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Market Timing and Stock Selection Strategies in *Shariah*-Compliant Stock Portfolio

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ABSTRACT

This study focuses on market timing and stock selection strategies that could be implemented by individual investors of *Shariah*-compliant equity using the top ten constituents of the FTSE Bursa Malaysia *Hijrah Shariah* Index. Investors are assumed to enter and exit the stock market following the buy-and-sell signal from Moving Average Crossover. Meanwhile, for stock selection, this study aims to construct the optimal portfolio using the Sharpe Ratio Maximisation model and Naïve (1/N) portfolio. The level of market timing and selectivity skills of individual investors following the suggested investment strategies will be measured by using the Treynor-Mazuy model. The empirical results showed that the best Moving Average Crossover gave plausible trading frequencies and provided the most return to investors was the (1, 100, 0.01) strategy. Albeit, the stock allocation for the constructed portfolio was less diversified compared to the Naïve (1/N) portfolio, the composition of portfolio weights of the constructed portfolio was able to offer a more than average risk to reward ratio. Furthermore, in the out-of-sample framework, both portfolios outperformed the market benchmark. Unlike previous studies, this study backed tests the strategy and found that it was beneficial for individual investors of *Shariah*-compliant equities to enhance market timing and selectivity skills in stock investment.

Keywords: Individual investors, market timing, Moving Average Crossover, *Shariah*-compliant equities, Sharpe Ratio Maximisation, stock selection

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INTRODUCTION

The *Islamic* Financial Institutions (IFI) have seen rapid growth and gained worldwide prominence over the last decades. This positive development was driven by

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the increase in demand not only from institutional investors but also from individual investors. Therefore, from the individual investors' point of view, it is necessary to equip themselves with the knowledge to steer their investment through the ebbs and flows of the stock market movements. Furthermore, in *Islam,* risk management practices are deemed very important to protect ones' wealth which is in line with one of the facets of *Maqasid Shariah*. With the availability of almost 80% of all stocks traded in the Malaysian market to be *Shariah*-compliant, it will be beneficial for investors as this would broaden the investable stocks universe to grasp the diversification benefit. The main question is how could an individual investor decide on when he should enter and exit the market and what are stocks to buy.

This research concentrated on market timing and stock selection of the *Shariah*–compliant equities in Malaysia. Fama (1972), divided forecasters into two different components, which were micro forecasting and macro forecasting which refer to selectivity skills and market timing, respectively. Market timing is an active strategy by predicting the future market direction to outperform buy-and-hold or passive strategy. One of the common methods that were implemented by investors in market timing is Moving Average (MA) Crossover. Meanwhile, stock selection is another fundamental element in investing to select the right stocks in a portfolio. The Mean-Variance Optimisation (MVO) model is one of the stock selection strategies which was developed by Markowitz (1952), for portfolio analysis in Modern Portfolio Theory (MPT). Furthermore, market timing and stock selection are the main methods that focus on technical analysis when analysing and making investment decisions in the stock market based on historical price.

Based on a previous study that focussed on market timing and stock selection, Malaysian mutual fund managers had a strong positive relationship between these abilities in investment (Alam et al., 2016; Nassir et al., 1997). At the same time, implementing these strategies could improve the confidence level of investors and enhanced their sense of market movement, especially for mutual funds to outperform in the long run. The performance of *Shariah* market and the conventional market is similar but the sensitivity of performance is different in different economic conditions (Shaikh et al., 2019). The conditions for pursuing market timing and selectivity skills strategies could be detected with economic and financial variables in Malaysia. In contrast to these active strategies, the Naïve (1/N) portfolio allocation is a common strategy for passive investors. By following this strategy, the investor simply invests the same amount of capital on each stock that was selected. Some studies stated that Naive (1/N) diversification could hardly outperform in portfolio investment strategy due to lack of accuracy consistency in modelling, although it was less risky in portfolio (Pflug et al., 2012). This was supported by Bessler et al. (2017), that active strategy outperformed better than passive strategy (naïve portfolio) where diversifying in investing stock might reduce the default risk.

The purpose of this research is to determine the buy-and-sell signals using the MA Crossover for market timing strategy. Meanwhile, for stock selection, this study aims to construct an optimal portfolio using the Sharpe Ratio Maximisation (SRM) model and Naïve (1/N) portfolio. Then, a comparison for the out-of-sample performance of both portfolios will be analysed. Finally, the level of market timing and selectivity skill will be measured.

LITERATURE REVIEW

In order to focus on market timing and stock selection strategies in *Shariah*-compliant investment, two main fundamental investment questions need to be answered by investors. Investors need to be aware of when they should enter and exit the market and what stock compositions are in their portfolios. Hence, investors need the knowledge and expertise of investment strategies to achieve a higher return (profit) on one hand and controlling the risk level on the other. Investment managers in Malaysia have been found to be lacking in market timing and selectivity skills (Fikriyah et al., 2007; Nassir et al., 1997). Selectivity skills and market timing are the most dominant variables in comparison with other Malaysian economic indicators that are related to the performance of mutual funds (Fikriyah et al., 2007).

In essence, the MA method of market timing is not only an investment strategy for the conventional market but also for *Shariah* market. Mansor and Bhatti (2011), stated that the Kuala Lumpur *Shariah* Index (KLSI) 0.107 performed better than the Kuala Lumpur Composite Index (KLCI) with 0.053 in Sharpe ratio. Moreover, fund managers have a positive market timing strategy and significantly at a 5% significance level. Generally, the market timing strategy is an active strategy by generating buy-and-sell signals on the stock market (Zakamulin, 2014). According to Faber (2007), the MA method could forecast the stock market movements and contributed significantly higher profit than buy-and-hold strategy. From previous findings, investors were provided with relevant information on investment timing and this benefitted the individual investors who were seeking diversification on their investment in a modern financial economy, especially in the Malaysian *Shariah* stock market. Therefore, more research in market timing ability is required to create more advanced technical methods especially using the MA. El-Khodary (2009), investigated the Egyptian Stock Exchange (EGX) market for predictive capabilities of the MA Crossover in three sub-periods from January 1998 until December 2008. The results showed that the MA Crossover could predict the EGX index and returns from the strategy which was higher compared to the passive strategy. This was supported by Wong et al. (2010), where the MA was useful to help investors by predicting future prices in technical trading. However, some researchers found that investors lacked market timing ability or did not give significant profits instead of consistent excess return and lower risk by using the MA Crossover (Anghel, 2013).

The classical MVO Markowitz (1952) played an important role in MPT and it was widely deliberated and tested in recent literature. In MPT, the investors are able to construct an optimal MVO if there is information of parameter, future assets return and covariance provided. Siew et al. (2016) constructed an optimal portfolio using the Markowitz model that consisted of weekly data from January 2010 to December 2013. The results showed that constructed portfolio was able to achieve a higher return within 0.22% compared to the FTSE Bursa Malaysia Index (FBMKLCI) 0.19%. Besides, another group of researchers looked at 20 component stocks of the FBMKLCI by defining a few constraints; the portfolio variance, target rate of return, and weight allocations in order to get an optimal portfolio return (Hoe and Siew, 2016). The results were also consistent whereby minimising the level of risk was able to construct using optimal mean-variance to get a high rate of return. Studies on optimal portfolio construction using the Markowitz model were carried out by Ivanova and Dospatliev (2017) and Kulali (2016) in Bulgaria and Germany, respectively.

The investors have various alternatives to grow up their assets either to invest in conventional or *Islamic* money market. These two types of market capitalization clearly differ from each other as a fund from *Shariah* view will only be invested in permitted *Shariah* treasury stock similar likes *Sukuk.* On contrary, the point of view for conventional manage the underlying finance or capital money absolutely in all sources of marketable securities of financial instrument (Alam et al., 2016). A study found that FTSE Global *Islamic* Index persistently outperformed than FTSE All-World Index during bull markets but underperformed in bear markets from the period of 1996 until 2003 (Kreander et al., 2005). Hassan and Autoniou (2005) also stated that Dow Jones *Islamic* Indices (DJII) underperformed for overall and decline period, but it outperformed during growing period from 1995 to 2003 in Dow Jones Industrial Average (DJI). However, many various studies found that there is no significant difference in the Kuala Lumpur *Shariah* Index (KLSI) and Kuala Lumpur Composite Index (KLCI) (Ahmad & Ibrahim, 2002; Albaity & Ahmad, 2008, 2011). In conclusion, there is no clear evidence that *Shariah* stocks underperform conventional stocks. The possibility for *Shariah* investors to obtain the highest potential return while at the same time being socially and ethically conscious about their investment is still open to debate. Thus, further study is required about Naïve (1/N) portfolio in order to compare with *Shariah* stock market.

The empirical evidence on various strategies stated above shed light on the applicability of the strategy for individual investors to actively manage their portfolios. From the perspective of stock allocation in a portfolio, the application of active strategy to find portfolio weight is frequently compared with naïve allocation strategy. Up to this date, rare to find any article that uses the naive portfolio as a comparison with the constructed portfolio. Naive allocation strategy is also known as passive strategy, whereby investors simply invest equally in several different stocks to make a profit in return and to minimise the risk (variance) of the portfolio sufficiently. Some researchers investigated the difference and effectiveness of the Naïve (1/N) portfolio with other alternatives. (DeMiguel et al., 2009) compared the out-of-sample performance of MVO and Naïve 1/N portfolio of 14 asset allocation models in the US stock market. The sample was analysed, taken from around 25 years for 25 stocks and 50 assets in the portfolio within 50 years. As a result, none of them (14 models) consistently performed better in Sharpe's ratio than Naïve (1/N) portfolio. Pflug et al. (2012), also found that the 1/N portfolio outperformed the MVO. In contrast, the outperformance of the MVO portfolio over the 1/N portfolio was discovered in Behr et al. (2013), which used monthly data from July 1963 until December 2008 in six datasets of the US stock market. The result showed that the MVO portfolio performed better in Sharpe's ratio (32.5%) which was higher compared to the 1/N portfolio.

Several studies had examined the market-timing abilities and selectivity skills of investors. Das and Rao (2015), found that there was positive significance in selectivity skills and market timing ability. Monthly data among fund managers in the US from July 2002 until June 2012 were analysed by using Henriksson and Merton (1981) and Treynor and Mazuy (1966) models. At the same time, Lee and Rahman (1990), showed that there was evidence for market timing and selectivity skill abilities for unit trust level in the US. Low (2012) and Paramita et al. (2018), found that fund managers in Malaysia and Indonesia had market timing ability but not superior in selectivity skills. Chang and Lewellen (1984), also stated that mutual funds in the US were superior in market timing ability only which contributed a positive effect in return. However, Oliveira et al. (2019), found that European fund managers had poor superior in market timing abilities and stock selection. Meanwhile, Ashraf (2013), found that the Saudi Arabian *Islamic* Mutual Funds (IMF) was only superior in stock selection but not in market timing from 2007 until 2010. The study was analysed by using the Treynor and Mazuy (1966) model and Capital Asset Pricing Model (CAPM) regression.

In a nutshell, the exploration of market timing and stock selection strategies is still very much needed, especially for *Shariah*-compliant investors. Hence, using the MA Crossover, assisted individual investors to determine the buy-and-sell signals on the stock market. The usage of MVO was also justified in order to allocate an optimal portfolio. Comparison between active strategy and passive strategy will also be carried out in this study. Lastly, market timing and selectivity skills of individual investors will be measured in order to help individual investors in the investment strategy of the stock market.

RESEARCH METHODOLOGY

Data

For the purpose of the study, the MA Crossover and SRM models were applied using daily data of *Shariah*–compliant equities listed in FTSE Bursa Malaysia *Hijrah Shariah* Index (FBMHS) from January 2010 until December 2018 collected from Bloomberg Database. In total, there were 30 constituents of FBMHS. Companies were selected from the top ten constituents of FBMHS and were below RM10 to be considered affordable for individual investors. Besides, the daily 3-month KLIBOR (Kuala Lumpur Interbank Offered Bank) was used to act as the risk-free rate proxy, r_f.

Table 1
Top 10 selected constituents FBMHS index

No.	Sector	Selected Companies
1.	Mobile Telecommunications	3
2.	Oil Equipment Services & Distributions	1
3.	Food Producers	1
4.	Transportation & Logistic Services	1
5.	Basic Materials	1
6.	Healthcare Equipment & Supplies	2
7.	Industrial Conglomerates	1
	Total	**10**

Moving Average Crossover

The Moving Average (MA) Crossover is a straightforward method that is commonly used in the technical trading rule. This method generates buy-and-sell signals in equations (2) and (3) within short and long-term MA. In this study, 1% band was considered in order to eliminate the insignificant signals [–1%, 1%] in MA (M'ng and Zainudin, 2016).

$$MAC_{N,j} = \frac{1}{N}\left(x_j + x_{j-1} + \cdots + x_{j-N+1}\right) \tag{1}$$

Buy (long) signal formula

$$MA_{1,j} > MA_{2,j} \tag{2}$$

Sell (short) signal formula

$$MA_{1,j} < MA_{2,j} \tag{3}$$

where j = 1, 2,….., n, MA_1 = short moving average, MA_2 = long moving average

Sharpe Ratio Maximisation Model

The rate of return determines whether the investors gain or lose money from an investment (Baresa et al., 2018). Daily stocks return will be calculated by using the arithmetic rate of return r_{it} on investment in stock i between time t and $t-1$ and P_{it} represents the price of stock at time t as shown in equation (4). The result of the rate of return will be calculated as a percentage.

$$r_{it} = \frac{P_{it} - P_{it-1}}{P_{it-1}} \tag{4}$$

After the daily return was calculated, we will optimise the weights of the constructed portfolio by maximum return to minimalise the risk. The formula of portfolio return is as follows:

$$\mu_p = \sum \omega_i \, r_i \tag{5}$$

where ω_i is the weight of the stock in the constructed portfolio. The total portfolio is equal to 1. Meanwhile, the risk of the constructed portfolio will be measured using the following formula:

$$\sigma_p^2 = \sum \omega_i^2 \sigma_i^2 + \sum \sum \omega_i \omega_j \sigma_i \sigma_j \rho_{ij} \tag{6}$$

where ρ_{ij} represents the correlation between returns on stocks i and j. Finally, by considering Markowitz (1952), we constructed the portfolio by maximising the Sharpe ratio whereby the highest level of expected return per unit of risk (standard deviation of Sharpe ratio) is as equation (7). In addition, SRM is the tangency point of MVO.

$$Objective\ Function =$$

$$Maximise\left[S_p = \frac{E(r_p) - r_f}{\sigma_p}\right] \tag{7}$$

Performance Measurement of Portfolios

Capital Asset Pricing Model. Theorem of CAPM: the expected excess rate of return of asset i, $E(r_p) - r_f$ is proportional by the coefficient of β_p to the expected excess rate of return of the Market Portfolio, $E(r_m) - r_f$. The coefficient of β_p will measure the linear dependence of the asset's return and return of the market in proportion to the asset to the market volatility ratio.

$$E(r_p) = r_f + \beta_p\big(E(r_m) - r_f\big) \tag{8}$$

Sharpe Ratio. Sharpe ratio was used to measure the trade-off between reward and volatility. The risk premium or excess return was calculated as the difference between total portfolio return, $E(r_p)$ and the risk-free rate, r_f divided with the portfolio's standard deviation of return, σ_p. It could be expressed in the following equation:

$$S_p = \frac{E(r_p) - r_f}{\sigma_p} \tag{9}$$

Treynor Ratio. Treynor ratio is similar to Sharpe ratio, which measures the average excess return $\big(E(r_p) - r_f\big)$ per unit of systematic risk β_p. The Treynor ratio is considered as per the following equation:

$$T_p = \frac{E(r_p) - r_f}{\beta_p} \tag{10}$$

Jensen's Alpha. Jensen (1969) defined Jensen's alpha where α_p measures the unsystematic or diversifiable risk of a portfolio. It gave the return portfolio that is over and above that was predicted by CAPM, given the portfolio's beta and the market return. Hence, the equation for Jensen's alpha was considered as per equation 11.

$$\alpha_p = E(r_p) - [r_f + \beta_p\big(E(r_m) - r_f\big)] \tag{11}$$

Holding Period Return (HPR). HPR is the total return earned from holding an investment for a given period of time. Analysts typically used the HPR withholding periods of one year or less. In this research, the holding period was based on the market timing where buy, B and sell, S occur within six months.

$$HPR\ (\%) = \frac{S-B}{B} \qquad (12)$$

Robustness Test

For this purpose, this study was extended by testing back for other constructed portfolios based on FTSE Bursa Malaysia EMAS *Shariah* Index (FBMS) with the same constituents listed (Table 1) to determine the consistency of analysis. FBMS Index is an alternative for FBMHS Index. The main difference is FBMHS Index is being screened using *Yasaar Shariah* screening methodology apart from *Shariah* Advisory Council (SAC) screening. We used the same procedure of Equation (1) until (7) to determine buy-and-sell signals using the MA Crossovers and construct an optimal portfolio by using the SRM model. The consistency and robust results were achieved once there was a resemblance of the out-of-sample performance of the constructed portfolios.

Market Timing and Selectivity Skills

Based on Treynor and Mazuy (1966) model, the market timing and stock selection performance of each stock were estimated as t:

$$R_{pt} = \gamma_p + \theta_1 R_{mt} + \theta_2 R_{mt}^2 + \varepsilon_{pt} \qquad (13)$$

Where

R_{pt}: the excess return on portfolio p in daily t

R_{mt} : the excess return on the FBMHS in daily t

γ_p : the estimated selectivity of portfolio p

θ_1 : the beta risk of market

θ_2 : the estimated market timing of portfolio p

ε_{pt} : the residual excess return on portfolio p in daily t

RESULTS AND FINDINGS

Moving Average Crossover

From Table 2, the MA rule was described in the form of (N_l, N_s, B) where N_s = length of short term, N_l = length of long term and B = bands (this study used band = 1%). The number of days in the table above showed the number of positions that individual investors could take with respect to each rule either a long or short position. Most of the previous literature, used MA (1,200) as the one-day short term while 200 days as a long term, where it took almost a year to detect abnormal return (Brock et al., 1992). In this study, MA in short terms which were 1, 5, and 20 days while 100, 150, and 200 days were for the long term of MA, will be investigated. For additional conditions in others to eliminate the "uncertainty" signals, a band within 1% was included.

From the selection of the MA rules which were (1,100,0.01), (1,150,0.01), (1,200,0.01), (5,100,0.01), (5,150,0.01), (5,200,0.01), (20,100,0.01), (20,150,0.01), (20,200,0.01), the study found that as the

Table 2
Number of days and trading frequency of FBMHS

Moving average rule	Number of days		Trading frequency		
	N_l	N_s	Buy	Sell	Total
(1, 100, 0.01)	1107	517	16	16	32
(1, 150, 0.01)	1181	445	12	12	24
(1, 200, 0.01)	1161	462	10	10	20
(5, 100, 0.01)	1098	511	12	12	24
(5, 150, 0.01)	1151	449	9	9	18
(5, 200, 0.01)	1163	452	7	7	14
(20, 100, 0.01)	1051	487	12	12	24
(20, 150, 0.01)	1148	418	8	8	16
(20, 200, 0.01)	1148	421	6	6	12

moving average rule increase, the number of trading frequency will become smaller. Based on Table 2, it is suggested that the individual investor invests for at most 32 times in nine years which is approximately 4(32/9) times annually, and for at least 12 times in nine years or once a year in FBMHS. Thus, it is suitable to use this trading strategy for individual investors where they need to trade in the stock market for 1 to 4 times annually. Shortly, individual investors would be better off by choosing the lower short-term and lower long-term MA rule which was (1,100,0.0.1). From this viewpoint, the MA Crossover is the best strategy in the market timing to predict the future price as presented in El-Khodary (2009), Faber (2007) and Kannan et al. (2010). Moreover, this technical trading gives the ability to produce abnormal returns, especially individual investors to seek profit instead of risk in *Shariah*-compliant equities.

Following the MA Crossover method, the extracted buy-and-sell signals in the sample and out-of-sample data will be determined based on the signal data in Table 3. The in-sample data will be six months' data preceding the signal date while the out-of-sample data will be the day after an extracted signal until the next signal date. Basically, the duration of out-of-sample will be held semi-annually or less than that to ensure that investors not to hold on the same portfolio too long doing portfolio revision if the MA does not give any sell signal within the six months period. Hence, this MA Crossover could give profitability for *Shariah* individual investors to optimise their portfolios in selectivity skills.

Portfolio Optimisation

Based on the Markowitz model, the results on the portfolio allocation (Table 3) were obtained in the appendix. Overall, it could be seen that during each sub-period there will be at most six stocks being invested. However, during a certain sub-period, only one stock was included in the portfolios. This could be seen during the in-sample date of 6 May-9 Nov 2011 and 27 May-30 Nov 2011 for DSOM stock. During that time, DSOM gave higher returns and Sharpe ratio compared to other stocks. It might be affected by the news that DSOM had announced a stock split in order to attract more investors to invest. SRM model is commonly known in the financial literature (Kourtis, 2016; Schmid & Zabolotskyy, 2008). This model gives the opportunities, especially for individual investors to monitor their portfolio by getting higher returns instead of lower risk (Ivanova & Dospatliev, 2017; Vo et al., 2019). Moreover, the SRM model contributed to the efficient frontier in the Markowitz optimisation problem and also gave a strong opinion to minimise the risk of the portfolio (Bodnar & Zabolotskyy, 2017). Although constructed portfolio was less diversified compared to Naïve (1/N) allocation, the composition of portfolio weights of the constructed portfolio was able to achieve high annual returns per unit of risk that was suitable for individual investors (Hoe & Siew, 2016). Hence, it was nominated to give the best portfolio from the analysis that gives the highest return and lowest risk of the portfolio.

Portfolio Performance and Comparison Measures

From Table 4, the results show that both constructed portfolio and Naïve (1/N) portfolio gave a higher Sharpe ratio compared to FBMHS Index with 1.2509 and 1.0550, respectively. The constructed portfolio was more profitable than the Naïve (1/N) portfolio where constructed portfolio gave a higher return (22.63%) than Naïve (1/N) portfolio (11.72%). This proved that by executing the buy-and-sell signal from the MA rule of (1, 100, 0.01) and selecting stocks using the SRM model, individual investors had the opportunity to get higher returns. FBMHS Index gave the lowest return (4.35%) and lowest Sharpe ratio (0.1042) compared to both portfolios. This was expected as the market benchmark normally consisted of a basket of stock that was well diversified and had very low risk. This was also reflected by the low return offered. Investors believed that high return comes with high risk where risk is the exposure of occurring losses associated with the expected return in investment. Thus, a higher average excess return with lower risk gives a higher Sharpe ratio.

Nevertheless, a significant difference is shown in Table 4 where the constructed portfolio presents a higher risk-adjusted return (39.48%) against the Naïve (1/N) portfolio (19.60%). A high Treynor ratio means high excess return per unit of systematic risk beta. Thus, it showed that the investors were still able to gain an excess return from the investments even in the presence of market risk. The value for Alpha of the constructed portfolio is 0.07%, which was slightly higher than Naïve (1/N) portfolio (0.03%). A higher Jensen's Alpha gave advantages to individual investors. Then, Holding Period Return (HPR) measures the total return generated during the investment period. This study compared the return between these two portfolios, based on the out-of-sample period in Table 3

Table 4
Measurement the Out-of-Sample Performance for Constructed Portfolio and Naïve (1/N) Portfolio

Portfolio	**Return, μ (%)**	**Risk, σ(%)**	**Beta CAPM, β**	**Sharpe ratio, S**	**Treynor ratio, T(%)**	**Jensen's alpha, α(%)**	**Annualised HPR (%)**
FBMHS Index	4.35	9.48*	1.0000	0.1042	0.99	-	-
Constructed	22.63*	15.40*	0.4878	1.2509	39.48	0.07	19.49
Naïve (1/N)	11.72	7.93*	0.4266	1.0550	19.60	0.03	10.03

Notes. * Denotes rejection of hypothesis at 5% significance level in *F-test* (risk) and *T-test* (mean)

by using equation (12). The results show that the constructed portfolio had an annualised HPR of 19.49% higher than the Naïve (1/N) portfolio.

Comparing the results for both portfolios, we could simplify that both portfolios outperformed the market index in terms of return, Sharpe ratio, and Treynor ratio. For risk, the Naïve (1/N) portfolio was less risky compared to the constructed portfolio. In addition, beta portfolios were less than the beta of the FBMHS Index, which was less risky as it was less responsive towards the market movement. Overall, the constructed portfolio gave a better performance than Naïve (1/N) portfolio. This encouraging result by the related study, which was by constructing MVO, performed better than the passive strategy (Bessler et al., 2017; Kulali, 2016). Thus, it would provide a clearer understanding for individual investors to use market timing strategy and SRM model in the *Shariah* stock market.

Robustness Test

As shown in Table 5, the result indicated almost the same values with respect to performance measurement. In particular, for both constructed portfolios' risk and return within 22.63% and 15.40% for FBMHS were not very different from FBMS's return and risk within 22.36% and 14.81%, respectively. This directs from the performance of FBMHS which was higher than the FBMS; there was consistency as the values were still lower than the constructed portfolio that gave the constructed portfolio an outperformance. Similarly, in the findings presented by Lean and Parsva (2012), both indices showed the same result in terms of risk respectively. Moreover, we also used the F-Test and T-Test for the difference in risk and return of indices and both constructed portfolios. The empirical results were consistent with fail to reject the null hypothesis within a 5% significance

Table 5
Comparison of Out-of-Sample for constructed portfolio for FBMHS and FBMS indices

Portfolio	**Average Return, μ (%)**	**Average σ(%)**	**Beta CAPM, β**	**Sharpe ratio, S**	**Treynor ratio, T(%)**	**Jensen's alpha, α(%)**
Constructed Portfolio	22.63	15.40	0.4878	1.2509	39.48	0.07
	22.36	14.81	0.4583	1.2822	41.44	0.07

Notes. ● Denotes to out-of-sample performance constructed portfolio for FBMS Index level where both indices and constructed portfolios had similar values in risk and return, respectively. Therefore, robustness checks were necessary to determine the consistency of our results under different specifications.

Market Timing and Stock Selection

Ordinary Least Square (OLS) regression was used in this study in order to estimate equation (13) based on Treynor and Mazuy (1966) model. Referring to Table 6, the result of constructed portfolio showed that individual investors in Malaysia had selectivity skills and market timing from 2010 until 2018 with a positive coefficient (0.0006) and (2.3084). Both coefficients gave significance at a 5% significance level. This indicated that individual investors in Malaysia had potential in both market timing and stock selection abilities using the constructed portfolio during the bullish and bearish market conditions. Meanwhile, Naïve (1/N) Portfolio showed a significantly negative (-4.4013) in market timing while selectivity skills showed significantly positive in coefficient (0.0005) at a 5% significance level. Hence, this indicated that investors had only the selectivity skill ability but not in market timing. Besides, both portfolios had positive value beta with 0.4532 and 0.9657, respectively. This designated that investors were able to choose the best time to buy and sell the stocks during bullish market conditions, where the stock price movements tended to increase. Therefore, it could generate a positive return for both portfolios. The value R^2 of Naïve (1/N) portfolio was higher (0.6356) compared to the constructed portfolio, which was lower (0.0856). Thus, positive and significant market timing and selectivity skills were chosen as the best model as a constructed portfolio for individual investors. This was supported by Paramita et al. (2018) and Das and Rao (2015), where positive and significant would contribute to investors in achieving superior in market timing and stock selection.

CONCLUSION

Through the variability of *Shariah*-compliant portfolio return, this study obtained the best buy-and-sell signal using MA Crossover which satisfied the first objective. For the next objective, this study focussed on the optimal portfolio to be obtained. The optimal portfolio would be the most efficient portfolio that aimed to construct an optimal portfolio using the SRM model and Naïve (1/N) portfolio by using the top ten constituents of FBMHS. Furthermore, the performance of the constructed portfolio

Table 6
Treynor and Mazuy Model (1966)

Estimate	Selectivity skills, γ	Beta of FBMHS, Θ_1	Market timing, Θ_2	R^2
Constructed	0.0006*	0.4532*	2.3084*	0.0856
Naïve (1/N)	0.0005*	0.9657*	-4.0413*	0.6356

Notes. * Denotes rejection of hypothesis at 5% significance level and Naïve (1/N) portfolio was measured by using CAPM, Sharpe ratio, Treynor ratio, and Jensen's alpha. All the measurements showed better performance of a constructed portfolio compared to Naïve (1/N) portfolio. Lastly, this study could be summarized that individual investors can decide on timing their portfolios and also selecting stocks by following the outlined strategy for investment decision making especially in *Shariah*-compliant portfolio as compared to the naïve (1/N) strategy that has lack of market timing ability only. Therefore, *Shariah*-compliant individual investors should take this opportunity to actively manage their portfolios in order to ensure that their portfolios will be revised according to the market movement. The entry and exit signals provided by the MA Crossover strategy combined with a simple SRM model could be implemented to improve portfolio performance. Moreover, it is very important for individual investors to follow *Maqasid Shariah* to manage their portfolios' risk and also invest during the market doing well. For further research, it is suggested to include transaction costs in the analysis to make the results more precise (Zhang et al., 2019; Elias et al., 2015). Since the rebalancing portfolio is only occurring twice a year, the less frequent will gives lower transaction costs in the portfolio.

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APPENDIX

Table 3
Expected outcome on the Weight of Constructed Portfolio and Naïve (1/N) Portfolio

No		**Out-of-Sample Date**	**Stock(Max Sharpe, %)**									
			AXIA	**DSOM**	**DIAL**	**MXSC**	**IOIB**	**MISC**	**PMET**	**HTHB**	**SIME**	**TPGC**
1.		04 July 2010 – 03 Jan 2011	35.66	0.47	0.06	-	-	-	-	8.50	-	55.31
2.		04 Jan 2011 – 05 May 2011	16.26	1.39	42.96	-	-	-	20.14	-	19.25	-
3.		27 May 2011 – 04 Aug 2011	-	49.41	50.59	-	-	-	-	-	-	-
4.		09 Nov 2011- 20 Nov 2011	-	100.00	-	-	-	-	-	-	-	-
5.		30 Nov 2011 – 17 May 2012	-	100.00	-	-	-	-	-	-	-	-
6.		31 May 2012 – 18 Nov 2012	1.51	15.76	0.07	56.05	-	-	-	26.62	-	-
7.		18 Dec 2012 – 20 Jan 2013	16.08	39.99	0.06	-	-	-	-	41.34	-	2.52
8.		02 Apr 2013 – 22 Aug 2013	-	-	0.07	-	-	39.14	29.88	20.76	-	10.15
9.	**Constructed Portfolio**	19 Sept 2013 – 27 Jan 2014	-	39.61	0.06	-	8.90	-	5.34	44.47	-	1.61
10.		12 Feb 2014 – 08 Aug 2014	-	48.08	13.13	-	-	38.79	-	-	-	-
11.		29 Oct 2014 – 04 Dec 2014	13.77	36.81	-	-	-	-	46.58	2.84	-	-
12.		21 Jan 2015 – 21 May 2015	-	37.17	-	2.10	-	41.25	3.56	15.04	-	0.87
13.		06 Oct 2015 – 20 Jan 2016	-	-	0.07	-	-	3.91	-	7.17	-	88.86
14.		08 Aug 2016 – 09 Nov 2016	-	-	0.06	-	-	-	93.91	-	-	6.02
15.		06 Feb 2017 – 13 July 2017	-	-	-	7.34	-	-	56.16	13.11	15.07	8.32
16.		27 Oct 2017 – 26 Apr 2018	-	-	21.99	-	0.75	-	40.19	29.96	-	7.11
17.		27 Apr 2018 – 17 May 2018	-	-	45.65	-	4.64	-	-	29.51	6.70	13.50
18.		23 Aug 2018 – 08 Oct 2018	-	-	52.94	-	-	-	-	45.13	-	1.93
19.		**Naïve (1/N) portfolio**	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00

Notes. Both portfolios’ weight allocation was set equal to 1 (100%).