs should be considered and may affect the portfolio strategy implementation. In addition, the active and passive portfolio construction upheld the assumption that all the stocks are invested with equal weight in every constructed portfolio. However, this may not be the case if aggressive investors require active monitoring or frequent reconstruction of their portfolios.

Neither the Sharpe nor Treynor ratio measured the exact return as they are only meant for ranking criterion. Portfolios that are ranked based on the Treynor ratio are only useful if the portfolios under consideration are sub-portfolios of a broad, fully diversified portfolio. If this is not the case, portfolios with identical systematic risk but different total risk, will be rated the same. The use of R-squared (R^2) as a diversification measure in this study might not be perfect. R-squared is calculated as the square of the correlation coefficient between the original and modelled data series.

As opposed to the GARCH model, R-squared is inadequate to determine whether a model is fit with the data series, but instead indicates how diversified a model is. R-squared provides an estimate of the strength of the relationship between the model and the response variable, however, it does not provide a formal hypothesis test for this relationship. A high R-squared does not necessarily indicate that the model has a good fit. If too many large positive correlated stocks are present in a portfolio, the R-squared measure may distort the effect of diversification and may no longer be an effective measure of diversification benefits.

The overall comparison of both the correlation and co-integration analysis suggested that investors who hold a long run investment and are concerned about a long-term risk reduction measure should focus more on co-integration analysis. The implementation of both correlation and co-integration analysis is not mutually exclusive.

In practice, investors are recommended to consider both analyses when constructing their portfolio. For long-term buy-and-hold investments, conservative investors should focus more on co-integration analysis, while for short-term actively managed investments, aggressive investors should target correlation analysis for frequent reconstruction of their portfolios.

Due to the limited diversification benefits on the Malaysian stock market, Malaysian investors are recommended to invest globally, or invest in a portfolio with different asset holdings, for instance investing in bonds or mutual funds. As most countries are integrated in the world financial markets from regional and cross country cooperation, international diversification would bring substantial regional or global diversification benefits for domestic investors. According to Driessen and Laeven (2007), investors can largely benefit from international diversification by investing in a well-diversified economy or a well-developed stock market. Diversification in bonds across time horizons can be done by investing in bonds with different terms of maturities or different degrees of default risk. Bonds with higher yield are always associated with higher default risk, and it depends heavily on the market situation to decide the appropriate weight of bonds in portfolio investment (Kemper *et al.* 2012). In mutual fund diversification, by investing in a basket of securities via index funds, mutual funds, ETFs, managed funds and funds across industries, the risks are spread across the broad holding of funds (Shy and Stenbacka 2003).

This study limits the portfolio strategy to the active and passive portfolio strategy. Other portfolio strategies have emerged and been recommended in recent studies that are feasible for future research, namely the Sample-based mean-variance portfolio, Bayesian diffuse-prior portfolio, Bayes-Stein shrinkage portfolio, Bayesian portfolio based on asset-pricing model, Minimum-variance portfolio and Value-weighted portfolio. Future researchers may consider portfolio construction with various weights for a more comprehensive view on the diversification effects.

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