Combining Momentum, Value, and Quality for the Islamic Equity Portfolio: Multi-style Rotation Strategies using Augmented Black Litterman Factor Model

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Abstract

This study constructs active Islamic portfolios using a multi-style rotation strategy, derived from the three prominent styles, namely, momentum, value, and quality investing. We use the stocks that are consistently listed in the U.S. Dow Jones Islamic index for a sample period from 1996 to 2012. We also include two macroeconomic mimicking portfolios to capture the premiums of industrial production growth and inflation innovation, accommodating the economic regime shifts.

Based on the information coefficients, we find the six-month momentum and the fractal measure as momentum factors; the enterprise yield (gross profit/TEV) and the book to market ratio as valuation factors; the gross profit to total assets, the return on capital, and the scaled total accruals as quality factors. We further construct active portfolios using the augmented Black Litterman (ABL) factor model to avoid the factor alignment problem, with the factor views predicted using Markov Switching VAR, MIDAS, and Bayesian Model Averaging. The out-of-sample performance of our portfolios can produce information ratios of 0.7 – 0.8 over the composite indices, and information ratios of 0.42 – 0.48 over the style indices, with the annualized alphas of 10 – 11%. Even when we put the constrained tracking error of 1% over the benchmark, our portfolios still produce information ratios of 0.9 – 1.2 before transaction costs, and 0.6 – 0.8 after transaction costs. We provide intuitive explanations for each premium changing over time, and suggest the promising strategy for Islamic equity investors to outperform the market.

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1. Introduction

The primary goal of active equity portfolio management is to beat the market or any benchmark at a regular basis. The performance of active managers is measured by alpha (residual return) relative to its tracking error (residual volatility), which is defined as information ratio. A strand of literature suggested the need of style allocation to achieve this objective. Particularly, widespread empirical findings have documented three most prominent equity styles for active management. The first two are value and momentum investing (Cakici and Tan, 2014; Asness, Moskowits, and Pedersen, 2013; Yeh and Hsu, 2011). Value strategies exploit the ratio of multiple measures of fundamental value over equity price in order to identify underpriced stocks. Momentum strategies use the principle that high cumulative returns over the past years continue to outperform. The two are driven by strong empirical studies such as value effects (Fama and French, 1992, 1996; Lakonishok, Shleifer, and Vishny, 1994; Fama, 1991; Schwert, 2003) and momentum effects (Jegadeesh and Titman, 1993, 2001). The third style comes from a recent major interest to incorporate quality, which include earnings quality (Sloan, 1996), financial strength (Piotroski, 2000; Piotroski and So, 2012), gross profitability (Novy-Marx, 2013), and so on.

Despite the superior returns gained from each of these three prominent styles, some studies showed that the different styles behave differently at different points in time (Arshanapalli, Coggin and Doukas, 1998; Oertmann, 1999; Ahmed, Lockwood and Nanda, 2002; Amenc et al., 2003). This is reasonable since each style goes in and out of favor, subject to different economic and financial risk factors. Hence, a certain style-consistent strategy cannot deliver consistent performance (Arshanapalli, Switzer, and Panju, 2007). Its main implication is that active managers should blend and rotate multiple styles consistently, with timing abilities, in order to add value. Many studies documented the promising performance of multi-style rotation strategies, due to either return enhancement or factor diversification (Vayanos and Woolley, 2013; Rousseau and van Rensburg, 2004; Bird and Casavecchia, 2007; Leivo and Pätäri, 2011; Piotroski and So, 2012; Kozlov and Petajisto, 2013; etc.).

Apart from a strand of literature on multiple equity styles' strategies in the mainstream equity markets, there is no similar study in the context of Islamic equities. The main objective of our study therefore is to formulate active equity portfolio strategies using the three prominent equity styles, namely momentum, value, and quality. There are three major reasons that motivate our research.

Firstly, the Shariah (Islamic) screening excludes some firms with any non-compliant activity and imposes a certain upper limit of interest-based leverage, interest income, cash-equivalent assets (Derigs and Marzban, 2008). Its consequence is a unique optimal multi-style rotating allocation, which is a central contribution of our study. Secondly, prior studies in Islamic equities focus merely on measuring the performance of either Islamic equity indices[1] or Islamic mutual funds. Our study attempts to fill the gap by formulating equity portfolio strategies with a constraint to invest only in the Islamic equity universe. Thirdly, some researches in Islamic mutual funds' performance found that Islamic funds perform averagely similar to their conventional counterparts, subject to multiple regimes (Hassan, Antoniou and Paudyal, 2005; Elfakhani, Hassan and Sidani, 2005; Hassan and Antoniou, 2006; Abdullah, Hassan, and Mohamad, 2007). The recent study by Kamil et al. (2013) discovered that the Malaysian Islamic equity funds do not outperform market benchmarks. When their performance is superior, only 1.95% of funds are

[1] For example, see Hakim and Rashidian (2002), Hussein (2004, 2005) Girard and Hassan (2005), Al-Zoubi and Maghyereh (2007)

genuinely skilled, whereas 47% of the observed positive fund alpha is statistically due to luck. In that case, our study provides an insight to Islamic portfolio managers regarding the use of multi-style rotation strategies to produce a persistent alpha.

2. Literature review

The main motivation to implement multi-style rotation is that each style performs differently at different periods. The seminal work of Sharpe (1975) found that rotating the funds between stocks and cash-equivalent assets using market timing has delivered promising returns. This finding encouraged further studies on the asset mix between risk free and risky assets (Ferson and Harvey, 1991; Slonick, 1993; Nam and Branch, 1994; and Bossaerts and Hillion, 1999).

The recent studies emphasized on style timing to achieve superior returns. They used different methods in order to optimally rotate across different styles. For example, Jacobs and Levy (1996) found that both high-definition style rotation (using individual stocks) and index-based style rotation (using style indices) outperformed the Russell 3000 index. A further study by Levis and Liodakis (1999) used a binary logit and an OLS model, with a sample of the U.K. equities from 1968 to 1997, and formed rotation strategies between value and growth styles to achieve superior returns. Copeland and Copeland (1999) applied a trading rule using the changing implied volatility of options on stock index futures as timing signals for rotating between value and growth equities to produce superior returns. Amenc et al. (2003) produced superior returns by using a market-neutral strategy based on a dynamic multi-factor model that exploits the returns differentials between several style indices.

The other studies showed the promising rewards of rotating strategies. For example, Ahmed et al. (2002) found that an active manager with an initial wealth of $10,000 in 1981 would generate $92,000 in 1997 by investing 65% and 35% in large and small stocks, respectively. On the other hand, the one who implements multi-style rotation strategies would end up with a terminal wealth of $264,000 for the same period. Levis and Tessaromatis (2004) also found promising returns by using value and growth indices for FTSE 100 and FTSE 250 in U.K. with some constraints to control for risk. Arshanapalli, Switzer and Karim (2005) performed multi-style rotation using Russell value and size style indices, and found their outperformance, accounting for transaction cost.

Our study focuses on stocks within the Islamic investment universe using the recent Black Litterman method, augmented Black Litterman factor model, in order to rotate the three prominent styles. We also use some forecasting methods to avoid forward-looking bias.

3. Data

3.1. Islamic stock universe

Our sample covers the U.S. equity market which consists of the largest number of Islamic equities. We take Islamic stocks that are listed in the U.S. Dow Jones Islamic index. There are two reasons of choosing this index. First, the Dow Jones Islamic has the strictest filtering criteria, especially the upper limit of debt to equity ratio. Second, this index has the longest observation, with the inception date started from 1996.

Our sample covers the period of 1996 to 2012. The first five years from 1996 to 2000 are the sample that we take as our historical data for our model. The out-of-sample results start from

2001 to 2012 to evaluate our performance. Moreover, the constituent lists of the U.S. Dow Jones Islamic index are slightly changing from year-to-year basis due to the requirement of fulfilling its screening criteria consistently. Therefore, we only take Islamic stocks which are consistently listed in this index. We end up with 488 Islamic stocks used for the entire observations.

3.2. Factor variables on demand

3.2.1. Fundamental variables

For momentum investing, we use the price momentum calculated as a price return over a certain period of *J* in the past (Leivo and Pätäri, 2011). The lag of *J* is defined as a formation period (Rey and Schmid, 2007). This is a common measure for momentum, where the lags may vary from one month to twelve months[2]. Price acceleration momentum is calculated as a ratio of price momentum in the short term (12 months) over price momentum in the long term (24 months) (Bird and Casavecchia, 2007) as a measure to capture the tendency of stock price to accelerate in the future. We also use a measure imported from fractal finance. The most recent methods are derived from econophysics; namely multi-fractal de-trended fluctuation analysis (MF-DFA), proposed by Kantelhardt et al. (2002), to test and measure long-range dependence, level of persistency, and efficiency in time series. Its application provides a single measure that accommodate both persistency and anti-persistency of the stock price. The high value of this measure at a certain period of time implies that the stock price is far from random walk or inefficient in the weak form of EMH.

For value investing, Gray and Carlisle (2013) recently have done a complete survey for all possible variables that capture the premium of value and quality according to a large number of empirical evidences[3]. The first is earnings yield as the inverse of price to earnings ratio. The second is enterprise yield (EBITDA/enterprise value) defined as the acquirer's multiple. The third is a variation of the enterprise yield by substituting EBIT for EBITDA, which belongs to the Greenblatt's magic formula as a value measure combined with quality investing (Greenblatt, 2010). Another variation is to substitute free cash flow or gross profit for EBITDA. The fourth is book to market ratio (Fama and French, 1992).

For quality investing, it focuses on franchise value, financial strength, and earnings quality[4]. We use ROA, ROE, and return on capital/ROC (Greenblatt, 2010), to measure franchise value. Another variation is the ratio of gross profit over total assets (Novy-Marx, 2013). We use F-scores of Piotroski (2000) and Gray and Carlisle (2013) to measure financial strength beyond financial distress. For earnings quality, we use a simple accruals of Sloan (1996) detect earnings manipulation and overinvestment. Its variation is scaled net operating assets (a ratio of net operating assets over total assets) (Hirshleifer et al., 2004) and total accruals (by adding the change in noncurrent operating assets to the change in working capital) (Richardson et al., 2005).

All of these variables, including their variation, are the common measures that have been used in momentum, value, and quality investing.

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[2] (Jegadeesh and Titman, 1993; Asness, 1994; Moskowitz and Grinblatt, 1999; Fama and French, 1996, 2008)

[3] (Nicholson, 1960; Fama and MacBeth; 1973; Ball, 1978; Basu, 1977, 1983; Fama and French, 1992; Lakonishok, Schleifer and Vishny, 1994; Fama and French, 1998; Brown, 2007)

[4] (Graham, 1973; Piotroski and So, 2012; Kozlov and Petajisto, 2013; Sloan, 1996; Frazzini, Kabiller, and Pedersen, 2012; Novy-Marx, 2013)

3.2.2. Macroeconomic variables: mimicking portfolios

We use inflation innovation and industrial production as additional factor variables, in order to account for their systematic effects during economic regime shifts[5]. Our study follows Kroencke et al. (2013) and Duarte (2013) in constructing mimicking portfolios. We first regress excess returns of each individual stock on inflation innovations or the change in industrial production, using observations only up to time *t*. The smaller weight is given to more distant observations by using exponential kernel with a half-life of five years. This produces beta at time *t*, and we run regressions up to the end of our observations in order to generate time series of beta for each stock.

4. Methodology: active portfolio construction process

4.1. Information coefficients (ICs)

The first step in our portfolio construction process is to select some relevant factor variables for each style, among the above-stated variables, which can produce promising premium within the sample of our Islamic stocks. We refer to the fundamental law of active management by Grinold (1989) which mentioned the importance of skills (IC), breadth (N), and value added (IR). Qian and Hua (2003) provided an extension, where the value added depends on the average IC and its volatility, due to time-varying alpha signals. Since our study applies the ABL factor model to diversify factor variables, we therefore only use the positive average IC to identify relevant factor variables.

To compute the IC of momentum variables at time *t*, we run correlation between cross-sectional Islamic stock ranks at time *t* and cross-sectional Islamic stock excess returns at time *t* + 1 month. The IC of fundamental variables is calculated using correlation between cross-sectional Islamic stock ranks at time *t* (December at year *t*) and cross-sectional Islamic stock excess returns at time *t* + 1 month, *t* + 2 months, *t* + 3 months,…., *t* + 12 months. The IC therefore incorporates both current IC and lagged IC (Qian et al., 2007). The Islamic stock rank is computed using normalized z-score. By running correlation every month, we generate the time series of IC for each factor.

4.2. Factor mimicking portfolio

The second step of our construction process is to generate factor returns from each of the selected factor variables. We create factor mimicking portfolios in the form of long-short portfolios. Mimicking the factor returns reliably is essential since the observed premium is considered as the alpha source. We use the long-short portfolio using optimization-based approach introduced by Cheung and Mittal (2009) and Cheung (2013). They proposed a composite factor mimicking tilt (MFM) as follows:

$$M_{FM\,[f\times n]} = [(\Sigma^{+})^{-1} B \Sigma_F^{+}]^T \tag{1}$$

[5] Empirical evidences for macroeconomic factors (Vassalou, 2003; Koijen, Lustig, and Nieuwerburgh, 2012; Cochrane, 1996; Yogo, 2006; Belo, 2010; Ludvigson, 2012)

$\Sigma^{+}_{(n\times n)} = B\Sigma^{+}_{F}B^{T} + \Sigma^{+}_{\xi}$ is the covariance matrix of stock returns which is updated only by factor and stock-specific views; $\Sigma^{+}_{F\,(f\times f)} = [(\tau\Sigma_F)^{-1} + P_F^T\Omega_F^{-1}P_F]^{-1}$ denotes the covariance matrix of factor returns which is updated only by factor views; and $\Sigma^{+}_{\xi[n\times n]} = [(\tau\Sigma_\xi)^{-1} + P_\xi^T\Omega_\xi^{-1}P_\xi]^{-1}$ denotes the covariance matrix of stock-specific returns that is updated only by stock –specific views. This implies that M^T_{FM} represents the ABL endogenous FM transition technique,

$$\vec{\omega}^{*} = M^T_{FM}\vec{\omega}_F \tag{2}$$

They mentioned that this approach is equivalent to the minimal tracking-error optimization portfolio, which is the most accurate in mimicking factor returns as compared to FF ranking, OLS and GLS transition matrices. The unconditional form of the transition matrix is computed as follows:

$$\begin{aligned}\vec{\omega}^{(i)} &= M^T_{FM}\vec{I}_i \\ &= (\Sigma^{-1}B\Sigma_F)\vec{I}_i \end{aligned} \tag{3}$$

4.3. Active portfolio construction in multi-style rotation strategies

The third step of our construction process is to formulate rotation strategies. Particularly, the above dollar-neutral (long-short) portfolio is commonly not investable since investors need to substantially put negative weights in the short portfolio to capture premium. To tackle this issue, the common approach for investors is to use factor risk model.

For portfolio optimization, Black and Litterman (1992) built a bridge between statistical methods and expert judgment. The robustness problem of traditional portfolio optimization is not due to portfolio optimizer but to the quality of inputs. They suggested a Bayesian framework by recognizing the capital asset pricing model (CAPM) as a proper starting point for expected returns (prior distributions). Hence, combining investors' views (private information) with CAPM (public information) will generate both intuitive and diversified allocations. The PM views use the private information and is the main interest of portfolio managers to outperform the market.

Despite the BL model produces a better portfolio, it does not incorporate factor risk model. Specifically, the factor model is used to produce input for PM views rather than inherently built in the Bayesian framework. The recent study by Ceria et al. (2012) pointed out the factor alignment problem, which is the misalignment between the predicted alpha and its forecasted risk. They strongly suggested that the factor risk model should be used completely in the alpha generation process. To tackle this issue, Cheung (2013) has improved the Black Litterman model to incorporate factor risk model. A linear factor model can be written as follows:

$$\vec{\tilde{r}}_{[n\mathrm{x}1]} = \vec{a}_{[n\mathrm{x}1]} + \mathrm{B}_{[n\mathrm{x}f]}\vec{\tilde{r}}_{F[f\mathrm{x}1]} + \vec{\tilde{\xi}}_{[n\mathrm{x}1]} \tag{4}$$

, where $\vec{\tilde{r}}$ is the vector of stock returns; $\vec{a}$ is the intercept vector; B is the factor loadings matrix; $\vec{\tilde{r}}_F$ is the vector of factor returns; and $\vec{\tilde{\xi}}$ denotes the vector of stock-specific returns which are considered to be independent of factor returns as well as of each other. Therefore, the risk model can be described as follows:

$$\Sigma_{[nxn]} = \mathrm{B}\Sigma_{F[fxf]}\mathrm{B}^{\mathrm{T}} + \Sigma_{\xi[nxn]} \tag{5}$$

, where $\mathbf{\Sigma}$ is the covariance matrix of stock returns; B is a matrix of factor loadings; $\mathbf{\Sigma}_F$ denotes the covariance matrix of factor returns; and $\mathbf{\Sigma}_\xi$ represents the covariance matrix of stock-specific returns which are considered orthogonal. To incorporate the PM's (portfolio manager) factor views in the Bayesian framework, we augment the universe from *n* stocks by including all the $f\ (\leqslant n)$ relevant factors as well as the *n* idiosyncratic components. As to the return, the view universe can be represented by $\vec{\tilde{\gamma}}^a_{[(2n+f)\times 1]} = \left\{\vec{\tilde{r}}^{\mathrm{T}}_{[n\times 1]}, \vec{\tilde{r}}^{\mathrm{T}}_{F[f\times 1]}, \vec{\tilde{\xi}}^{\mathrm{T}}_{[n\times 1]}\right\}^{\mathrm{T}}$. Consequently, we can express the views on all the three parts as follow:

$$\mathrm{Q^a}_{[K\mathrm{x}(2n+f)]}\vec{\tilde{\gamma}}^a_{|H,G} = \vec{\tilde{Y}}^a_{|H,G[K\text{ x }1]} + \vec{\tilde{\varepsilon}}^a_{[K\text{ x }1]} \tag{6}$$

, where

$$\mathrm{Q^a}_{[K\mathrm{x}(2n+f)]} = \begin{pmatrix} \mathrm{P}_{[k_1\mathrm{x}n]} & & 0 \\ & \mathrm{P}_{F[k_2\mathrm{x}f]} & \\ 0 & & \mathrm{P}_{\xi[k_3\mathrm{x}n]} \end{pmatrix} \tag{7}$$

is defined as the augmented view structure matrix, which contains $k_1\ (\leqslant n)$ stock (or portfolio) return view structures $\mathbf{P}_{[k_1\times n]}$, $k_2\ (\leqslant f)$, factor return (or their linear combinations) view structures $\mathbf{P}_{F[k_2\times f]}$, $k_3\ (\leqslant n)$, and stock idiosyncratic return (or their linear combinations) view structures $\mathbf{P}_{\xi[k_3\times n]}$, whereby, $K = k1 + k2 + k3$;

$$\vec{\tilde{\gamma}}^a_{|H,G[(2n+f)\mathrm{x}1]} = \begin{pmatrix} \vec{\tilde{r}}_{|H,G[n\mathrm{x}1]} \\ \vec{\tilde{r}}_{F|H,G[f\mathrm{x}1]} \\ \vec{\tilde{\xi}}_{|H,G[n\mathrm{x}1]} \end{pmatrix} \tag{8}$$

is defined as the unknown yet required augmented posterior vector of returns, which contains *n* posterior stock returns $\vec{\tilde{r}}_{|\mathcal{H},\mathcal{G}[n\times 1]}$, *f* posterior factor returns $\vec{\tilde{r}}_{F|\mathcal{H},\mathcal{G}[f\times 1]}$, and *n* posterior stock idiosyncratic returns $\vec{\tilde{\xi}}_{|\mathcal{H},\mathcal{G}[n\times 1]}$;

$$\vec{\tilde{Y}}^a_{|H,G[K\text{ x }1]} = \begin{pmatrix} \vec{\tilde{y}}_{|H,G[k_1\mathrm{x}1]} \\ \vec{\tilde{y}}_{F|H,G[k_2\mathrm{x}1]} \\ \vec{\tilde{y}}_{\xi|H,G[k_3\mathrm{x}1]} \end{pmatrix} \tag{9}$$

is defined as the augmented vector of updated views, which contains *k1* views $\tilde{\vec{y}}_{|\mathcal{H},\mathcal{G}[k_1\times 1]}$ on stock returns, *k2* views $\tilde{\vec{y}}_{F|\mathcal{H},\mathcal{G}[k_2\times 1]}$ on factor returns, and *k3* views $\tilde{\vec{y}}_{\xi|\mathcal{H},\mathcal{G}[k_3\times 1]}$ on stock idiosyncratic returns; and

$$\tilde{\vec{\varepsilon}}^{a}_{[K\text{x}1]} = \begin{pmatrix} \tilde{\vec{\varepsilon}}_{[k_1\text{x}1]} \\ \tilde{\vec{\varepsilon}}_{F[k_2\text{x}1]} \\ \tilde{\vec{\varepsilon}}_{\xi[k_3\text{x}1]} \end{pmatrix} \tag{10}$$

is defined as the augmented vector of view estimation errors, which contains *k1* view errors $\tilde{\vec{\varepsilon}}_{[k_1\times 1]}$ on stock returns, *k2* view errors $\tilde{\vec{\varepsilon}}_{F[k_2\times 1]}$ on factor returns, and *k3* view errors $\tilde{\vec{\varepsilon}}_{\xi[k_3\times 1]}$ on stock idiosyncratic returns.

The factor model dictates that $\tilde{\vec{r}}$, $\tilde{\vec{r}}_F$ and $\tilde{\vec{\xi}}$ are linearly dependent. In order to ensure full-rank representation, our analytical universe is represented by $\tilde{\vec{r}}^{a}_{[N\times 1]} = \left\{\tilde{\vec{r}}^{\mathrm{T}}_{[n\times 1]}, \tilde{\vec{r}}^{\mathrm{T}}_{F[f\times 1]}\right\}^{\mathrm{T}}$, where $N = n + f$. The view formulation in equation (13) can be expressed in this universe as follows:

$$\mathrm{P}^{\mathrm{a}}_{[K\text{x}N]}\, \tilde{\vec{r}}^{a}_{|H,G[N\text{ x }1]} = \tilde{\vec{y}}^{a}_{|H,G[K\text{ x }1]} + \tilde{\vec{\varepsilon}}^{a}_{[K\text{ x }1]} \tag{11}$$

, where

$$\mathrm{P}^{\mathrm{a}}_{[K\text{x}N]} = \begin{pmatrix} \mathrm{P}_{[k_1\text{x}n]} & 0_{[k_1\text{x}f]} \\ 0_{[k_2\text{x}n]} & \mathrm{P}_{F[k_2\text{x}f]} \\ \mathrm{P}_{\xi[k_3\text{x}n]} & -\mathrm{P}_{\xi[k_3\text{x}n]}\mathrm{B}_{[n\text{x}f]} \end{pmatrix} \tag{12}$$

is defined as our augmented (analytical) view structure matrix;

$$\tilde{\vec{r}}^{a}_{|H,G[N\text{ x }1]} = \begin{pmatrix} \tilde{\vec{r}}_{|H,G[n\text{x}1]} \\ \tilde{\vec{r}}_{F|H,G[f\text{x}1]} \end{pmatrix} \tag{13}$$

is defined as the unknown yet required augmented (analytical) posterior vector of returns, which contains *n* posterior stock returns $\tilde{\vec{r}}_{|\mathcal{H},\mathcal{G}}$, and *f* posterior factor returns $\tilde{\vec{r}}_{F|\mathcal{H},\mathcal{G}}$, and $\tilde{\vec{y}}^{a}_{|\mathcal{H},\mathcal{G}} = \tilde{\vec{Y}}^{a}_{|\mathcal{H},\mathcal{G}} + \vec{c}_{[K\times 1]}$, where

$$\vec{c}_{[K\text{x}1]} = \begin{pmatrix} \vec{0}_{[k_1\text{x}1]} \\ \vec{0}_{[k_2\text{x}1]} \\ P_{\xi[k_3\text{x}n]}\vec{a}_{[n\text{x}1]} \end{pmatrix} \tag{14}$$

is a constant vector. This obtains the extra returns, attributable to the deterministic term in the linear multifactor model that is not captured by the factor set. Similar to the Black Litterman specification, there is an assumption with respects to the prior view, given only public information

G. Therefore, based on this information G, the prior return forecasts are normally distributed as follow:

$$\vec{\tilde{r}}^{a}_{|G[N \text{ x } 1]} \xrightarrow{delegate} \vec{\tilde{\mu}}^{a}_{M[N \text{ x } 1]} \sim \mathbb{N}(\vec{\tilde{\pi}}^{a}_{[N \text{ x } 1]}, \tau\Sigma^{a}_{[N\text{x}N]}) \tag{15}$$

, where

$$\vec{\tilde{\mu}}^{a}_{M[N \text{ x } 1]} = \begin{pmatrix} \vec{\tilde{\mu}}_{M[n\text{x}1]} \\ \vec{\tilde{\mu}}_{MF[f\text{x}1]} \end{pmatrix} \tag{16}$$

is defined as the augmented vector of market return forecasts, which contains *n* market estimates on stock returns $\vec{\tilde{\mu}}_M$, and *f* market estimates on factor returns $\vec{\tilde{\mu}}_{MF}$;

$$\vec{\tilde{\pi}}^{a}_{[N \text{ x } 1]} = \begin{pmatrix} \vec{\tilde{\pi}}_{[n\text{x}1]} \\ \vec{\tilde{\pi}}_{F[f\text{x}1]} \end{pmatrix} \tag{17}$$

is defined as the augmented vector of CAPM-assessed equilibrium returns, which contains *n* equilibrium stock returns , and *f* equilibrium factor returns;

$$\Sigma^{a}_{[N\text{x}N]} = \mathbb{C}\text{ov}\left(\vec{\tilde{r}}^{a}, \left(\vec{\tilde{r}}^{a}\right)^{\mathrm{T}}\right) \tag{18}$$

is defined as the covariance matrix of the augmented returns $\vec{\tilde{r}}^{a}$; and τ is the Black Litterman scalar which represents the PM's uncertainty about the estimation of the equilibrium returns. On the other hand, by using private information *H*, the view estimation errors are normally distributed as follow:

$$\vec{\tilde{\varepsilon}}^{a}_{[K \text{ x } 1]} \sim \mathbb{N}(\vec{0}_{[K\text{x}1]}, \Omega^{a}_{[K\text{x}K]}) \tag{19}$$

, where $\vec{0}$ is a vector of zeros; and

$$\Omega^{a}_{[K\text{x}K]} = \begin{pmatrix} \Omega_{[k_1\text{x}k_1]} & & 0 \\ & \Omega_{F[k_2\text{x}k_2]} & \\ 0 & & \Omega_{\xi[k_3\text{x}k_3]} \end{pmatrix} \tag{20}$$

is defined as the augmented block-diagonal variance matrix for the view-estimation errors provided by the PM (portfolio managers), which contains the view uncertainty matrices $\mathbf{\Omega}_{[k_1 \times k_1]}$ for stock (or portfolio) returns, $\mathbf{\Omega}_{F[k_2 \times k_2]}$ for factor returns, and $\mathbf{\Omega}_{\xi[k_3 \times k_3]}$ for stock idiosyncratic returns. These can be individually considered as diagonal matrices. Therefore, we define the perception conditional on a realization of $\vec{\tilde{r}}^{a}_{|\mathcal{H},\mathcal{G}}$ or $\vec{\tilde{\gamma}}^{a}_{|\mathcal{H},\mathcal{G}}$

$$\vec{\tilde{y}}^{a}_{|\vec{\tilde{r}}^{a},H,G} \sim \mathbb{N}\left(\mathrm{P}^{a}\, \vec{\tilde{r}}^{a}{}_{|H,G}, \Omega^{a}\right) = \mathbb{N}\left(\mathrm{Q}^{a}\, \vec{\tilde{\gamma}}^{a}{}_{|H,G} + \vec{c}, \Omega^{a}\right) \tag{21}$$

We can blend the prior knowledge $\vec{\tilde{r}}^{a}_{|\mathcal{G}} \sim \mathbb{N}(\vec{\tilde{\pi}}^{a}, \tau\boldsymbol{\Sigma}^{a})$ and the PM views with the final conviction $\vec{\tilde{Y}}^{a}_{|\vec{\tilde{\gamma}}^{a},\mathcal{H},\mathcal{G}} \stackrel{\text{belief}}{\longrightarrow} \vec{\tilde{q}}^{a}_{[K\times 1]}$ (the 'ultimate' view mean estimation), which is equivalent to:

$$\vec{\tilde{y}}^{a}_{|\vec{\tilde{r}}^{a},H,G} \xrightarrow{belief} \vec{\tilde{q}}^{a} + \vec{c} \tag{22}$$

, where

$$\vec{\tilde{q}}^{a}_{[K\text{ x }1]} = \begin{pmatrix} \vec{\tilde{q}}_{[k_1\text{x}1]} \\ \vec{\tilde{q}}_{F[k_2\text{x}1]} \\ \vec{\tilde{q}}_{\xi[k_3\text{x}1]} \end{pmatrix} \tag{23}$$

is defined as the augmented vector for our best view estimates provided by the portfolio manager, which contains *k1* view estimates $\vec{\tilde{q}}_{[k_1\times 1]}$ on stock (or portfolio) returns, *k2* view estimates $\vec{\tilde{q}}_{F[k_2\times 1]}$ on factor (or combination of factors) returns, and *k3* view estimates $\vec{\tilde{q}}_{\xi[k_3\times 1]}$ on stock idiosyncratic returns. The posterior return estimates are normally distributed such that:

$$\mathrm{N}\ (\overrightarrow{m}^{a}, \widehat{\mathrm{V}}^{a}) \tag{24}$$

, where the updated mean estimates are:

$$\overrightarrow{m}^{a} = [(\tau{\textstyle\sum}^{a})^{-1} + (\mathrm{P}^{a})^{\mathrm{T}}(\Omega^{a})^{-1}\mathrm{P}^{a}]^{-1}[(\tau{\textstyle\sum}^{a})^{-1}\vec{\tilde{\pi}}^{a} + (\mathrm{P}^{a})^{\mathrm{T}}(\Omega^{a})^{-1}\left(\vec{\tilde{q}}^{a} + \vec{c}\right)] \tag{25}$$

and the updated variance-covariance matrix is:

$$\widehat{\mathrm{V}}^{a} = [(\tau{\textstyle\sum}^{a})^{-1} + (\mathrm{P}^{a})^{\mathrm{T}}(\Omega^{a})^{-1}\mathrm{P}^{a}]^{-1} \tag{26}$$

, where

$${\textstyle\sum}^{a}_{[N\text{x}N]} = \begin{bmatrix} \sum_{[nxn]} & \mathrm{B}_{[nxf]}\sum_{F[fxf]} \\ \sum_{F[fxf]}\mathrm{B}^{\mathrm{T}}_{[fxn]} & \sum_{F[fxf]} \end{bmatrix} \tag{27}$$

$$\vec{\tilde{\pi}}^{a}_{[N\text{ x }1]} = \begin{pmatrix} \vec{\tilde{\pi}}_{[n\text{x}1]} \\ \vec{\tilde{\pi}}_{F[f\text{x}1]} \end{pmatrix} = \kappa \begin{pmatrix} \sum \\ \sum_{F}\mathrm{B}^{\mathrm{T}} \end{pmatrix} \vec{w}M[n\text{x}1] \tag{28}$$

$$\kappa = \frac{\mathbb{E}\left(\tilde{R}_{M}|G\right) - r_f}{\sigma_M^2} \tag{29}$$

R_M represents the long-term gross return of the market; σ_M denotes the long-term volatility of the market return; and w_M is the market portfolio weight vector.

4.4. Forecasting to add value

For the next step, to avoid forward-looking bias in our portfolio performance, we forecast every single factor returns when we construct our portfolio over the out-of-sample period[6]. We use three forecasting methods, namely, exponential-weighted factor returns, Markov-switching vector autoregressive MS-VAR (Ang and Bekaert, 2004; Guidolin and Timmermann, 2007; Guidolin and Hyde, 2012), and MIDAS (Ghysels and Wright, 2009; Ghysels, Santa-Clara, and Valkanov, 2006). The advantage of MS-VAR is to forecast future returns by accounting for regime shifts. The benefit of MIDAS is to forecast with a mixed data sampling so that, for example, we can forecast 6-month return in the future using monthly historical data. The different forecasting methods will be used according to the constraint in our rebalancing period.

Before we apply our forecasting methods, our study uses Bayesian Model Averaging (BMA) to select the best predictors which can explain our factor returns at a certain point in time (Fernandez et al., 2001a; Masih et al., 2010). Table 1 presents the list of total predictors used in the BMA model.

Table 1. List of predictors

List of Predictors	
Industrial Production Total	SandP 500 Value
IP Manufacturing	SandP 500 Growth
IP Industrial and Other Equipment	Broad Index of Dollar's FX Value
Composite Leading Indicator (Trend)	Trade-weighted Value of $ Against Major Currencies
Composite Leading Indicator (10 Index)	U.S. Dollar to SDR
Composite Leading Indicator (Normalized)	U.S. Dollar to Euro
Disposable Income	One Month Bond VIX
Money Supply (M1)	SandP 500 VIX
Monetary Base Currency	CBOE SPX VIX
Retail Money	Default Premium
Unemployment Rate	Equity Premium
Total Unemployment	Term Structure Premium
Consumer Sentiment (Expectation)	Currency Premium (Global)
Consument Sentiment (Current)	Inflation
Current Financial Situation	
Federal Total Debt Outstanding	
Federal Funds Target Rate	
Federal Funds Rate	
U.S. Interbank Rate 3 months	
U.S. Smoothed Recession Prob.	

[6] For predictability of factor returns (see, Arnott et al. (1989), Levis and Liodakis (1999), Asness et al. (2000), Lucas et al. (2001))

5. Out-of-sample results

5.1. Relevant factor variables to generate alpha

5.1.1. Average ICs

Table 2 and Table 3 show the results of average ICs and hit rates for all factor variables. We compare the strength of alpha signals based on the magnitude and the sign of their average IC. For the magnitude, Gleiser and McKenna (2010) mentioned that the information coefficient (IC) of 0.05 is considered as a good alpha signal, whereas the IC of 0.1-0.15 is considerably excellent. For the sign, we need a positive IC in line with the underlying theory of each style. Looking at Figure 1, some of the estimated ICs reach 0.1–0.15, which indicate promising sources of alpha. Nonetheless, the variation of ICs are high overtime, altogether with the low value of average ICs below 0.05, which can be understood as the Islamic market has a smaller number of stock relative to that in the conventional market. This condition further encourages Islamic active managers to implement multi-style rotation strategies.

According to the average IC, for momentum investing, Table 2 shows that the 6-month momentum can be considered as a better alpha signal relative to the 12-month momentum from 1996 to 2010. This implies that investors has a faster reaction to the new information towards our Islamic stocks. Active managers therefore need to focus on momentum effect in the medium term to capture its premium. Interestingly, the one-month momentum has negative average ICs consistently, which represents a more of reversal. Qian et al. (2007) here pointed out that this factor may cause high turnovers as the signal only predict returns for the very near term. On the other hand, the result of price acceleration momentum show not only a very low average IC but also inconsistent signs. This confirms our earlier results regarding the faster response of investors towards our Islamic stocks. We also notice that our MF-DFA factor (fractal measure) can be considered as a good alpha signal from 1996 to 2010. It seems that our Islamic stocks are not completely efficient, and active investors may capture gains from this discrepancy. The negative average IC for this variable in 1996 to 2000 indicates the superiority of a random-walk-based strategy. Among all these momentum factors, we select the 6-month momentum and MF-DFA factor as our variables to capture momentum effect. The MF-DFA factor may provide a diversification benefit for the 6-month momentum, attributable to the different signs of their average ICs.

For value investing, Table 2 shows that all the valuation factors, except for earnings yield, can be considered as good alpha signals. The outperformance of gross profit relative to the other types of earnings is understandable since gross profitability is reported in the top-most profit figure in the financial statements, and therefore is the most difficult number to manipulate (Novy-Marx, 2013). The gross profit is also the purest measure of true economic profitability since it only captures revenue and production cost, regardless operating expenses that may poison the measure. Moreover, the high IC of the book to market ratio is reasonable according to many empirical findings related to the HML portfolio (Fama and French, 1992, 1996, 2008). Among all these valuation factors, we select enterprise yield, related to gross profit, and book to market ratio. Although the remaining enterprise yields (using EBIT and EBITDA) have a relatively good alpha signal, the stability of the book to market ratio may assist value investors to avoid a certain stock that appears underpriced according to some income-based metrics but is expensive because the income is at a cyclical peak (Fama and French, 1992; Gray and Carlisle, 2013).

Table 2. Average ICs for momentum and value factor variables

	Momentum (av. ICs)					Value (av. ICs)					
Periods	Momentum (12m)	Momentum (6m)	Momentum (1m)	Price Acceleration	Efficiency (MFDFA)	Earnings Yield	Enterprise Yield (EBITDA)	Enterprise Yield (EBIT)	Enterprise Yield (Gross Profit/TEV)	BM Ratio	Earnings Multiple (Free Cashflow)
1996-2000	0.0364	0.0454	-0.0177	0.0026	-0.0214	0.0003	0.0126	0.0123	0.0354	-0.0014	0.0033
2001-2005	0.0074	0.0151	-0.0338	0.0021	0.0300	0.0030	0.0105	0.0112	0.0128	0.0297	0.0029
2006-2010	-0.0112	-0.0035	-0.0039	-0.0065	0.0185	-0.0371	0.0101	0.0024	0.0171	0.0093	0.0212
1996-2010	0.0103	**0.0162**	-0.0189	-0.0017	**0.0099**	-0.0104	0.0095	0.0074	**0.0210**	**0.0119**	0.0076

	Momentum (Hit Rate)					Value (Hit Rate)					
Periods	Momentum (12m)	Momentum (6m)	Momentum (1m)	Price Acceleration	Efficiency (MFDFA)	Earnings Yield	Enterprise Yield (EBITDA)	Enterprise Yield (EBIT)	Enterprise Yield (Gross Profit/TEV)	BM Ratio	Earnings Multiple (Free Cashflow)
1996-2000	60.00%	61.67%	43.33%	55.00%	31.67%	48.33%	53.33%	56.67%	70.00%	50.00%	53.33%
2001-2005	55.00%	60.00%	50.00%	53.33%	60.00%	51.67%	58.33%	58.33%	51.67%	60.00%	56.67%
2006-2010	50.00%	56.67%	45.00%	38.33%	65.00%	36.67%	51.67%	50.00%	60.00%	55.00%	55.00%
1996-2010	54.69%	**57.81%**	45.31%	48.44%	**52.60%**	45.83%	53.13%	54.17%	**59.38%**	**56.25%**	54.17%

Table 3. Average ICs for quality factor variables

Quality (av. ICs)												
Profitability								Financial Strength		Earnings Manipulation		
Periods	ROE	ROA	Gross Margin	Gross Profit/TA	Free Cashflow/TA	Return on Capital	EBIT/TA	FS	FS (P)	Simple Accrual	SNOA	Total Accrual
1996-2000	0.01809	0.00845	0.00255	0.03351	0.00932	-0.00727	0.00700	-0.00248	0.00602	0.00921	0.01797	-0.00711
2001-2005	0.00140	-0.00613	0.00356	0.01846	-0.01593	0.00875	-0.00360	-0.00291	0.00240	0.00327	-0.01473	-0.00674
2006-2010	-0.00628	-0.03093	-0.00335	-0.00903	-0.02359	0.00416	-0.03022	-0.01378	-0.01230	0.02059	0.01614	0.01377
1996-2010	0.00317	-0.00926	0.00267	**0.01556**	-0.01081	**0.00330**	-0.00824	-0.00721	-0.00286	**0.01003**	0.00795	-0.00111

Quality (Hit Rate)												
Profitability								Financial Strength		Earnings Manipulation		
Periods	ROE	ROA	Gross Margin	Gross Profit/TA	Free Cashflow/TA	Return on Capital	EBIT/TA	FS	FS (P)	Simple Accrual	SNOA	Total Accrual
1996-2000	61.67%	55.00%	46.67%	68.33%	58.33%	50.00%	56.67%	51.67%	53.33%	53.33%	55.00%	48.33%
2001-2005	50.00%	51.67%	55.00%	58.33%	48.33%	53.33%	53.33%	50.00%	46.67%	46.67%	55.00%	38.33%
2006-2010	50.00%	50.00%	55.00%	43.33%	45.00%	51.67%	48.33%	46.67%	46.67%	63.33%	53.33%	50.00%
1996-2010	53.65%	51.56%	52.60%	**57.29%**	48.96%	**52.08%**	52.60%	47.92%	47.40%	**54.17%**	55.73%	45.31%

Figure 1. Monthly ICs

Table 3 presents the results for quality investing. For profitability, our results show that only ROE, gross margin, earnings multiple related to gross profit, and return on capital that can be considered as good signals. The lower average IC of gross margin relative to others is reasonable as it merely captures the pricing power of the firm's products in its industry rather than a complete franchise value. On the contrary, the gross profit to total assets ratio is considered as the best signal, attributable to its purest measure of true economic profitability. This reaffirms the recent study by Novy-Marx (2013) which found that, as compared to earnings and free cash flow, the ratio with gross profit has higher predictive power on the cross-sectional expected stock returns, as well as long-run growth in earnings and free cash flows. The second best signal is the return on capital (ROC). EBIT takes into account the earnings to all forms of capital instead of only to the equity, while the inclusion of net debt and equity may capture either unusual debt to equity ratio or some important assets carried in the balance sheets (Greenblatt, 2010). Among all these profitability measures, we choose the gross profit to total assets ratio and ROC. The different signs of their average ICs may provide a diversification benefit in capturing the profitability premium.

Table 3 also presents the other quality factors. For financial strength, both F-score of Piotroski (2000) and F-score of Gray and Carlisle (2013) have a negative average IC in the entire observations. This indicates that the financial strength indicators have been incorporated in the current price of our concerned Islamic stocks, due to their consistent limit of leverage ratio. For earnings quality, both the negative scaled total accruals (STA) and the negative scaled net operating assets (SNOA) can be considered as good signals, confirming their role as contrarian predictors with some possible explanations from either earnings manipulation or overinvestment (Papanastasopoulos et al., 2011; Sloan, 1996; Dechow, Richardson, and Sloan, 2008).

Table 4. The correlation matrix across the different ICs from 1996-2010 and 1996-2000

Period (1996-2010)	Momentum (6m)	Efficiency (MFDFA)	Enterprise Yield (Gross Profit/TEV)	BM Ratio	Gross Profit/TA	Return on Capital
Momentum (6m)						
Efficiency (MFDFA)	0.088					
Enterprise Yield (Gross Profit/TEV)	-0.018	0.034				
BM Ratio	-0.032	0.083	0.288			
Gross Profit/TA	-0.062	-0.059	0.586	0.025		
Return on Capital	-0.142	0.043	0.277	0.200	0.465	
Simple Accrual	-0.019	-0.060	0.048	-0.182	-0.191	-0.309

Period (1996-2000)	Momentum (6m)	Efficiency (MFDFA)	Enterprise Yield (Gross Profit/TEV)	BM Ratio	Gross Profit/TA	Return on Capital
Momentum (6m)						
Efficiency (MFDFA)	-0.042					
Enterprise Yield (Gross Profit/TEV)	-0.245	0.131				
BM Ratio	-0.198	0.332	0.223			
Gross Profit/TA	-0.229	0.024	0.732	-0.150		
Return on Capital	-0.244	-0.018	0.427	-0.021	0.553	
Simple Accrual	-0.131	0.057	0.054	-0.020	0.016	-0.004

Table 5. The correlation matrix across the different ICs from 2001-2005 and 2006-2010

Period (2001-2005)	Momentum (6m)	Efficiency (MFDFA)	Enterprise Yield (Gross Profit/TEV)	BM Ratio	Gross Profit/TA	Return on Capital
Momentum (6m)						
Efficiency (MFDFA)	0.311					
Enterprise Yield (Gross Profit/TEV)	0.012	0.121				
BM Ratio	-0.038	-0.001	0.462			
Gross Profit/TA	-0.159	-0.078	0.507	0.324		
Return on Capital	-0.082	-0.002	0.424	0.642	0.631	
Simple Accrual	0.054	-0.061	-0.206	-0.550	-0.467	-0.724

Period (2006-2010)	Momentum (6m)	Efficiency (MFDFA)	Enterprise Yield (Gross Profit/TEV)	BM Ratio	Gross Profit/TA	Return on Capital
Momentum (6m)						
Efficiency (MFDFA)	0.0147					
Enterprise Yield (Gross Profit/TEV)	0.1902	-0.0560				
BM Ratio	0.0645	-0.0368	0.2684			
Gross Profit/TA	0.2322	-0.0686	0.4961	-0.1178		
Return on Capital	-0.0581	0.1127	-0.1319	-0.2048	0.1160	
Simple Accrual	-0.0396	-0.1480	0.2654	0.1565	-0.1780	-0.2176

5.1.2. IC correlations

Despite all the selected variables have positive average ICs, their hit rates fall within the range of 50% to 60%, suggesting the importance of multi-style rotation. Table 4 and Table 5 show the correlation matrices of the ICs. From 1996 to 2010, we notice that the six-month momentum has negative correlations with the other styles like valuation and quality factors. The negative correlation may deliver a better portfolio diversification (Vayanos and Woolley, 2012). In this case, the flows between investment funds can be considered as the main source of conflicting effects (Vayanos and Woolley, 2011).

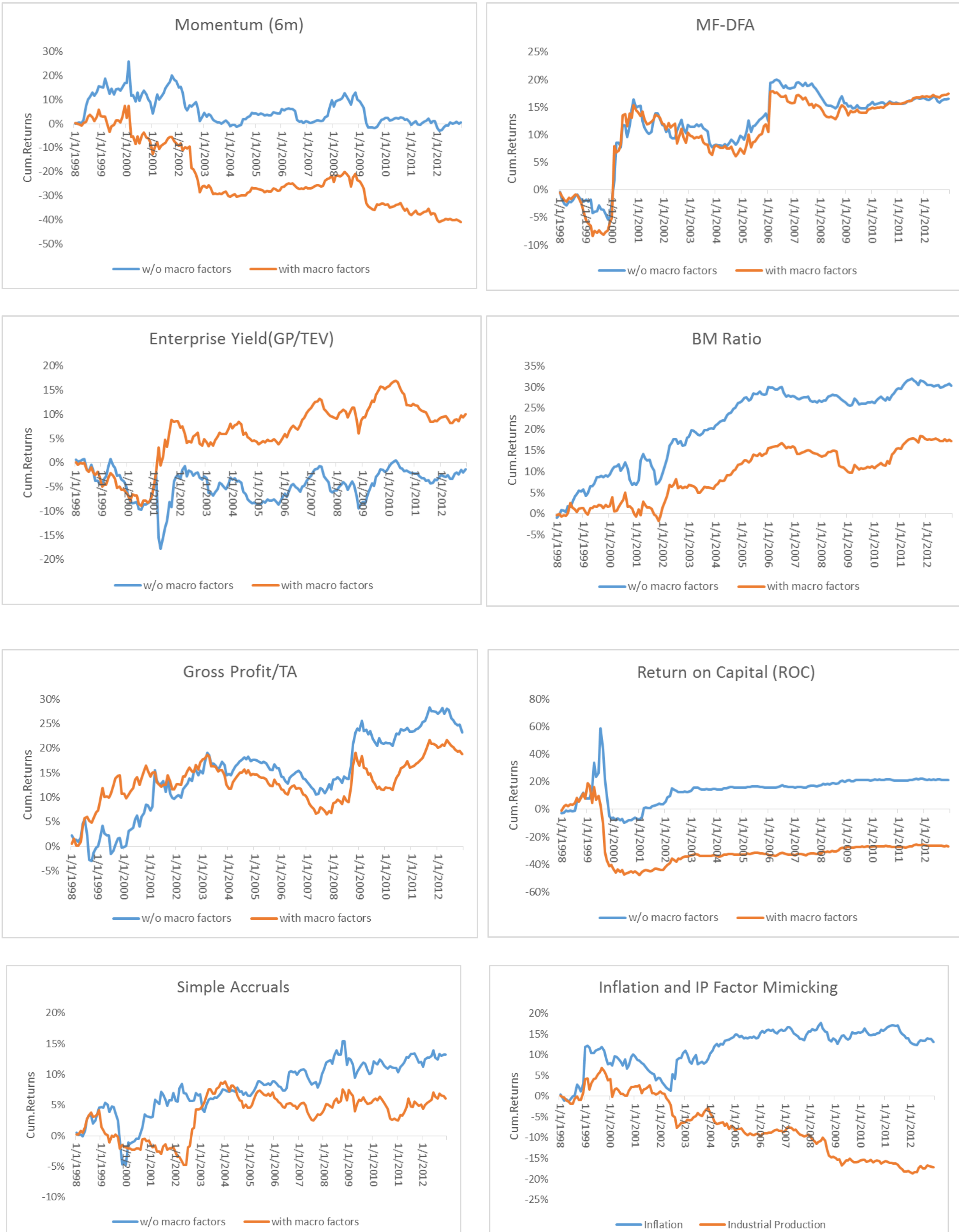
Our results also show a positive correlation between the six-month momentum and the MF-DFA factor, which confirms their role in capturing momentum effect. Interestingly, the MF-DFA factor has positive correlations with the valuation factors. It further implies that this fractal measure is particularly useful to play as timing triggers to acquire value shares (Rousseau and van Rensburg, 2004; Bird and Casavecchia, 2007; Leivo and Pätäri, 2011). In other words, this efficiency measure not only solves a value-trap problem but also plays as a return enhancer for value investing. Lastly, our results show positive correlations between the valuation factors and the profitability measures. Hence, by integrating valuation and quality metrics, we can detect any stock that are expected to grow but available at a fair or reasonable price (Piotroski and So, 2012; Kozlov and Petajisto, 2013).

5.2. Time-varying factor premium to capture

Out study constructs the MFM portfolio of each factor from 1998 to 2012. The mimicking portfolio starts in 1998 using the sample period from the beginning of 1996 to the end of 1997. The portfolio is rebalanced every month with the extended observations. We also include industrial factors based on the ICB Supersector classification, and we divide into seven major sectors in our Islamic stock universe: Health Care (16.6%), Industrial Goods (20,9%), Oil and Gas (8.9%), Pers and Household Goods (7.6%), Retail (11.7%), Technology (20.7%), and others (13.9%). A mimicking portfolio for a certain factor represents pure factor returns from this factor, being controlled by the remaining factors.

We constructs two mimicking portfolios for each factor, where we include our macroeconomic variables in a multifactor model for the second portfolio. Figure 2 shows that each factor has its own unique pattern of the returns. Although the two mimicking portfolios' returns for each individual factor have a similar pattern, the cumulative returns of the second mimicking portfolio are generally lower. This implies that the positive premium is driven partially by the macroeconomic premium priced in our Islamic market. Many studies found the contribution of macroeconomic factors to the changing style premium (Cochrane, 1991, 1996; Vassalou, 2003; Li, Vassalou, and Xing, 2006; Yogo, 2006; Ludvigson, 2012; etc.).

Figure 2. Cumulative factor returns



Interestingly, the substantial impacts of our macroeconomic variables on the styles' premium mostly occur from 1998 to 2003, which further can be linked to the dot-com bubble and burst and the Enron's collapse. These major events, associated with momentum, valuation, and earnings quality in the market, have considerably affected the U.S. business cycle. The macroeconomic impacts in the period of 1998 to 1999 can be explained by the Asian crisis and the Russian default. The global economic events may trigger flows between investment funds, which consequently affect the styles' premium (Vayanos and Woolley, 2011). Figure 2 also shows that the returns of the two mimicking portfolios for the MF-DFA factor are almost similar. This implies that the MF-DFA factor, imported from fractal finance, is slightly influenced by any macroeconomic condition, and is purely driven by the inefficiency of the stock prices related to persistency and anti-persistency.

For the macroeconomic factors, we notice a negative relationship between the industrial production premium and the inflation premium after the year 2002. This is consistent with Campbell, Sunderam and Viceira (2010) who documented that the covariance between the inflation and the real economy is positive but turns into negative starting from the economic downturn in 2001. Our results also show that the industrial production growth has a negative price after the year 2002. We reaffirms a broader finding of a negative correlation between stock returns and per capita GDP growth (Ritter, 2005). Specifically, the growth occurs mainly from the increase in labor participation, higher personal savings, and technological change. The first two sources go into new corporations, while the technological change will not increase profits unless the firms have a monopoly power. Hence, the economic growth does not offer promising opportunities in equity investment unless the valuations are sufficiently low.

On the contrary, we can see that the inflation has a positive price, contradicting Duarte (2013) who found a negative price of inflation within the sample of all the U.S. equities. Their negative premium is related to the inflation illusion hypothesis, where higher inflation today, perceived as bad states of the economy, may predict low growth in future real consumption. Investors are willing to pay an insurance by way of lower mean returns when they hold an inflation-mimicking portfolio (Duarte, 2013). However, Duarte (2013) still argued that the inflation betas vary across different stocks. It seems that our findings, limited to the sample of only Islamic stocks, confirm another study which documented the hedging role of the U.S. common stocks against inflation since the early 1950s (Kim and Ryoo, 2011).

Figure 3 presents the style allocation weights, where the percentage of each factor (from the second mimicking portfolio) represents the contribution of each factor returns from a particular factor to the total factor returns from all factors. For the valuation factors, their allocation weights are mostly positive and stable for the entire observations, which are reasonable since valuation signals decay very slowly (Qian et al., 2007). The changing important role between the enterprise yield and the book to market ratio across different periods may imply that the advantage of income-based metrics and the stability of assets' book value can complement each other to capture the value premium. In contrast, both of the momentum factors are highly cyclical as their alpha signals have a short-term information horizon. In some periods, either momentum or inefficiency strategies may help the valuation factors to avoid a value trap, while, in the other periods, either contrarian or random-walk-based strategies may provide a diversification benefit between momentum and value investing.

Figure 3. Style allocation weights

Our results also demonstrate that the profitability measures relatively more fluctuates than the valuation factors. This is attributable to their exposures to the income cycle of the firms (Gray and Carlisle, 2013). Therefore, the advantage of combining valuation and quality metrics may vary across different periods. For the negative scaled total accruals, it generally has positive allocation weights in line with the underlying theory of earnings quality and overinvestment. Its negative weights at some certain periods may imply that the raising working capital can give a good signal for future excess returns.

5.3. Outperformance results

5.3.1. Turnover constraint

There are two main constraints that we set in our portfolio construction. First, our funds are fully invested in the stocks, without allowing for short-selling or investing in risk-free assets. This is in line with the prohibition of short-selling in Shariah rules. Second, we impose a limit for the annual turnover rate when we rebalance our portfolio. Dow (2007) documented that the average turnover rates for the professionally managed pension funds is about 70%, which indicates an average holding period around 17 months. He also mentioned that the 435 Large-cap Growth mutual funds, the 195 Mid-cap Growth mutual funds, and the 183 Small-cap Growth mutual funds have the average annual turnover rates of 93% (a 12.9-month average holding period), 108% (an 11.1-month holding period), and 120% (a 10-month holding period), respectively. In the contrary, the twenty-five most active growth funds, which are covered by Morningstar, have the average turnover rates of 320%.

We impose a limit for the quarterly turnover rate to be 20% every quarterly rebalancing. This results in the annual turnover rate of 80%, which is in the range between the managed pension funds' rate and the large-cap mutual funds' rate. In addition, our study also imposes a limit for the semi-annual turnover rate to be 20% every 6-month rebalancing. This results in the annual turnover rate of 40%, satisfying the requirement of the funds which focus more on the longer-term investment.

5.3.2. Forecasting performance

The factor returns that we estimate earlier are the ideal premium available in the market. However, to avoid a look-ahead bias, we need to forecast the factor returns of each factor variable, and use these forecasted values as our factor views in the multi-rotation strategies.

We use the exponential-weighted factor returns and Markov-switching VAR for quarterly rebalancing, while we use MIDAS to satisfy six-month rebalancing. As the last two methods obtain forward-looking factor returns, we need some best predictors to forecast each factor, which are selected by Bayesian Model Averaging (BMA) every quarter for the quarterly rebalancing, and every six months for the semi-annually rebalancing. In particular, we choose the variables with their PIP higher than 50% to be selected as our best predictors. Table 6, Table 7, and Table 8 show the samples of BMA results. In Table 6, the predictive power of the market variables as the best predictors (default premium, equity premium, VIX) is understandable since this can be linked to the downturn in the U.S. equity market, attributable to the dot-com bubble burst. The contribution of the macroeconomic variables (national debt, industrial production manufacturing, retail money, interbank, recession probability) may explain the economic contraction in the U.S. business cycle starting from March 2001. In Table 7, the potential predictors are dominated by the macroeconomic variables. This is due to the fact that these variables (monetary base, bond VIX, leading indicator, recession probability, and financial situation) may have a high explanatory power during the U.S. subprime crisis in 2008. Looking at Table 8, the equity premium and the leading indicator may signal the bullish market during the recovery period in U.S., while the inflation and the term structure premium indicate the market expectation towards the future inflationary regime attributable to the quantitative easing.

Table 9 shows the performance evaluation for the two forecasting methods by analyzing the mean squared forecast error (MSFE) and the root mean squared forecast error (RMSFE). Overall, the small forecast errors for all the factor variables indicate that our forecasting is sufficient to produce directional views in our multi-style rotation strategies.

Table 6. The BMA predictors for momentum factor in 2001

Predictors (Momentum_2001)	PIP	Post Mean	Post SD
Total Debt	97.7%	1.873	0.593
Default Premium	96.0%	0.880	0.332
Equity Premium	94.4%	-0.328	0.136
IP Manufacturing	83.3%	-1.425	0.907
Recession Prob	75.5%	-0.002	0.001
Retail Money	64.6%	0.363	0.337
SandP 500 VIX	59.5%	0.116	0.126
U.S. Interbank	55.6%	1.687	1.949
SandP 500 Growth	51.1%	-0.080	0.100
Federal Reserve Rate	37.5%	-1.000	1.858

Table 7. The BMA predictors for BM ratio factor in 2008

Predictors (BM_2008)	PIP	Post Mean	Post SD
Monetary Base	72.7%	0.307	0.242
Bond VIX	71.6%	0.012	0.009
CLI (10 Indices)	68.8%	0.317	0.271
Recession Prob	64.4%	0.000	0.000
Financial Situation	63.7%	0.018	0.018
FX Major Currencies	57.3%	-0.122	0.148
IP Manufacturing	49.6%	-0.139	0.176
M1	40.0%	-0.044	0.069
Fed Rate Target	32.6%	-0.078	0.157

Table 8. The BMA predictors for GP/TA factor in 2011

Predictors (GPTA_2011)	PIP	Post Mean	Post SD
Equity Premium	90%	-0.115	0.058
Term Structure Premium	71%	7.275	7.766
Default Premium	67%	-0.099	0.091
Inflation	54%	-0.422	0.485
CLI (10 Indices)	51%	0.287	0.358
U.S. Interbank	49%	0.113	0.168

Table 9. Forecasting performance

	Momentum (6m)	Efficiency (MFDFA)	Enterprise Yield (Gross Profit/TEV)	BM Ratio	Gross Profit/TA	Return on Capital	Simple Accrual	Inflation Mimicking	Industrial Production Mimicking
BMA-MSVAR (quarterly)									
MSFE	0.0001	0.0001	0.0004	0.0002	0.0001	0.0005	0.0001	0.0001	0.0001
RMSFE	0.010	0.008	0.020	0.013	0.007	0.023	0.008	0.010	0.011
BMA-MIDAS (semi-annually)									
MSFE	0.000055	0.000020	0.000076	0.000020	0.000031	0.000040	0.000019	0.000013	0.000025
RMSFE	0.0074	0.0044	0.0087	0.0045	0.0056	0.0064	0.0044	0.0037	0.0050

5.3.3. Portfolio performance

The forecasted factor returns as our directional factor views are incorporated in the ABL factor model. We benchmark our portfolio performance to the U.S. Dow Jones Islamic index, the U.S. Dow Jones Total Market index (conventional), the S&P 500 Composite index, the S&P 500 Value index, and the S&P 500 Growth index. WE use the U.S. Dow Jones Islamic index as our market portfolio in the augmented BL factor model, where our active weights deviate from the market capitalization weights of this Islamic index. We set the scalar (τ) value of 0.1 to be close to the market weights but allowing our active weights to be able to capture our directional views (Black and Litterman, 1992; Lee, 2000)

Table 10 and Table 11 show our portfolio performance with maximizing its Sharpe ratio. With the exponential-weighted factor returns (EWFR) as our factor views, our portfolio still can produce the annualized alphas of 5.5% (IRs of 0.4–0.49) and 6–6.5% (IRs of 0.25–0.27) over the Dow Jones indices and the S&P 500 indices, respectively. The theoretical level for the information ratio of 0.2835 is considered as a good level, while the average annual information ratio estimated on 300 funds is 0.36 based on the statistics (Grinold and Kahn, 1995; Bertrand and Protopopescu, 2010). In this case, the IRs of our portfolio over the composite indices are still above 0.36, suggesting the promising performance of our multi-style rotation strategy using merely the six-month EWFR. Although EWFR does not have a forward-looking feature, this simple method still can capture the directional premium in three months ahead, attributable to the decaying process of alpha signals.

Table 10. Active performance with optimal Sharpe ratio

Optimized Sharpe Ratio	Benchmark				
	DJ Islamic U.S.	DJ Conv. U.S.	SandP 500 Comp.	SandP 500 Value	SandP 500 Growth
Exponential-weighted factor views					
Annualized alpha	5.55%	5.60%	6.27%	6.45%	6.46%
Annualized tracking error	0.138	0.127	0.129	0.257	0.238
Information Ratio	0.402	0.442	0.486	0.251	0.271
Turnover constraint (20% per 3 months)					
BMS-MSVAR factor views					
Annualized alpha	10.22%	10.27%	10.98%	11.16%	11.17%
Annualized tracking error	0.143	0.136	0.138	0.263	0.235
Information Ratio	0.713	0.755	0.798	0.425	0.476
Turnover constraint (20% per 3 months)					
BMS-MIDAS factor views					
Annualized alpha	6.94%	6.99%	7.67%	7.85%	7.86%
Annualized tracking error	0.124	0.120	0.121	0.270	0.249
Information Ratio	0.561	0.583	0.632	0.290	0.315
Turnover constraint (20% per 6 months)					

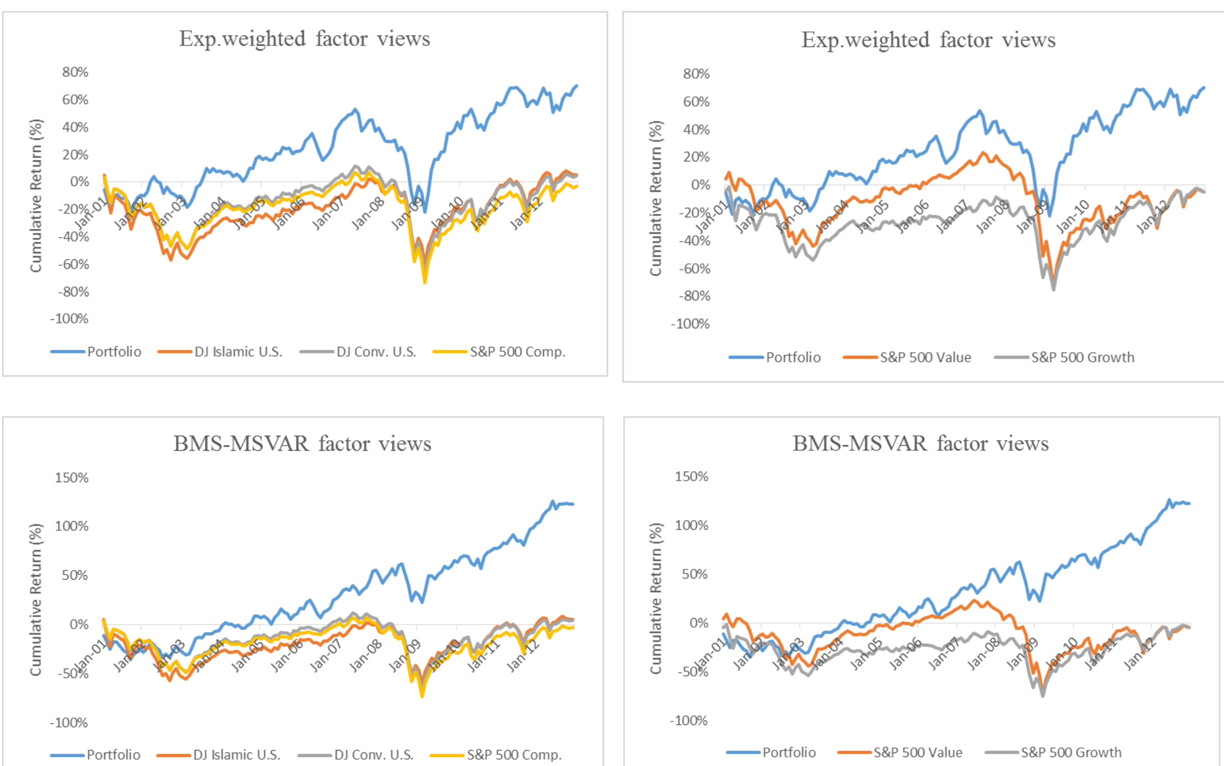
Table 11. Portfolio performance with optimal Sharpe ratio

Optimized Sharpe Ratio	Exp.weighted factor views	BMS-MSVAR	BMS-MIDAS	Benchmark				
				DJ Islamic U.S.	DJ Conv. U.S.	SandP 500 Comp.	SandP 500 Value	SandP 500 Growth
Monthly return	0.489%	0.852%	0.598%	0.038%	0.034%	-0.019%	-0.0336%	-0.0339%
Monthly std. deviation	0.056	0.053	0.055	0.053	0.053	0.052	0.056	0.050
Monthly Sharpe Ratio	0.087	0.161	0.109	0.007	0.006	-0.004	-0.006	-0.007
Turnover contraint	20% (per 3 months)	20% (per 3 months)	20% (per 6 months)					

We also use Bayesian Model Selection (BMS) with the BMA method to obtain the best predictors, as well as MS-VAR and MIDAS as our forecasting methods which have a forward-looking feature. We notice that our portfolio with MS-VAR can produce the IRs of 0.7–0.8 over the composite indices, and the IRs of 0.42–0.48 over the style indices. The source of our superior performance comes from the improvement in the annualized alphas of 10–11%. Moreover, our portfolio with MIDAS produces the IRs of 0.5–0.6 over the composite indices, and the IRs of around 0.3 over the style indices. The lower IRs of this method, relative to MS-VAR, is due to the lower annualized alphas since we impose the turnover rate only up to 40% per year. This constraint on the active weights has limited our active strategy to be able to capture higher factor premium available in the market.

In Figure 4, we notice that the performance of our portfolios is relatively close to that of the S&P 500 Value index, which implies the important role of value investing in our portfolio. However, we still outperform the value-style index with high IRs, attributable to a combination of the different styles rather than being a style-consistent. This result can be justified by our tracking errors over the value-style index, which are considerably higher than those over the composite indices. Our portfolios rely more on multi-style investing while remain tilt closely to the market. Relating Figure 3 and Figure 4, we can see the substantial outperformance of our 3-month rebalancing portfolios in 2002 to 2003, attributable not only to the two valuation factors but also to the other factors like the profitability, momentum, and macroeconomic factors. Another substantial outperformance can be observed in 2005, due to the combination of valuation and inefficiency factors.

Figure 4. Cumulative returns: optimal Sharpe ratio



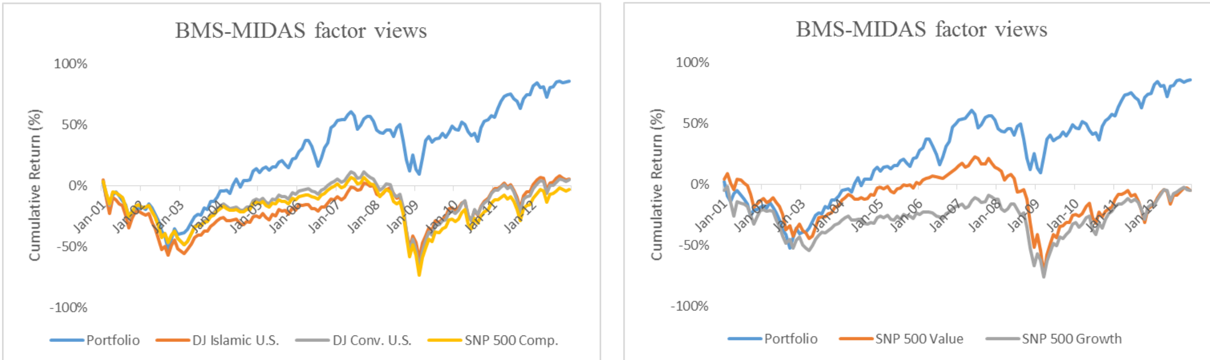
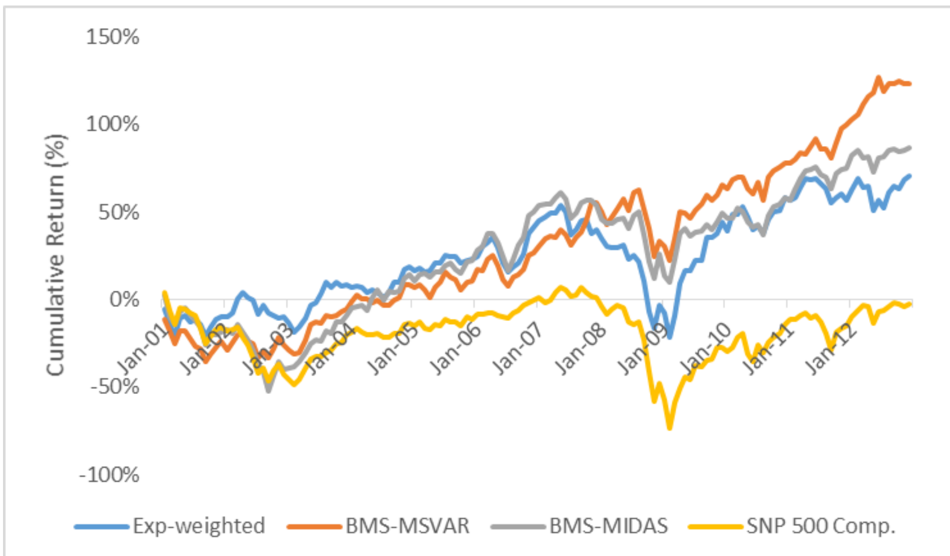


Figure 5. Cumulative returns: three methods with optimal Sharpe ratio



We also notice that our portfolios' excess returns with MS-VAR and MIDAS keep increasing during the U.S. subprime crisis in 2008. This is mainly driven by the combination of momentum, profitability, earnings quality, efficiency, and macroeconomic factors. The contrarian strategy seems to play a major role in mitigating the losses in 2009. When we look at Figure 5, our portfolio with EWFR performs worse as compared to the other two portfolios with MS-VAR and MIDAS. This shows the importance of forward-looking factor views in our active portfolio. The outperformance of EWFR in the earlier observations can be explained by the less historical data available for both MS-VAR and MIDAS, which starts in 1998.

In Table 12, we optimize our portfolio with target risk of 1% lower than our market portfolio. Table 12 and Table 13 show that our portfolios still deliver the IRs of above 0.36 over the composite indices.

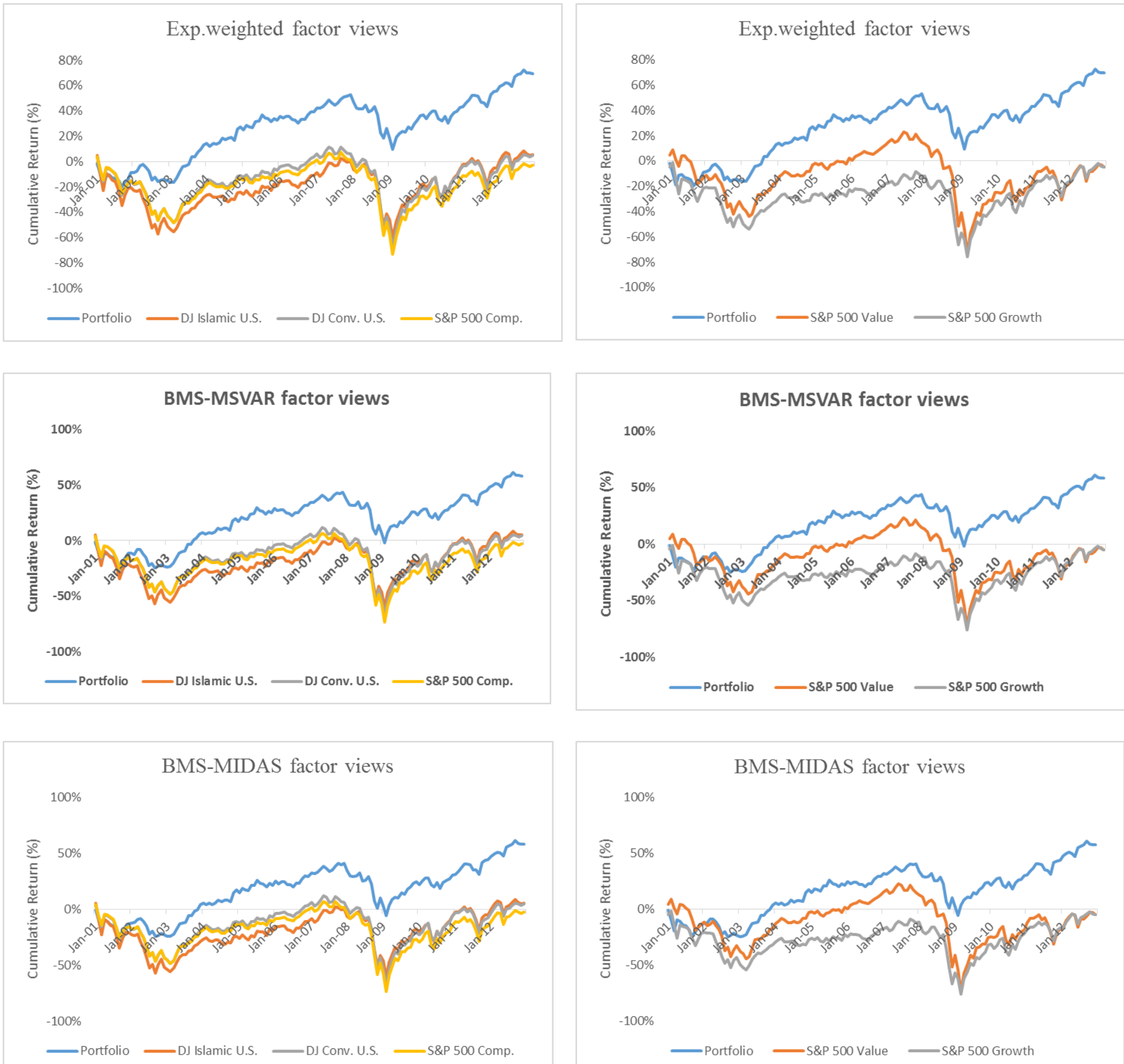
Table 12. Active performance with target risk

Target Risk Portfolio	Benchmark				
	DJ Islamic U.S.	DJ Conv. U.S.	SandP 500 Comp.	SandP 500 Value	SandP 500 Growth
Exponential-weighted factor views					
Annualized alpha	5.47%	5.52%	6.19%	6.37%	6.38%
Annualized tracking error	0.101	0.100	0.097	0.235	0.212
Information Ratio	0.544	0.552	0.639	0.271	0.301
Turnover constraint (20% per 3 months)					
BMS-MSVAR factor views					
Annualized alpha	4.49%	4.54%	5.21%	5.39%	5.40%
Annualized tracking error	0.094	0.095	0.092	0.235	0.212
Information Ratio	0.478	0.480	0.566	0.229	0.254
Turnover constraint (20% per 3 months)					
BMS-MIDAS factor views					
Annualized alpha	4.45%	4.50%	5.17%	5.34%	5.35%
Annualized tracking error	0.090	0.090	0.088	0.236	0.215
Information Ratio	0.494	0.500	0.590	0.226	0.249
Turnover constraint (20% per 6 months)					

Table 13. Portfolio performance with target risk

Target Risk Portfolio	Exp.weighted factor views	BMS-MSVAR	BMS-MIDAS	Benchmark				
				DJ Islamic U.S.	DJ Conv. U.S.	SandP 500 Comp.	SandP 500 Value	SandP 500 Growth
Exponential-weighted factor views								
Monthly return	0.483%	0.405%	0.401%	0.038%	0.034%	-0.019%	-0.0336%	-0.0339%
Monthly std. deviation	0.037	0.038	0.039	0.053	0.053	0.052	0.056	0.050
Monthly Sharpe Ratio	0.131	0.106	0.103	0.007	0.006	-0.004	-0.006	-0.007
Turnover contraint	20% (per 3 months)	20% (per 3 months)	20% (per 6 months)					

Figure 6. Cumulative returns: target risk

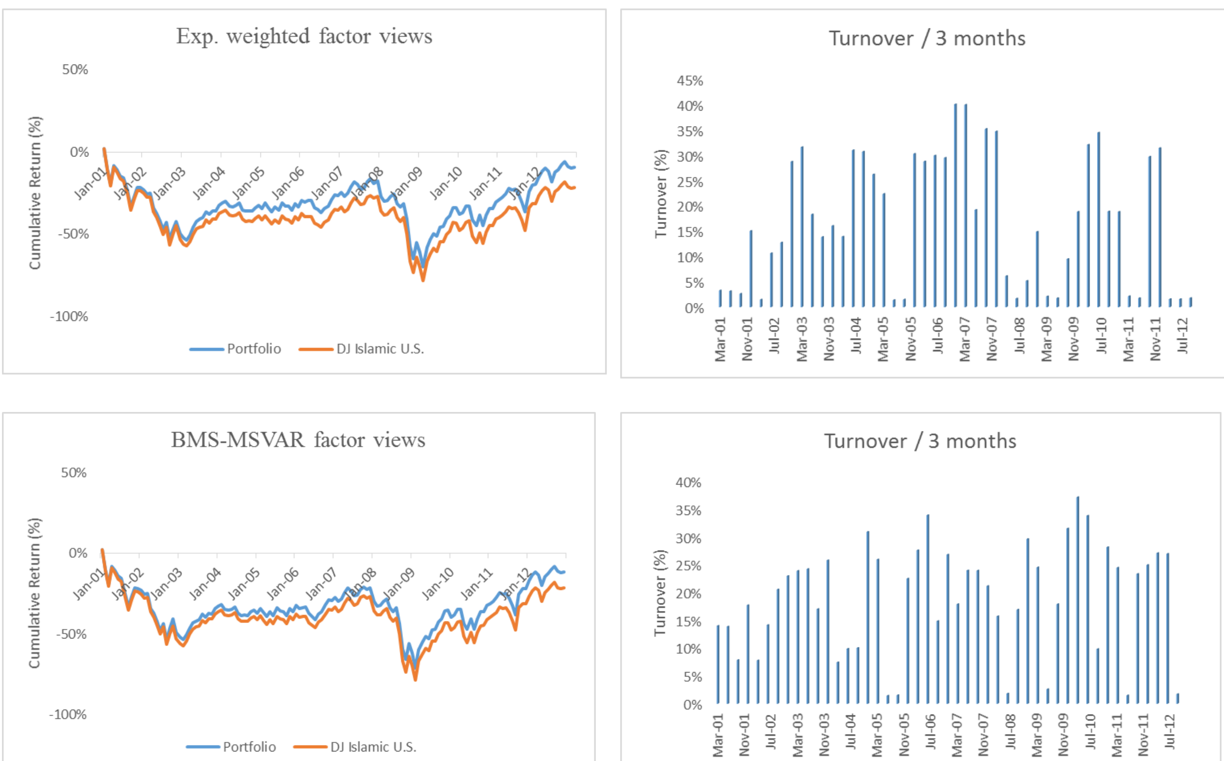


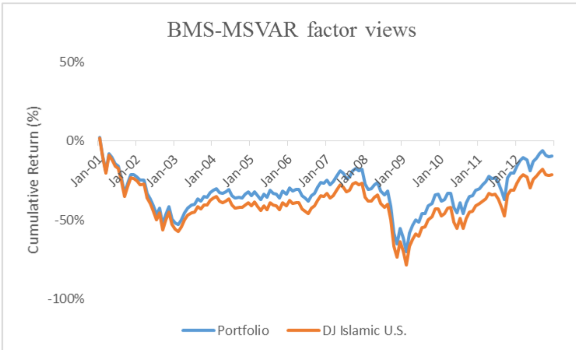
Finally, we optimize our portfolios using the constraint in tracking error since active managers normally are given a mandate subject to a certain additional volatility. We limit our tracking error up to 1% over the Dow Jones Islamic index as our market portfolio. In Table 14, our portfolios deliver more promising results, with higher IRs of 0.9 to 1.2. The annualized alphas are between 0.85 – 1.02%, with the annual average turnover rates of less than 80%. Assuming that the transaction cost for each stock equals to 50 bps, our portfolios still produce high information ratios of 0.6–0.8, above the standard IR of 0.36.

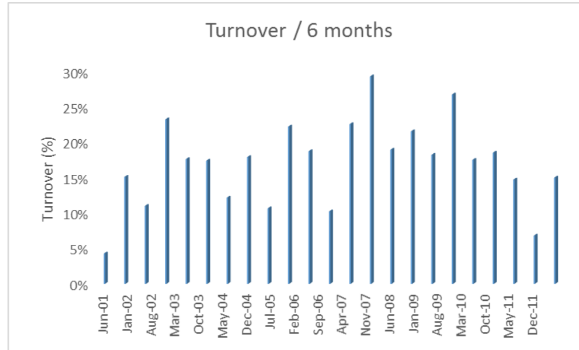
Table 14. Active performance with the constrained tracking error

Tracking Error Portfolio	Exp.weighted factor views	BMS-MSVAR	BMS-MIDAS
Exponential-weighted factor views			
Annualized alpha	1.02%	0.85%	1.02%
Annualized alpha (after transaction cost)	0.68%	0.47%	0.68%
Annualized tracking error	0.011	0.010	0.008
Information Ratio	0.905	0.842	1.242
Information Ratio (after transaction cost)	0.601	0.467	0.831
Average Turnover	17.14%	18.90%	16.94%
	(per 3 months)	(per 3 months)	(per 6 months)

Figure 7. Cumulative returns and turnover rates with the constrained-tracking error







6. Conclusion

This study constructs active Islamic portfolios using a multi-style rotation strategy. We use the stocks that are consistently listed in the U.S. Dow Jones Islamic index for a sample period from 1996 to 2012. The rotation strategy combines the three prominent styles that consist of momentum, value, and quality investing. The quality metrics cover franchise value, financial strength, and earnings quality. We also include two macroeconomic variables, which are industrial production growth and inflation innovation, to accommodate the economic regime shifts.

The first process of our portfolio construction is to select relevant variables that represent each style. We assess the strength of alpha signals by looking at the average information coefficients (ICs) as well as the ICs' correlation. We find that the six-month momentum and the efficiency measure (multi-fractal de-trended fluctuation analysis) as momentum factors; the enterprise yield (gross profit/TEV) and the book to market ratio as valuation factors; the gross profit to total assets, the return on capital, and the scaled total accruals as quality factors. We also create mimicking portfolios for the two macroeconomic variables in order to capture their premium available in our sample of the U.S. Islamic stocks.

The second process is to construct a mimicking portfolio for each factor to capture the factor returns available in the market, where we use a composite factor mimicking tilt (MFM) technique that is able to mimic any premium at minimal tracking error. While the factor returns from valuation factors are generally stable as their alpha signals decay very slowly, the premium from momentum factors are highly cyclical. The style allocation weights strongly suggest that the combination of all factors can provide either returns enhancement or the risk diversification. For the combination between momentum and value investing, either momentum or inefficiency strategies may help the valuation factors to avoid a value trap since the price persistency is useful as timing triggers in acquiring value shares. In some periods, either contrarian or random-walk-based strategies can provide a diversification benefit between momentum and value investing. As to the combination between valuation and quality metrics, it can detect any stock that are expected to grow but available at a fair or reasonable price. However, the advantage of this integration varies across different periods. We also find the changing important role between the enterprise yield and the book to market ratio across different periods, which implies that the advantage of income-based metrics and the stability of assets' book value can complement each other to capture the value premium. For the macroeconomic factors, the industrial production growth and the inflation are negatively and positively priced, respectively, which are in line with some empirical findings. The use of macroeconomic factors is very important since all of our styles' returns are partially driven by macroeconomic premium.

The third process is to apply the augmented Black Litterman (ABL) factor model to blend the market view and our specific views. The ABL method allows us to incorporate our factor views in the Bayesian framework, without creating the factor alignment problem. The factor views are obtained by using the exponential-weighted factor returns, MS-VAR, and MIDAS, in order to avoid a look-ahead bias in our portfolio construction. We select the relevant predictors by using Bayesian Model Averaging to improve our forecasts. Our forecasting performance is sufficient to produce directional views in factor returns.

Finally, this study optimizes the portfolio subject to a constraint in the annual turnover rates of 80% and 40% for our 3-month rebalancing portfolio and 6-month rebalancing portfolio, respectively. These turnover rates fall in the range between the managed pension funds' rate and the large-cap mutual funds' rate. The out-of-sample performance of our portfolios for a period from 2001 to 2012 deliver the promising rewards for active investors. In particular, our portfolios can produce information ratios of 0.7 – 0.8 over the composite indices, and information ratios of 0.42 – 0.48 over the style indices, with the annualized alphas of 10 – 11%. Even when we put the constrained tracking error of 1% over the benchmark, our portfolios still produce information ratios of 0.9 – 1.2 before transaction costs, and 0.6 – 0.8 after transaction costs. This is considerably higher than the theoretical level for the information ratio of 0.2835, as well as the average annual information ratio of 0.36 estimated on 300 U.S. funds based on the statistics. The overall results of this study suggest the importance of multi-style rotation strategies, combined with the market view and the macroeconomic factors, for Islamic active investors to outperform the market.

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