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Heads we win, tails you lose: Is there equity in Islamic equity funds?☆

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ABSTRACT

We made the first estimate of the proportion of fund alpha statistically attributable to luck rather than skill for a sample of Malaysian Islamic equity funds. Broadly, the funds do not outperform market benchmarks. In the limited instances where performance is superior, based on a contemporary methodology, as much as 47% of the observed positive fund alpha is statistically attributable to luck. Thus, at 5% significance level, we find only 1.95% of our funds to be genuinely skilled. Our findings raise questions regarding the equitability of these funds levying fixed fees, making a case for potential innovation in fund remuneration structure.

1. Introduction

In finance literature, both historically as well as currently, there is the debate as to whether actively managed funds add value. More specifically, the polemic centers on the issue of whether fund managers possess specific skills such as insightful asset allocation strategies, stock picking ability and market timing, or are observed fund performance due to merely luck. This issue is not purely academic and has significant implications and importance to investors and industry players alike. It is not difficult to see why. Actively managed funds impose fees for the services they provide in the form of front or end loads, and annual management fees, to name a few. It would be in the interest of investors to know what they are paying for.

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A typical prudent investor would be interested in two things. Firstly, do funds meet performance expectations and secondly, if favorable performance is observed, is this attributable to skills of the fund manager or is it mainly due to luck? Investors may not be comfortable with the notion of fund managers earning fees for outcomes not substantially due to the managers' competence. At a philosophical level, there is the question of equity or fairness in the manner in which fund managers extract fees. In practical terms, if luck is the name of the game, shrewd investors may want to consider investing themselves or opting for passive funds (for example, index-tracking funds). In either case, investors end up paying substantially less fees. Put simply, why should investors pay fund managers fees if fund performance is due to luck?

There can be a number of reasons which make investment in mutual funds (or unit trusts, as they are more commonly known in Malaysia) advantageous. Investors with small initial outlays can get a diversified portfolio. Investors also do away with potentially distracting and costly portfolio monitoring costs. Most importantly, or at least most pertinent to this discussion, investors are beneficiaries of the collective competence of the fund management company, gaining from the fund manager's expertise, industry knowledge and research capabilities. It can be argued that the first two aforementioned reasons are less compelling for a growing number of investors. Stock exchanges around the world are reducing the size of standard board lots to encourage retail participants. The value of diversification itself has been questioned and even if one subscribes to it, a portfolio need not comprise scores of stocks to benefit from diversification. In today's age of ever-advancing technology in telecommunications and electronic media, the ordinary investor can monitor stock portfolios in real time or periodically at negligible pecuniary cost. The point is, just about any investor with a reasonably-sized investment outlay does not benefit substantially from mutual funds in terms of diversification or monitoring costs. That being said, the key selling point for mutual funds is the fund manager's competence. What should convince investors to handover their investment monies to mutual fund companies instead of opting to invest directly themselves is the belief that fund managers possess superior investment skills. Doubts over the actual prevalence of such skills among fund managers may question the very *raison d'être* of mutual funds.

Interest in this issue need not be limited to investors. Mutual fund companies should be clear about their customer value proposition and subject themselves to self-enquiry to substantiate the existence of such value. As investors become more discerning and well-informed, mutual funds have to make a more convincing case for their product offerings. From a regulator's perspective, as the market for mutual funds grows and matures, adequate supervision is required to ensure that investors' interests are protected and that the less astute or misinformed investor is not taken for a ride.

Islamic or *Shari'ah* compliant mutual funds are a category of mutual funds. Their key differentiating factor is that they are subjected to a set of *Shari'ah* compliance rules, chief of which is that assets in the portfolio must abide by Islamic principles and tenets. In the case of Islamic equity funds, this means that stocks making up a given fund must be categorically *Shari'ah* compliant. Towards this end, the *Shari'ah* Advisory Council (SAC) of the Securities Commission is the gatekeeper, in Malaysia.[1] Stocks are screened to filter firms involved in prohibited sectors like conventional finance and insurance, gambling and gaming, tobacco, alcohol and entertainment. Financial ratios are also applied to limit the firms' interest-based income and interest-bearing securities and receivables. If the Islamic equity fund allocates part of the portfolio to cash or short-term securities, they must be non-interest bearing.[2]

While the issue of the role of luck in fund performance is applicable to both mainstream and Islamic mutual funds, we have chosen to focus on the latter, for at least two reasons. Firstly, Islamic finance is comparatively nascent (albeit growing at healthy rates) and hence understandably less subjected to empirical analysis. Secondly, Islamic finance has been founded on cornerstone principles such as equity and fairness. Evidence, if such exists, that luck plays a primary role in observed fund performance, challenges the philosophical foundations of Islamic finance, at least with respect to Islamic equity funds. At present, mutual fund firms gain (by charging fees) regardless of the outcome of stock investment. In Islamic legal nomenclature, Islamic mutual funds are operationalized using the Islamic nominate contract of *wakalah istithmar* (agency combined with investment).[3] In essence, the client investor appoints the

[1] In other jurisdictions, *Shari'ah* advisory boards maintained by financial institutions may carry out similar functions.
[2] For more details of *Shari'ah* stock screening and *Shari'ah* rules pertaining to Islamic mutual funds, see www.sc.com.my.
[3] See Ayub (2007, p.349).

fund manager to become his agent to carry out investment of stocks on his behalf. If fund performance is primarily the result of some random exercise (luck) instead of value-adding investment analysis, one cannot be blamed for raising somewhat cynical questions as to whether the fees imposed by fund managers are justified or equitable. The teaser title "heads we win, tails you lose" is aimed at capturing this sentiment. It is not our intention here to question the *Shari'ah* compliance status of Islamic funds. Rather, we seek to find empirical evidence that can potentially elevate Islamic equity funds to better embody the spirit of justice that Islam propagates. Policy implications arising from expected results are arguably distinct. The intention is to propose and make a case for changes to the remuneration structure or mechanism for Islamic equity funds, moving from fee-based to profit-sharing arrangements. This undertone fits current stylized calls for Islamic finance to embrace risk-sharing principles in its products and structures. We seek to ensure that there is indeed equity in Islamic equity funds, pun intended.

In the next section, we formalize the research questions of this paper. Section 3 is a review of related literature, Section 4 details the research methodology employed and Section 5 discusses empirical findings and offers some intuitive interpretation of the results. In Section 6, we conclude the paper by highlighting key implications and putting forth some humble suggestions.

2. Research objective

The objective of this paper is to gauge the quantum of risk-adjusted[4] performance of Islamic equity funds in Malaysia attributable to random acts or simply, luck. The intention is not so much to present a "report card" on the affected fund managers. Rather, it is to make a case to propose possible innovation in remuneration structures of mutual funds. We can decompose this research aim into three essential steps:

i. Measure risk-adjusted performance of Islamic equity funds.
ii. Apportion part of the observed performance and attribute it to a random element (luck), using statistical techniques.
iii. Analyze performance of Islamic equity funds after accounting for luck.

Given the chosen yardstick of mutual fund performance (fund alpha), some auxiliary research objectives can be addressed. We investigate the robustness or applicability of common risk factors accepted in contemporary research on mutual funds to *Shari'ah* compliant equity funds. To some extent, this will give insights into the landscape of *Shari'ah* compliant equity funds in Malaysia, the prevalence of dominating investment strategies (if any) and potential presence of idiosyncrasies. In particular, we seek to find statistical evidence to substantiate the presence of some common or elementary investment strategies, namely:

i. High versus low beta stocks
ii. Large versus small market capitalization stocks
iii. Value versus growth stocks
iv. Momentum versus contrarian strategies

3. Literature review

We begin our review of literature by addressing the related issue of socially responsible investing (SRI) or ethics-based investing. The question of whether there is a financial cost associated with SRI is certainly not a new one. There are voluminous works that have empirically tested the return performances of SRI funds vis-à-vis mainstream ones. For instance, Renneboog et al. (2008b) find evidence that investors pay a price for ethics, given that SRI funds in the US, the UK, and a number of countries in Europe and Asia-Pacific underperform their respective domestic benchmarks. Renneboog et al. (2008a) argued similarly that SRI investors are willing to accept suboptimal financial performance to pursue ethical objectives. Notwithstanding that, there is little evidence that the risk-adjusted returns of SRI funds are statistically different from those of mainstream funds (Bauer et al., 2005). Blanchett (2010) finds that SRI funds slightly underperformed on pure return basis but outperformed non-SRI peers after accounting for

[4] Recording positive returns numbers alone is not sufficient as returns must commensurate the risk profile of the given fund.

risk, although the results lacked statistical robustness. Faith-based funds (such as Islamic mutual funds) are often compared with SRI funds. In a study by Lyn and Zychowicz (2010), it was found that generally, faith-based funds did better than SRI funds. It is noteworthy that while there are some common grounds between socially responsible investing and faith-based investing, there is little justification to argue that the latter is a sub-category of the former, much less to equate the two. Forte and Miglietta (2007) offered qualitative and quantitative evidence that Islamic funds were characteristically different from SRI funds in terms of asset allocation and econometric profile.

The dearth in empirical literature studying performance of Islamic funds is both understandable (given that in terms of size, they are currently still dwarfed by mainstream funds) and increasingly being addressed. A growing number of published works compare the performance of Islamic mutual funds with that of their conventional counterparts. For the most part, it is a mixed bag of results. Alam and Rajjaque (2010) claim empirical evidence of Islamic funds outperforming conventional ones, while Hayat and Kraeussl (2011) find results of Islamic investment funds underperforming. A number of studies also conclude that Islamic funds are market competitive, finding that risk-adjusted returns of *Shari'ah*-compliant funds are not statistically significantly different from those of mainstream funds (see Elfakhani et al., 2005; Girard and Hassan, 2008; Hakim and Rashidian, 2004; Hussein, 2004; Merdad et al., 2010). Apart from finding no discernible pecuniary penalty associated with adherence to religious tenets, these papers also observed that Islamic funds' returns tend to fare better during bearish markets while lag behind conventional funds during periods of market uptrend. Many hence claim that Islamic mutual funds are good hedging investment alternatives during market downturns and recessions. Dimensions of analysis extend beyond relative fund performance and risk/return characteristics. For example, Hoepner et al. (2011) also examined investment style and found Islamic funds favoring growth and small cap stocks. Afza and Rauf (2009) investigated fund attributes that significantly influence fund performance.

Malaysian *Shari'ah* compliant mutual funds have had their share of empirical analysis. Employing widely-used fund performance yardsticks such as the Sharpe and Treynor ratios, Jensen's alpha, the Modigliani Measure, and the Information ratio, Abdullah et al. (2007) concluded that Islamic funds fared better during bearish market conditions while conventional funds outperformed Islamic ones when the market is bullish. They also found that both fund types had poor diversification levels. Their empirical results suggest that the fund managers were not very competent at stock-picking and were bad market timers. Shamsher et al. (2000) found no significant differences in the performance of actively and passively managed Malaysian funds, where both underperformed the market portfolio. Annuar et al. (1997) offered some evidence of positive selectivity performance, but poor timing abilities and diversification levels among some Malaysian mutual funds studied. Interestingly, Mansor and Bhatti (2011) published empirical evidence wherein conventional and Islamic Malaysian mutual funds outperformed the market portfolio. In their sample and evaluation period, the Islamic portfolio slightly underperformed and was found to be riskier, when compared to conventional funds. Some papers analyzed different aspects of Malaysian mutual funds. As examples, Ismail and Shakrani (2003) used conditional CAPM to establish that beta explains cross-sectional differences in Islamic mutual fund returns while Saad et al. (2010) investigated the efficiency of Malaysian mutual funds and found some Islamic funds to perform better in this respect, compared to conventional funds.

Using statistical methods to empirically discern the performance of mutual funds attributable to fund managers' skills from just luck is not a new proposition. Barras et al. (2010) employs a direct yet statistically robust method, which this paper adopts, to estimate true fund alphas. Working with a substantial sample of US mutual funds, it was found that, among other things, proportions of truly skilled funds were close to zero, in recent time periods. Fama and French (2010) used bootstrap simulations on US equity mutual fund data and reported similar findings. Only few funds were able to produce benchmark-adjusted expected returns adequate to cover their imposed costs.

Finally, it is not difficult to find literature that discusses mutual funds from a *Shari'ah* or *fiqh* (Islamic legal rules) perspective. However, most if not all of these focus primarily on issues like stock screening, portfolio income purification, *zakah*, reporting and broad corporate governance matters. We have yet to come across published work that scrutinizes present Islamic mutual fund fee structures either from a legal standpoint or from economic intuition based on empirical findings. An eminent *Shari'ah* scholar, Sheikh Yusuf Talal DeLorenzo did however remark that “a significant number of managed Islamic equity funds function without *Shari'ah* supervision of any sort” and that “if management is slow to address the issue, then the remedy will come from the investors themselves".[5] We concur with DeLorenzo in that investors "expect more from the professionals who manage their money… in terms of performance, [and] … *Shari'ah* compliance". Advocating customer advocacy and moral purification, DeLorenzo scraped the surface of the subject of our paper by calling for reasonable fee structures which should be well-communicated. The idea that there should be justice in the fees imposed by funds is not uniquely *Shari'ah*-inspired but rather appeals to simple human expectations. Ramasamy and Yeung (2003) found transactional costs to be among the top three factors that matter when it comes to mutual funds.

In light of present literature on Islamic mutual funds as briefly discussed above, we believe that our paper is novel in at least two respects. Firstly, we apply empirical techniques to statistically identify performance of Islamic equity funds attributable to luck. Secondly, we offer our findings as a justification for a proposal to amend the fee structure of Islamic mutual funds, which we argue will better embody the spirit of the *Shari'ah*.

4. Research methodology

4.1. The basic idea

The objective of this paper is to compute the percentage of Islamic equity funds that exhibit *true* positive performance, after accounting for the 'luck' factor. The chosen performance yardstick is *fund alpha*, defined here as the excess return over a stipulated (market) benchmark. As alpha is computed as the constant coefficient resulting from a regression of a time series of fund and market returns, fund returns are in a sense risk-adjusted. Returns are computed on monthly basis based on total returns[6] and are net of a risk-free rate. The proxy for the risk-free rate is the Malaysian T-bill Band 4 mid-rate.[7]

We endeavor to offer multiple methods of computing alpha. This provides some degree of robustness in drawing conclusions. Three common models of alpha computation will be adopted, namely:

i. As per capital asset pricing model (CAPM) described in Sharpe (1964) and Lintner (1965)
ii. Fama and French's (1993) 3-factor model
iii. Carhart's (1997) 4-factor model

In essence, the approach here is to construct a performance attribution model — identifying factors that have empirically "explained" observed fund return. These factors represent elementary investment strategies, namely:

i. High versus low beta stocks
ii. Large versus small market capitalization stocks
iii. Value versus growth stocks
iv. Momentum versus contrarian strategies

CAPM addresses the first strategy, Fama and French's 3-factor alpha includes the first three while Carhart's model incorporates all four factors. We briefly elaborate on each of these factors below. After alpha is computed, we refer to the methodology used in Barras et al. (2010), described in brief below, to statistically identify the portion of alpha that is attributable to luck. Removing this component from observed alpha will give us the *true* fund alpha.

4.2. The dependent variable

We confine our sample to *Shari'ah* compliant equity funds currently operating in Malaysia, with adequate data points to execute regression. The following funds are excluded — balanced funds (mix of

[5] See "*Shari'ah* Supervision of Islamic Mutual Funds", presented by Sheikh Yusuf Talal DeLorenzo at the 4th Harvard Forum on Islamic Finance, downloadable at http://www.failaka.com.

[6] This measure takes into account dividend issuances, splits, bonus issues, etc.

[7] Basis of choice of this proxy is primarily availability of suitable data spanning over the estimation period. Band 4 is defined as having 68 to 91 days to maturity.

debt and equity), regional funds (funds investing substantially in non-Malaysian equities, typically within Asia Pacific), index (passively-managed) funds, and wholesale funds.[8] Applying this filter, from a total of 167 *Shari'ah* compliant funds, we are left with 63 funds, which form our sample. The estimation period is from September 2001 to June 2012, with a maximum of 130 (monthly) observations.[9] As mentioned above, the variable represents monthly total fund returns net of the proxy risk-free rate. Two sets of fund returns are computed — before and after fund expenses are deducted.[10]

4.3. The regressors

4.3.1. Market return

As proxy for the market return factor, we have relied on a number of benchmark stock indices, namely:

i. Kuala Lumpur Composite Index (conventional bellwether index, representing top 30 stocks by market capitalization)
ii. FBM *Shari'ah* Index (broad-based index of *Shari'ah* compliant stocks) [FBMSHA]
iii. FBM Hijrah Index (alternative index of *Shari'ah* compliant stocks)
iv. FBM Emas Index (broad-based index of all stocks on Bursa Malaysia)
v. FBM Top 100 Index (index of top 100 stocks by market cap)
vi. FBM Small Cap (index of small market capitalization stocks)
vii. FBM Mid 70 (index of mid-sized market cap stocks).
viii. A constructed value-weighted (by market capitalization) index of all *Shari'ah* compliant stocks included in this sample (similar in approach to Fama and French, 1993) [VWINDEX]

We intentionally explore multiple market proxies to introduce some robustness in our model. We select two indices – FBMSHA and VWINDEX – for subsequent regression equations to reduce complexity and make the empirical work less voluminous.[11] Note that the FBM *Shari'ah* and FBM Hijrah indices were only introduced in December 2006 and April 2007, respectively, making the estimation period shorter for regression equations involving those indices.

4.3.2. Size

There are ample reported empirical findings that small stocks outperform large stocks. Hence the size of firms is accepted by many as a common factor that typically “explains” observed returns. To incorporate this dimension in our analysis, we regress fund returns against a proxy for this common risk factor in stock returns. We do not regress against the actual size of the fund in question. Instead, portfolios are constructed to mimic the “size” factor and this represents a shared and undiversifiable risk factor. Similarly, many claim that value stocks tend to outperform growth stocks.[12] To represent this aspect, we rely on the book-to-market equity ratio.

Towards this end, we employ the method as per Fama and French (1993). Firstly, we sort all *Shari'ah* compliant stocks based on 2 criteria — size (measured by market capitalization) and book-to-market equity ratio.[13] For size, we use the median size of Main Board stocks to split all stocks into 2 groups — small (S) and Big (B). For the book-to-market ratio, we create 3 groups — bottom 30% (L), middle 40% (M) and top 30% (H). From there we can construct 6 portfolios:

i. S/L: small stock with low book-to-market equity ratio
ii. S/M: small stock with medium book-to-market equity ratio
iii. S/H: small stock with high book-to-market equity ratio

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8 Note that the typical equity fund does invest a small proportion of the portfolio in cash and short-term securities.
9 For some more recently launched mutual funds, the estimation period is shorter.
10 Reported expense ratios are used, which presumably includes management expenses. Front and/or back loads are not accounted for here. In a few cases where expense ratio data is not available, a conservative 1% per annum is assumed.
11 Selection of these two indices is mainly based on the fact they better reflect the nature of the funds' stock composition.
12 Values stocks are typically characterized by low price-to-book equity ratios, low price-to-earnings multiples or high dividend yields.
13 We limit ourselves to Main Board stocks. Out of 828 stocks, about 86% or 716 stocks are *Shari'ah* compliant (as at July 2012). From this, 23 stocks have missing or insufficient data, leaving us with 693 stocks to work with.

iv. B/L: big stock with low book-to-market equity ratio
v. B/M: big stock with medium book-to-market equity ratio
vi. B/H: big stock with high book-to-market equity ratio

The rationale for three groupings for the book-to-market ratio and only two for size is that there is empirical evidence that the former has a stronger role in influencing average stock returns (Fama and French, 1992). Monthly value-weighted returns are computed for the six portfolios. To mimic the risk factor in returns related to size, we take the difference between (i) the simple average returns of the three small stock portfolios and (ii) the simple average returns of the three big stock portfolios. In this way we observe the size effect while controlling for the book-to-market ratio factor. Portfolios are constructed annually, in June of every year, as per Fama and French (1993).

4.3.3. Book-to-market equity ratio

Along a similar vein, to mimic the risk factor in returns related to book-to-market equity, we take the difference between (i) the simple average returns of the two high book-to-market equity ratio stock portfolios and (ii) the simple average returns of the two low book-to-market equity ratio portfolios. Using mimicking portfolios for the common risk factors in returns minimize the variance of firm-specific factors.

To add a further dimension to our analysis, we also computed size and book-to-market equity ratios based on free float numbers. We compute market capitalization (free float) as the share price multiplied by number of shares freely traded on the exchanged (as compared to total number of shares on issue).

4.3.4. Momentum strategy short-term anomaly

There are empirical evidences that adopting a momentum strategy can result in short-term abnormal performance. This is sometimes termed the “hot hands” effect. Some have suggested that this is market inefficiency due to slow reaction to information. To account for this in our model, we employ a variation of the method of Jegadeesh and Titman (1993). At each month, stock returns of all *Shari'ah* compliant stocks are ranked. Two portfolios are constructed, using equal-weights, comprising the highest 30% and lowest 30% 6-month returns lagged one month of the said stocks.[14] We then find the difference in (current month t) returns of these two portfolios, and this is regressed against fund returns. Portfolios are re-formed monthly. We compute two versions of this “momentum” return — equal weighting and value-weighted.

4.4. Regression equations

Given the variables briefly discussed above, we formed 20 regression equations, listed below.

$$r_{i,t} = \alpha_i + \beta_{1,i} \cdot r_{m-klci,t} + \varepsilon_{i,t} \tag{1}$$

$$r_{i,t} = \alpha_i + \beta_{1,i} \cdot r_{m-fbmsha,t} + \varepsilon_{i,t} \tag{2}$$

$$r_{i,t} = \alpha_i + \beta_{1,i} \cdot r_{m-fbmhij,t} + \varepsilon_{i,t} \tag{3}$$

$$r_{i,t} = \alpha_i + \beta_{1,i} \cdot r_{m-emas,t} + \varepsilon_{i,t} \tag{4}$$

$$r_{i,t} = \alpha_i + \beta_{1,i} \cdot r_{m-top100,t} + \varepsilon_{i,t} \tag{5}$$

$$r_{i,t} = \alpha_i + \beta_{1,i} \cdot r_{m-scap,t} + \varepsilon_{i,t} \tag{6}$$

$$r_{i,t} = \alpha_i + \beta_{1,i} \cdot r_{m-mid70,t} + \varepsilon_{i,t} \tag{7}$$

$$r_{i,t} = \alpha_i + \beta_{1,i} \cdot r_{m-vwindex,t} + \varepsilon_{i,t} \tag{8}$$

$$r_{i,t} = \alpha_i + \beta_{1,i} \cdot r_{m-fbmsha,t} + \beta_{2,i} \cdot r_{size,t} + \beta_{3,i} \cdot r_{btm,t} + \varepsilon_{i,t} \tag{9}$$

[14] In essence, we take the average 6 month return of month t-7 to month t-1 for each stock.

$$r_{i,t} = \alpha_i + \beta_{1,i} \cdot r_{m-vwindex,t} + \beta_{2,i} \cdot r_{size,t} + \beta_{3,i} \cdot r_{btm,t} + \varepsilon_{i,t} \tag{10}$$

$$r_{i,t} = \alpha_i + \beta_{1,i} \cdot r_{m-emas,t} + \beta_{2,i} \cdot r_{size,t} + \beta_{3,i} \cdot r_{btm,t} + \varepsilon_{i,t} \tag{11}$$

$$r_{i,t} = \alpha_i + \beta_{1,i} \cdot r_{m-top100,t} + \beta_{2,i} \cdot r_{size,t} + \beta_{3,i} \cdot r_{btm,t} + \varepsilon_{i,t} \tag{12}$$

$$r_{i,t} = \alpha_i + \beta_{1,i} \cdot r_{m-fbmsha,t} + \beta_{2,i} \cdot r_{size,t} + \beta_{3,i} \cdot r_{btm,t} + \beta_{4,i} \cdot r_{mom,t} + \varepsilon_{i,t} \tag{13}$$

$$r_{i,t} = \alpha_i + \beta_{1,i} \cdot r_{m-vwindex,t} + \beta_{2,i} \cdot r_{size,t} + \beta_{3,i} \cdot r_{btm,t} + \beta_{4,i} \cdot r_{mom,t} + \varepsilon_{i,t} \tag{14}$$

$$r_{i,t} = \alpha_i + \beta_{1,i} \cdot r_{m-fbmsha,t} + \beta_{2,i} \cdot r_{size,t} + \beta_{3,i} \cdot r_{btm,t} + \beta_{4,i} \cdot r_{mom-vw,t} + \varepsilon_{i,t} \tag{15}$$

$$r_{i,t} = \alpha_i + \beta_{1,i} \cdot r_{m-fbmsha,t} + \beta_{2,i} \cdot r_{size-ff,t} + \beta_{3,i} \cdot r_{btm-ff,t} + \varepsilon_{i,t} \tag{16}$$

$$r_{AE,i,t} = \alpha_i + \beta_{1,i} \cdot r_{m-fbmsha,t} + \beta_{2,i} \cdot r_{size,t} + \beta_{3,i} \cdot r_{btm,t} + \varepsilon_{i,t} \tag{17}$$

$$r_{AE,i,t} = \alpha_i + \beta_{1,i} \cdot r_{m-vwindex,t} + \beta_{2,i} \cdot r_{size,t} + \beta_{3,i} \cdot r_{btm,t} + \beta_{4,i} \cdot r_{mom,t} + \varepsilon_{i,t} \tag{18}$$

$$r_{i,t} = \alpha_i + \beta_{1,i} \cdot r_{m-fbmsha,t} + \beta_{2,i} \cdot r_{size-trim,t} + \beta_{3,i} \cdot r_{btm-trim,t} + \varepsilon_{i,t} \tag{19}$$

$$r_{i,t} = \alpha_i + \beta_{1,i} \cdot r_{m-vwindex,t} + \beta_{2,i} \cdot r_{size-trim,t} + \beta_{3,i} \cdot r_{btm-trim,t} + \beta_{4,i} \cdot r_{mom,t} + \varepsilon_{i,t} \tag{20}$$

r_i and r_{AE} represent fund returns before and after expenses are deducted, respectively. r_m is the market return proxy for the various indices used. r_{size} and $r_{size\text{-}ff}$ are the "size" common risk factors resulting from the constructed portfolio, with the latter relying on free float numbers. Similarly, r_{btm} and $r_{btm\text{-}ff}$ represent the "book-to-market equity" risk factor. $r_{size\text{-}trim}$ and $r_{btm\text{-}trim}$ are constructed portfolios with the top 5% and bottom 5% (sorted by market capitalization per period) removed. Finally, r_{mom} and $r_{mom\text{-}vw}$ are the momentum strategy risk factors, computed on equal and value-weighted basis, respectively. Eqs. (1) through (8) are standard CAPM, while the remaining equations are a mix of Fama and French's 3-factor model and Carhart's 4-factor model. Given the sample size of 63 funds, a total of 1260 (63 × 20) regressions were run.

4.5. Identifying false discoveries in fund performance

Once the set of fund alphas are obtained, to measure funds that have been lucky rather than skilled, we employ the method used in Barras et al. (2010). From a cross section of alphas, we use the *t*-statistic as the performance measure. $t\text{-}hat_i = \alpha\text{-}hat_i \,/\, \sigma\text{-}hat_{\alpha\text{-}hat,i}$ where $\alpha\text{-}hat_i$ is the estimated alpha for fund i and $\sigma\text{-}hat_{\alpha\text{-}hat,i}$ is its estimated standard deviation. It has been shown that the *t*-statistic has superior statistical properties relative to alpha because alpha estimates have differing precision across funds with varying lives and portfolio volatilities (Kosowski et al., 2006). A significance level (γ) is chosen and thresholds implied by the chosen significance level are identified. A multiple hypothesis test is conducted to determine the percentages of funds belonging to three categories (i) unskilled funds, (ii) zero alpha funds and (iii) skilled funds.

The third category, "skilled funds" denoted $E(S_\gamma^+)$ comprises (a) true positive alpha funds, (b) zero alpha funds that have been lucky, and (c) negative alpha funds that have been lucky. The possibility of (c) is quite remote and thus is not considered. To identify the proportion of true positive alpha funds, we estimate (ii), denoted by $E(F_\gamma^+)$, and simply subtract it from $E(S_\gamma^+)$.

$$E\left(T_\gamma{}^+\right) = E\left(S_\gamma{}^+\right) - E\left(F_\gamma{}^+\right)$$

Zero alpha funds that are lucky are estimated by the equation:

$$E\left(F_\gamma{}^+\right) = \pi_0 \cdot \gamma/2$$

π_0 is estimated using an approach developed in Storey (2002) called the false discovery rate (FDR) approach. Its sole inputs are the two-sided p-values associated with the (alpha) *t*-statistics of each fund in the data set. Via a histogram of the funds' p-values we can estimate π_0. More precisely, $\pi_0(\lambda^*) = [W(\lambda^*) / M] \times [1 / (1 - \lambda^*)]$ where $W(\lambda^*)$ is the number of funds with *p*-values exceeding λ^* and M is the total number of funds. λ^* is selected using a simple bootstrap procedure.

Similarly, to estimate the proportion of true negative alpha funds, we use the formula $E(T_\gamma^-) = E(S_\gamma^-) - E(F_\gamma^-)$, where $E(F_\gamma^-) = E(F_\gamma^+)$.

Fig. 1 below illustrates graphically the logic of this method.

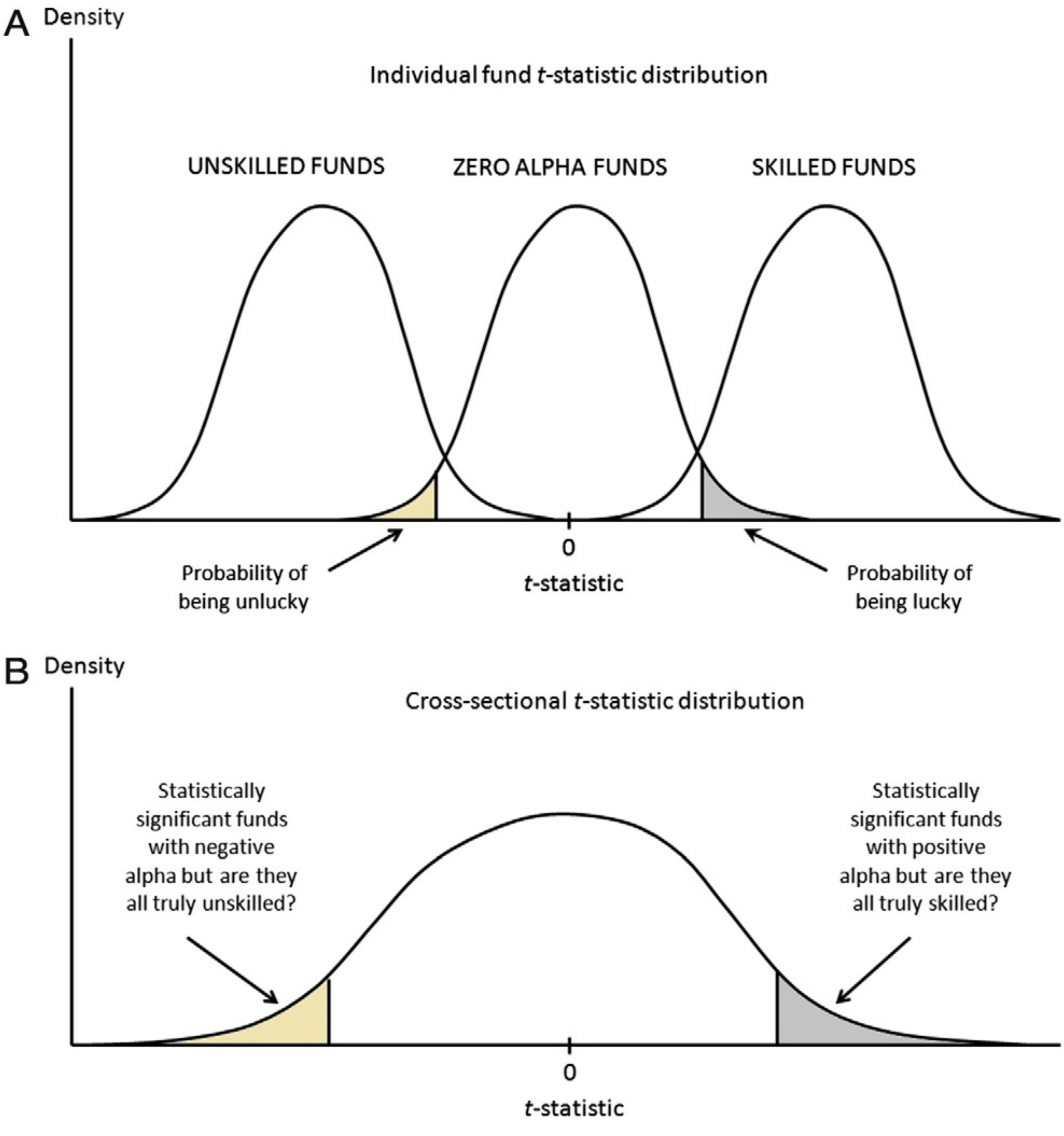


Fig. 1. Outcome of multiple performance tests. Panel A shows a hypothetical distribution of fund *t*-statistic across three groups of funds — skilled, unskilled and zero-alpha. Within each group there is probability of a given fund being lucky (right-tail) or unlucky (left-tail). For example, as panel A illustrates, within the zero-alpha group, there may be funds that are categorically (in fact) zero-alpha and yet may produce significant positive or negative fund alpha *t*-statistics (lucky and unlucky, respectively). Hence when we have a cross-section of alpha *t*-statistics, as panel B illustrates, a portion of the right and left tail of the distribution contains funds that are simply lucky and unlucky, respectively, despite observed significant (non-zero) *t*-statistics. The method described above attempts to quantify this proportion, thereby arriving at percentages of genuinely skilled and unskilled funds.

5. Results and interpretation

5.1. Regression statistics

We begin with results of the standard CAPM model regressions [Eqs. (1) through (8)].

We do not find it surprising that the top two indices are the *Shari'ah* based ones. After all, the dependent variable is returns of *Shari'ah*-compliant funds. The Kuala Lumpur Composite Index (KLCI), despite being the bellwether index, is lower down the list. Again, this is expected given that firstly, it is a much narrower index (only 30 stocks). Secondly and more importantly, between 33% and 40% of stocks that make up the index are non-*Shari'ah* compliant.[15] What makes for a more interesting observation is the fact that the funds in this sample appear to prefer larger capitalization stocks in their portfolio. At least on the basis of adjusted R^2, the Top100 index is a better market return proxy for these funds, vis-à-vis the Mid70 and Small Cap indices. A cursory examination of portfolio composition of these funds confirms this. The top 10 stocks by market value in each fund, typically large cap equities, on the average make up about 52% of the fund's portfolio.

Computed alphas are not statistically different from zero, indicating that zero-alpha funds dominate this sample of Islamic equity funds. Diagnostic testing of regression results reveals some cases of autocorrelation and heteroscedasticity, thus the Newey-West (1987) adjustment is applied to all regressions.[16] Given the results in Table 1, we opted to proceed with subsequent regressions with only two indices — FBMSHA and VWINDEX.[17]

Our results (see Table 2) appear to indicate that Fama and French's 3-factor model and Carhart's 4-factor model are not relevant to our analysis. In other words, firm size, value versus growth stocks and the momentum strategy anomaly do not empirically explain the observed performance of Islamic equity funds in our sample. Before we arrive at such a bold conclusion, it is important to note that even the market return parameter was found to be statistically insignificant. In light of our results from regression Eqs. (1) through (8), where all market return proxies were indeed significant, we entertain the notion of possible multicollinearity among the regressors in regression Eqs. (9) through (20). We conducted a non-exhaustive investigation of this possibility and found that in numerous instances, regressions pairing the said regressors resulted in very high adjusted R^2 values.

Other than this, data-related inadequacies could also explain our seemingly counter-intuitive results. Some of the funds included in our sample are relatively new ones, and hence only have a short time series of historical reported return performance. Lack of adequate data points could have affected the efficacy of our estimations. One needs to bear in mind that the reported p-values in Table 2 represent the average of the 63 funds. Showing aggregated results can sometimes conceal important statistical insights. For instance, we found quite a number of funds that reported very low p-values for all regressors (market return and constructed common risk factors), indicating that, for these funds at least, the 3-factor and 4-factor models do apply. It can be contended that some funds with data insufficiency issues may have distorted the overall summarized findings. We have opted against removing these potentially problematic funds from our sample because we are constrained by our already small sample size. The primary objective of our analysis is to analyze fund alphas and for our chosen methodology, a decent cross-section of alpha values is desirable. Trimming our sample will work against this objective. Another factor that could have contributed to this ostensible anomaly is the employed method of portfolio construction to mimic the risk factors. In our regressions above, we have emulated Fama and French (1993) which uses value-weighted portfolio returns reconstructed on an annual basis. In an alternative portfolio construction (not reported here but available upon request) which uses average portfolio returns reconstructed on a monthly basis, market return parameters were all found to be significant, albeit common risk factors variables still statistically insignificant.

We do not consider the results obtained for regression Eqs. (9) through (20) as show-stoppers. After all, we still have the computed alphas from the standard CAPM regressions. Given that this does imply that size, value-versus-growth and momentum strategies are irrelevant, in the paragraphs that follow, we

[15] Furthermore, typically half of the top 10 stocks by market cap are non-*Shari'ah* compliant and the KLCI is a market capitalization-weighted index.

[16] For example, for the set of regressions pertaining to Eq. (1), in 24 out of 63 cases, the Langrage multiplier (LM) test of residual serial correlation test statistic p-value was smaller than 0.05.

[17] FBMSHA has the highest adjusted R^2 amongst the indices while VWINDEX, despite its low adjusted R^2, is consistent with Fama and French (1993). Both indices reflect the substantial nature of the funds (*Shari'ah* compliant stocks).

Table 1
Regression statistics for standard CAPM model. The table lists results ranked by adjusted R^2.

	Alpha (constant term)				Index (regressor)		Adjusted R^2
	Coeff.	Std Err	t ratio	p-value	Coeff.	p-value	
FBMSHA	0.001	0.005	0.321	0.549	0.408	0.032	0.282
FBMHIJ	0.000	0.005	0.048	0.609	0.410	0.030	0.278
EMAS	0.001	0.004	0.359	0.522	0.417	0.032	0.275
TOP100	0.001	0.004	0.297	0.526	0.428	0.030	0.274
KLCI	0.001	0.004	0.317	0.529	0.438	0.031	0.268
MID70	0.002	0.004	0.410	0.518	0.334	0.028	0.259
SCAP	0.003	0.004	0.722	0.461	0.257	0.059	0.216
VWINDEX	0.004	0.004	1.133	0.304	0.061	0.036	0.044

briefly indulge in intuitively plausible explanations to consider the notion that these common risk factors are in fact uncommon, at least with respect to our sample set.

While the Fama and French, and Carhart models have gained recognition amongst published works, there are also numerous empirical findings that cast doubt on the efficacy of CAPM and its variations in explaining observed stock and fund returns. Some argue that these aforementioned models are merely empirically fitted and do not have solid theoretical foundations. As far as firm size goes, it could very well be that in Malaysian equities, there is a lack of a systematic difference in rate of returns between large and small firms. Alternatively, we could argue that even if such a difference in returns exists, if the funds in our sample limit their portfolios to mainly large cap equities, such a risk factor would not be statistically evident. Put simply, the “size” risk factor is intended to capture the claim that smaller firms are riskier (for example, less capable of weathering financial distress) and hence require higher rates of return to compensate. If mutual funds do not invest in these small firms, this risk factor becomes irrelevant. Our earlier observation above that the funds in our sample have a tendency to allocate portfolio funds to larger cap stocks render some support to this line of reasoning.

The same could be said of the “book-to-market equity” risk factor. Either there exists no consistent difference in returns of value stocks compared to growth stocks or funds tend to concentrate their portfolios on one category of stock. It is well known that trading in the Malaysian equity market is “top-heavy” in that a small number of stocks with the highest market capitalizations form the bulk of market trading activity. As for the momentum strategy, our empirical evidence suggests that such an investment strategy is not prevalent, at least not with the Islamic equity funds we have in our sample. Another possible explanation is that our account of the momentum strategy anomaly is not sufficiently robust.

Our results could also reflect an idiosyncrasy of *Shari'ah* compliant stocks. In other words, the size, value-versus-growth and momentum strategy anomalies may exist in Malaysian equities, just not among *Shari'ah* compliant Malaysian stocks. *Shari'ah* compliant stocks are differentiated, amongst other criteria, in that debt financing of firms is restricted to a particular ratio. Hence, *Shari'ah* compliant firms tend to be less leveraged. It has been argued in CAPM-related literature that smaller stocks have empirically outperformed larger stocks because the former commands for a higher risk premium reflecting greater risk of financial distress (which the standard CAPM beta does not specifically measure thus the value-adding “size” common risk factor). It follows that if *Shari'ah* compliant stocks, by virtue of debt-related financial ratios applied in the stock screening process, have contained levels of leverage, thereby reducing overall risk of financial distress, a statistically pronounced difference between small and large *Shari'ah* compliant stocks, may be absent. Put differently, the “size” common risk factor originates from risk of financial distress which financial leverage brings. If this leverage is low, such an additional risk premium may not be present, or brought down to statistically negligible levels. The same line of argument can be made with respect to the value-versus-growth empirical anomaly. If certain characteristics of *Shari'ah* complaint stocks can be associated with those prevalent among either value or growth stocks, it would not be surprising to find the empirical absence of this anomaly. While a case can be made to suggest the above, to maintain brevity and focus of our study we refrain from further empirical investigation into such a possibility.

While Fama and French attribute apparent failings of classical CAPM in explaining observed asset return performance to the size and value-versus-growth common risk factors, this is by no means the only line of reasoning that has garnered some following. Campbell and Vuolteenaho (2003) introduced the concept of “bad beta” and “good beta”. Essentially, they argue that CAPM beta comprises two components — one

Table 2
Regression statistics for Fama and French's 3-factor model and Carhart's 4-factor model. Adjusted R^2 values are comparable to the standard CAPM model regression equations. Computed alphas are statistically not different from zero, implying dominance of zero-alpha funds. A key empirical observation here is that not only are all common risk factor variables from constructed portfolios (size, book-to-market equity, momentum strategy) statistically non-significant (at a 5% significance level), even the market return reported p-values are above any reasonable significance thresholds. Reported p-values are Newey-West (1987) autocorrelation and heteroscedasticity consistent estimates, under the null hypothesis that regression parameters are equal to zero. Discussion of observed coefficients vis-à-vis theoretical expectations, as well as variations in indices used and methods of computation (value-weighted momentum returns, using free float numbers, fund returns after deducting expenses, removal of outliers) becomes somewhat unproductive given that reported p-values reflect statistically insignificant variables.

			Risk factors			Alpha		Market return		Size		Book-to-market		Momentum		Adjusted R^2
Regression Eq.	Note	Market proxy	Size	Book-to-market	Momentum	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	
9		FBMSHA	–	–		0.003	0.507	0.613	0.398	0.534	0.612	0.201	0.607			0.256
10		VWINDEX	–	–		0.001	0.548	−0.136	0.515	−1.048	0.522	−0.646	0.082			0.259
11		EMAS	–	–		0.002	0.525	0.473	0.202	0.322	0.633	−0.053	0.611			0.257
12		TOP100	–	–		0.002	0.536	0.469	0.165	0.223	0.657	−0.021	0.658			0.251
13		FBMSHA	–	–	–	0.002	0.542	0.720	0.334	0.729	0.512	0.364	0.503	−0.142	0.186	0.268
14		VWINDEX	–	–	–	0.000	0.549	−0.196	0.484	−1.205	0.468	−0.657	0.098	−0.078	0.371	0.267
15	Value-weighted mom.	FBMSHA	–	–	–	0.003	0.436	0.691	0.347	0.736	0.457	0.031	0.638	−0.315	0.317	0.301
16	Free float	FBMSHA	–	–		0.003	0.466	0.723	0.303	0.816	0.524	0.329	0.525			0.263
17	After expenses	FBMSHA	–	–		0.001	0.598	0.613	0.398	0.534	0.612	0.201	0.607			0.256
18	After expenses	VWINDEX	–	–	–	−0.001	0.510	−0.196	0.484	−1.205	0.468	−0.657	0.098	−0.078	0.371	0.267
19	Remove outliers	FBMSHA	–	–		0.001	0.549	0.253	0.249	−0.141	0.632	−0.524	0.476			0.289
20	Remove outliers	VWINDEX	–	–	–	0.003	0.446	−0.124	0.364	−1.214	0.129	−0.670	0.401	−0.010	0.160	0.269

reflecting news about the market's future cash flow prospects and the other pertaining to market-wide discount rates. Value of the market portfolio may drop when there is bad news about prospects of future cash flows. Likewise, market value can also diminish due to increases in the prevailing discount rate or cost of capital that is applied to the cash flows. In the case of the latter, while wealth decreases, future investment opportunities improve (when discount rates revert) thus making this component of beta "good", relative to the former type. Small and value stocks have empirically shown superior results because their beta is more predominantly "good beta".

Drawing upon the rich literature on asset pricing models, one can spawn a plethora of logical reasoning, many backed to some extent by empirical findings, to account for observed asset return performances. We have only highlighted but a few here. We reiterate that our focus is not on evaluating our chosen asset pricing model but rather to compute fund alphas. We have indulged in the above discussion simply to shed some light into otherwise nonsensical empirical results.

5.2. Analysis of fund alphas

In estimating π_0 we were not able to produce similar results as per Barras et al. (2010). In particular, the shape of the histograms of the funds' p-values did not level off beyond a certain value (indicative of λ^*) as suggested by the said paper.[18] We attribute this to the relatively much smaller size of our sample. Hence, instead of selecting λ^* by reference to the histogram or via bootstrap, we opted to estimate the λ^* value that produces the lowest π_0. We believe that this approach conservatively estimates proportions of zero alpha funds that are "lucky" and "unlucky".

In Table 3 we show the percentile breakdowns of fund alphas by varying levels of significance, averaged by varying methods of computing alpha.[19] Our results indicate that the bulk of non-zero alpha funds are in fact skilled funds. This is contrary to Barras et al. (2010) which found the reverse to be true. In their paper, which had a substantially larger sample of US mutual funds, there were more negative alpha (as well as unskilled) funds. However, this finding does not say much praise for the performance of *Shari'ah* compliant equity funds in Malaysia. This is because the quantum of skilled funds leaves much to be desired, at least from the perspective of the investor. At a 5% significance level, percentage of skilled funds range from 0% to a meager 1.95%. Of course when significance levels are increased, these percentages increase. We recognize that our method contains a bias towards "accepting" the null hypothesis (that funds have zero alphas).[20] We acknowledge type II errors (probability that we incorrectly categorize a fund as a zero alpha fund when in fact it has a non-zero alpha), but argue that the cost of type I error is comparatively higher, at least from the standpoint of the investor. Most investors would put their investment monies into one fund.[21] Hence, given that our results indicate that most funds are zero alpha funds, the cost (to the investor) of mistakenly choosing a fund that turns out yielding zero-alpha is higher than passing up a positive-alpha fund (thinking it was zero-alpha).

Based on our results, we estimate that between 35 and 47% of observed positive alpha in funds can be attributed to luck. The resulting quantum of skilled funds does not surprise us, and they are comparable to those reported in Barras et al. (2010). To add insult to injury, when we compute percentages of skilled funds net of expenses, they drop to zero or marginally above zero, with the exception of the 40% significance level.[22] We can summarize our findings above simply as follows. The bulk of funds in our study do not perform better than our set of stipulated benchmarks (that is, majority are zero alpha funds). The good news is, among those that are not zero-alpha funds, there are more that outperform than underperform. However, the percentages of this former category (skilled funds that outperform the benchmark) are arguably low. As far as the role of luck in recording superior return performance, we estimate that nearly half of these said performers were merely lucky. When we consider returns net of expenses, the presence of these superior performing funds are almost wiped out.

[18] Our histograms can be found in Appendix A.

[19] For similar statistics by regression equation, see Appendix B.

[20] Our p-values reflect the probability that we erroneously categorize a fund as having negative or positive alpha when In fact it has a zero alpha (type I error).

[21] It is unlikely that many investors, particularly retail ones, would spread their investment funds across multiple mutual funds. The diversification of risk sought is presumably achieved via the mutual fund instrument. Investors value the convenience of monitoring when dealing with only a single fund. Diversifying across many funds would defeat the very purpose of opting for mutual funds as the chosen investment vehicle. We believe this to be the case at least for Malaysia.

[22] Even at this level, only 4.64% are estimated to be skilled.

Table 3
Percentile breakdown of fund alphas by varying significance levels. The table above lists the percentages of statistically significant negative (positive) alpha funds, percentages of funds computed as unlucky (lucky) and hence percentages of remaining funds deemed truly unskilled (skilled), at varying levels of significance. Averages are on equal weighting basis, separated by method of computing alpha together with an overall average. Distribution of percentiles appears to be "skewed" towards positive alpha funds in that percentages of negative alpha funds as well as unskilled funds are substantially lower than positive alpha funds, across the board. Overall, unskilled funds make up 0% of the sample, at best, and 1.36% of funds with significance level stretched to 0.40. Skilled funds, on the other hand, are about 1.15% of funds sampled at the 0.05 significance level and 17.52% at the very "generous" significance level of 0.40. Understandably, the averages computed net of expenses show the smallest percentiles of skilled funds and highest for unskilled funds.

		Negative alpha funds						Positive alpha funds						
Significance level		0.05	0.10	0.15	0.20	0.30	0.40	0.05	0.10	0.15	0.20	0.30	0.40	
Average standard CAPM	Significant	0.00%	0.79%	1.98%	2.58%	4.76%	7.34%	2.98%	8.73%	13.10%	16.07%	23.41%	32.14%	Significant
	Unlucky	0.00%	0.74%	1.75%	2.34%	4.50%	7.25%	1.03%	3.41%	5.12%	6.77%	10.11%	13.65%	Lucky
	Unskilled	0.00%	0.05%	0.23%	0.24%	0.26%	0.09%	1.95%	5.32%	7.98%	9.30%	13.31%	18.49%	Skilled
Average 3-factor model	Significant	0.00%	0.45%	1.13%	2.04%	3.40%	5.90%	1.81%	4.76%	7.26%	8.84%	18.82%	28.57%	Significant
	Unlucky	0.00%	0.45%	1.13%	2.04%	3.40%	5.90%	1.03%	2.74%	3.92%	4.84%	8.00%	11.46%	Lucky
	Unskilled	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.78%	2.02%	3.34%	4.00%	10.82%	17.11%	Skilled
Average 4-factor model	Significant	0.32%	1.59%	3.17%	5.40%	8.57%	12.70%	1.27%	4.44%	8.25%	11.11%	18.41%	28.57%	Significant
	Unlucky	0.32%	1.22%	1.98%	2.75%	5.56%	7.41%	0.87%	2.37%	3.32%	4.85%	8.39%	12.03%	Lucky
	Unskilled	0.00%	0.37%	1.19%	2.65%	3.02%	5.29%	0.40%	2.07%	4.93%	6.26%	10.02%	16.54%	Skilled
Average net of expenses	Significant	0.00%	2.38%	4.76%	8.73%	11.90%	18.25%	0.79%	2.38%	3.17%	3.17%	5.56%	14.29%	Significant
	Unlucky	0.00%	1.46%	1.79%	2.12%	4.37%	5.03%	0.79%	2.25%	3.17%	3.17%	5.16%	9.65%	Lucky
	Unskilled	0.00%	0.93%	2.98%	6.61%	7.54%	13.23%	0.00%	0.13%	0.00%	0.00%	0.40%	4.64%	Skilled
Average — all	Significant	0.08%	0.87%	1.98%	3.10%	5.24%	8.17%	2.14%	6.27%	9.84%	12.30%	20.56%	30.00%	Significant
	Unlucky	0.08%	0.76%	1.59%	2.34%	4.38%	6.82%	0.99%	2.92%	4.25%	5.62%	8.94%	12.48%	Lucky
	Unskilled	0.00%	0.11%	0.39%	0.76%	0.86%	1.36%	1.15%	3.35%	5.59%	6.69%	11.61%	17.52%	Skilled

Table 4
Expense ratio, load factor, age and size of funds by alpha category. We compute the average expense ratio (annualized), load factor (front, end or both), age (in years) and size (average weighted market capitalization in MYR billion) for each fund category — negative, zero and positive alpha, for varying levels of significance. Averages are based on regression Eqs. (1) through (8), the standard CAPM model.

Sig. level	Fund alpha	Expense ratio	Load	Age	Size
0.05	Negative	n/a	n/a	n/a	n/a
	Zero	1.55%	5.99%	11.0	37.3
	Positive	1.40%	5.68%	7.1	27.6
0.1	Negative	1.02%	6.42%	11.7	107.7
	Zero	1.57%	5.98%	11.2	37.5
	Positive	1.27%	5.71%	6.8	25.8
0.15	Negative	1.04%	5.82%	11.5	119.4
	Zero	1.59%	5.98%	11.4	36.8
	Positive	1.25%	5.76%	6.0	28.7
0.2	Negative	1.10%	5.71%	12.1	118.1
	Zero	1.59%	5.99%	11.3	36.9
	Positive	1.27%	5.78%	6.2	29.6
0.3	Negative	1.27%	6.40%	22.4	58.3
	Zero	1.59%	6.00%	11.0	38.9
	Positive	1.34%	5.76%	6.8	30.5
0.4	Negative	1.45%	5.81%	20.2	51.2
	Zero	1.58%	6.13%	11.2	41.2
	Positive	1.40%	5.82%	7.3	28.9

5.3. Some additional dimensions of analysis

We also examine the average expense ratio, load factor, age and size of funds in our sample, categorized by negative, zero and positive alpha (Table 4). It was found that for all significance levels, the expense ratios and load factors for zero alpha funds were always higher than those of non-zero alpha funds.[23] As for age and size, they decrease monotonically from negative to zero to positive alpha funds, at all significance levels.

The implications of this finding, for the investor, are that these characteristics can somewhat serve as indicative of expected fund return performance. It appears that smaller and more recently launched funds tend to perform better. It could be the case that funds are inclined to divert their better resources and fund management talent to newer funds to chalk up more impressive return records so as to ensure survivability of the funds. There could also be impression management at play — it is easier to record superior return numbers when working with a smaller net asset base. To a lesser extent, expense ratios and load factors can be used to weed out zero alpha funds. Superior-performing funds generally tend to impose lower charges on their clientele.

6. Implications of findings and suggestions

Our empirical work provides some statistical evidence that the risk-adjusted performance of *Shari'ah* compliant equity funds in Malaysia does not exceed that of market benchmarks, for the most part. Further, in the limited instances where superior performance is observed, a significant proportion of it is statistically attributable to luck, rather than skill of fund managers. We iterate that our purpose here is not to evaluate the performance of the said fund managers per se. Instead, it is to make a case for an alternative structure of remuneration for Islamic mutual funds. Justice is an often quoted moot point of Islamic finance. We find reason to question the equitability of mutual funds levying charges upon fund unit holders when actual performance of investments rarely exceeds that of market benchmarks. The discerning investor would be better off investing in index-linked funds (where fees imposed are minimal) or considering making direct investments in equity markets. Why should investors pay fees to mutual funds when after accounting for fees, negligible percentages of funds can be deemed truly skilled? Bear in

[23] Interestingly, in almost all cases, the average expense ratio for negative alpha funds is lower than that for positive alpha funds.

mind also that in our analysis we have only incorporated expense ratios and excluded the one-off load factors, which range from 5% to as high as 13%, with the typical fund imposing 6%.

Within a *Shari'ah* compliance framework, mutual funds are commonly positioned as *wakalah*-based instruments. The fund manager is seen as serving the role as agent to the investor by providing the service of making equity investments. In light of our findings, we argue that this “service”, for which the fund manager charges a fee, warrants further deliberation. If it can be shown that the aforementioned service represents substantial value-add to the investor (in the form of superior stock-picking skills, astute market timing decisions, and portfolio allocation strategies that yield market-beating rates of return), there would indeed be justification for the fees imposed. On the contrary, if the general outcome of the agent's work is merely market rates of return (which the investor can easily replicate on his own minus the fees) or is the result of simply luck nearly half the time, as our empirical results suggest, we believe we have grounds to question the presence of equity (or lack thereof) in current mutual fund remuneration arrangements. Our bone of contention is that present Islamic equity funds are not equitable, in the manner that they levy fees for their purported services. As an alternative to be considered, we propose the adoption of a profit-sharing based arrangement.

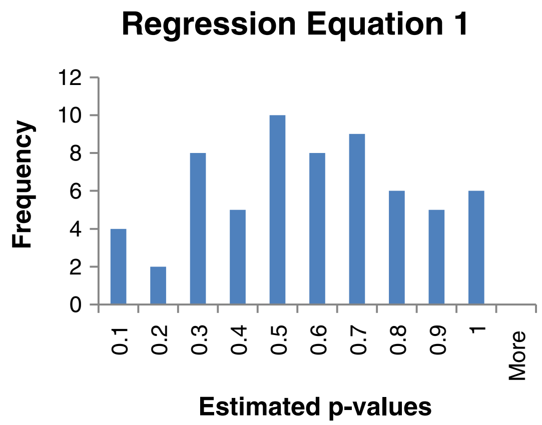
In essence, we suggest that the quantum of financial compensation to the fund manager should be a function of returns actually generated. More specifically, the fund manager gets a share of profits (predetermined percentage of profits) where profit is defined as return in excess of an agreed upon benchmark. This way, the spirit of sharing is imbued in the mutual fund structure. When the value of the investment portfolio rises, both parties (the client-investor and the fund manager) have a share in that gain. Similarly, when the portfolio diminishes in value, both parties embrace the event of loss — the investor bears diminution of his capital while the fund manager endures uncompensated effort. This arrangement is characteristic of the Islamic nominate contract of *mudarabah*. We believe that this structure is an improvement in at least two ways. Firstly, there is more equity in the way mutual funds make a profit for themselves. Secondly, it provides effective incentive for the fund manager to get his act together. After all, the fund manager will not get paid if the portfolio under his management does not earn an adequate return.

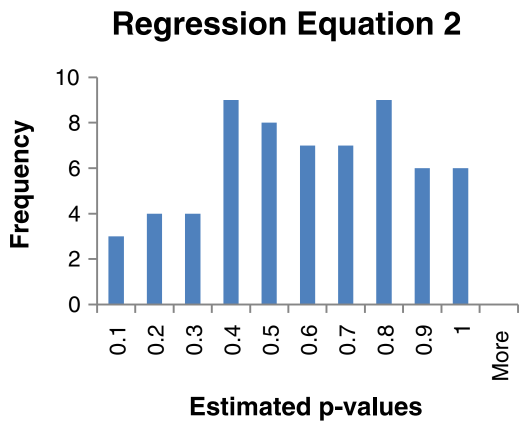
Our proposal is exploratory in nature. Our focus in this paper is to offer statistical evidence which is consistent with a case for an alternative remuneration structure, one based on profit sharing. Needless to say, the proposal requires further deliberation and refinement before receiving serious consideration for implementation. The mechanics of applying such a profit sharing scheme needs to be developed and put under scrutiny. We leave that for a potential future undertaking. One issue that may be raised is that of potential agency theory-related undesirable behavior. When we make the fund manager's remuneration contingent upon positive capital gain of the portfolio, while this may encourage fund managers to work harder to identify good investment opportunities, it may also induce them to throw caution to the wind and invest recklessly. With nothing to lose and all to gain, fund managers may be tempted to allocate much of the portfolio funds to highly risky stocks (with the potential of high returns). This may be detrimental to the investor who risks his capital. One way to mitigate this risk is to make fund manager remuneration based on risk-adjusted performance, but this may be problematic to implement, at best, and subject to abuse, at worst. Another possible way of attempting to realign the interests of the fund manager with those of the investor is through the use of equity kickers. Obiyathulla (1997) introduces this innovative use of equity kickers in a *mudarabah* contract. We briefly entertain the idea of using equity kickers in our context. In essence, the fund manager also puts up an equity stake in the portfolio under his management. In a stipulated event of “loss”, the fund manager stands to lose part of his said equity stake. This serves as both means to mitigate risk borne by the investor as well as to act as a deterrent to curb reckless investing by the fund manager.

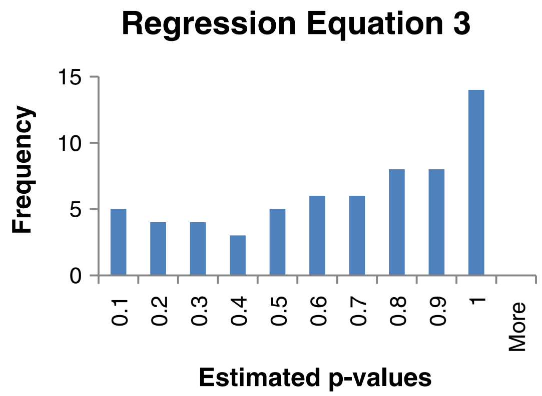
In a nutshell, our paper offers some tentative statistical evidence that *Shari'ah* compliant equity funds using Malaysia as a case study do not perform significantly better than the overall market. In addition, a significant proportion of superior performance can be attributed to simply luck. Given these, we propose that Islamic mutual funds explore the idea of altering the remuneration structure of their product offerings. In our humble opinion, embracing a profit-sharing mechanism might perhaps better embody the concept of equity which is fundamental in Islamic finance.

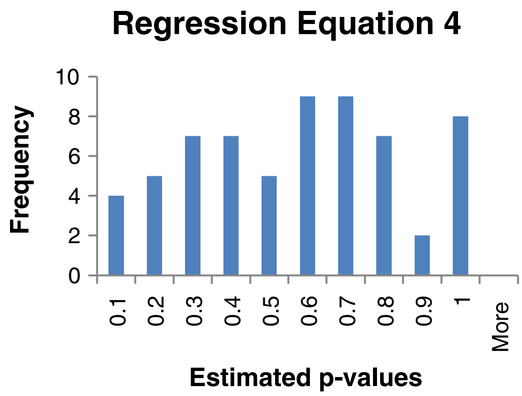
As a final note, we acknowledge that there are notable limitations inherent in our empirical work. Data adequacy issues can perhaps be addressed by expanding the sample to include other Islamic markets. Inclusion of other established performance measurement yardsticks could be useful for comparative purposes. Dissecting the estimation period to account for crisis events would certainly be of value-add. We leave these as suggestions for future research.

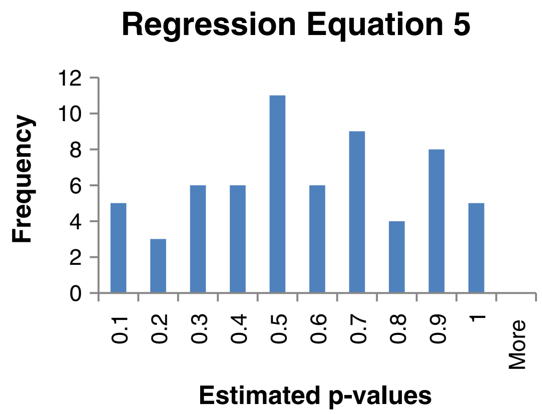
Appendix A. Histograms of distribution of estimated p-values by regression equation

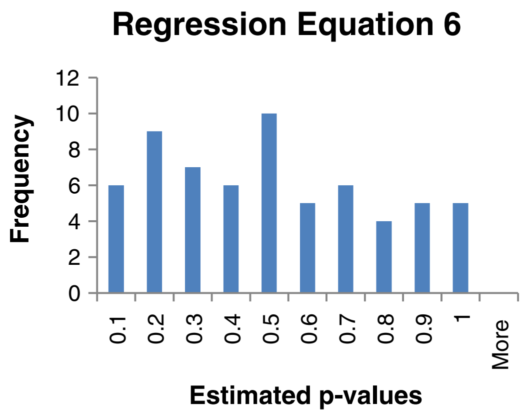


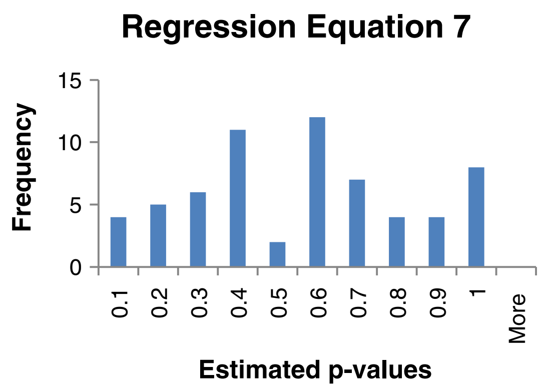


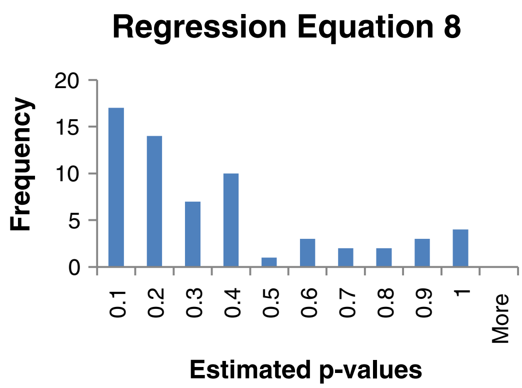


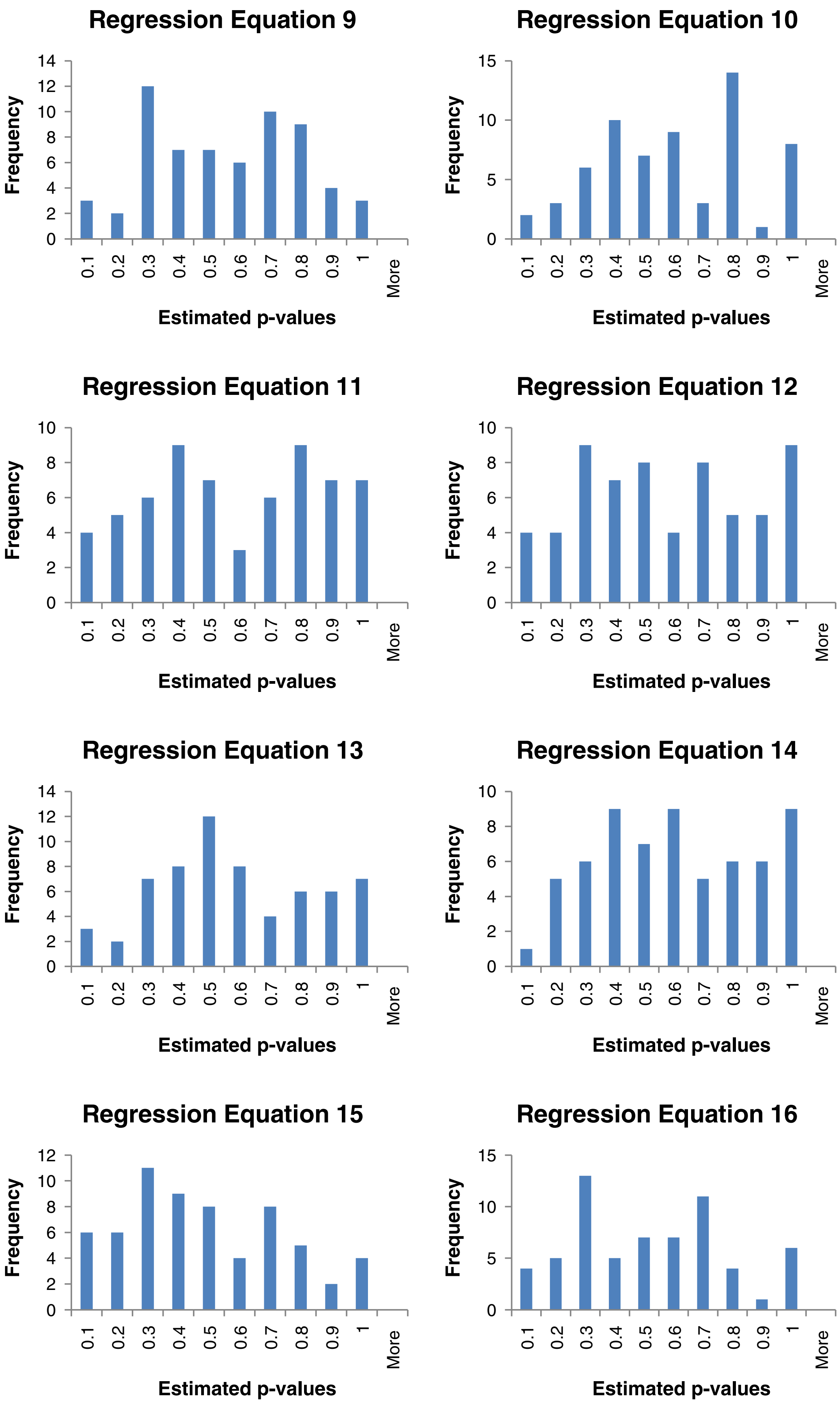




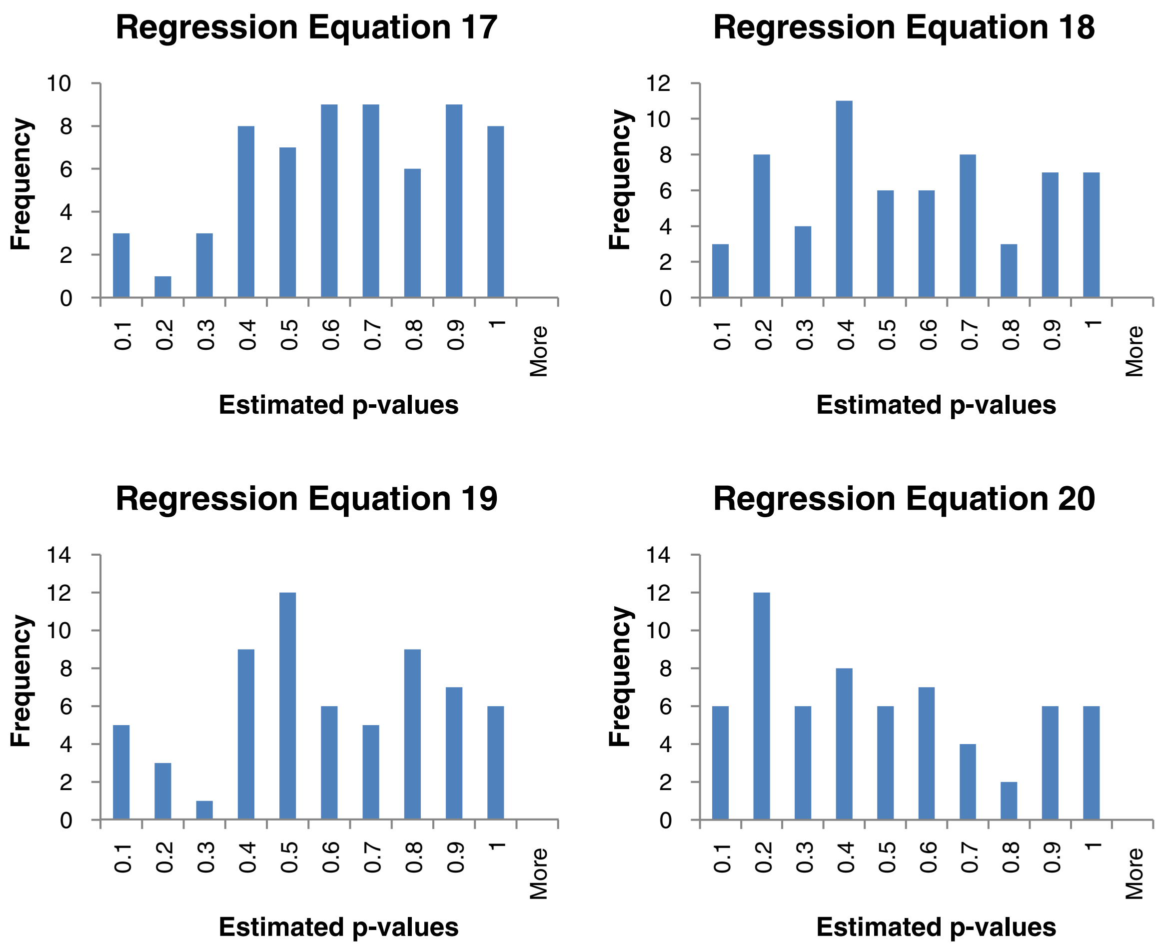








Appendix A (*continued*).



Appendix A (*continued*).

Appendix B. Percentile Breakdowns of Fund Alphas by Regression Equation

Regression equation		Negative alpha funds						Positive alpha funds						
	Sig. level	0.05	0.10	0.15	0.20	0.30	0.40	0.05	0.10	0.15	0.20	0.30	0.40	Sig. level
1	Significant	0.00%	0.00%	1.59%	1.59%	4.76%	7.94%	1.59%	6.35%	7.94%	7.94%	17.46%	22.22%	Significant
	Unlucky	0.00%	0.00%	1.59%	1.59%	4.76%	7.94%	1.59%	4.20%	6.30%	7.94%	12.61%	16.81%	Lucky
	Unskilled	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.15%	1.63%	0.00%	4.86%	5.42%	Skilled
2	Significant	0.00%	0.00%	1.59%	3.17%	4.76%	7.94%	1.59%	4.76%	7.94%	7.94%	12.70%	23.81%	Significant
	Unlucky	0.00%	0.00%	1.59%	3.17%	4.76%	7.94%	1.59%	3.97%	5.95%	7.94%	11.90%	15.87%	Lucky
	Unskilled	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.79%	1.98%	0.00%	0.79%	7.94%	Skilled
3	Significant	0.00%	3.17%	6.35%	7.94%	11.11%	12.70%	1.59%	4.76%	6.35%	6.35%	7.94%	12.70%	Significant
	Unlucky	0.00%	3.00%	4.50%	6.00%	9.00%	12.00%	1.50%	3.00%	4.50%	6.00%	7.94%	12.00%	Lucky
	Unskilled	0.00%	0.17%	1.85%	1.94%	2.11%	0.70%	0.09%	1.76%	1.85%	0.35%	0.00%	0.70%	Skilled
4	Significant	0.00%	0.00%	1.59%	1.59%	4.76%	7.94%	1.59%	6.35%	7.94%	12.70%	20.63%	26.98%	Significant
	Unlucky	0.00%	0.00%	1.59%	1.59%	4.76%	7.94%	1.59%	3.97%	5.95%	7.94%	11.90%	15.87%	Lucky
	Unskilled	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.38%	1.98%	4.76%	8.73%	11.11%	Skilled
5	Significant	0.00%	1.59%	1.59%	3.17%	6.35%	7.94%	0.00%	6.35%	7.94%	9.52%	15.87%	23.81%	Significant
	Unlucky	0.00%	1.59%	1.59%	3.17%	6.35%	7.94%	0.00%	3.97%	5.95%	7.94%	11.90%	15.87%	Lucky
	Unskilled	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.38%	1.98%	1.59%	3.97%	7.94%	Skilled
6	Significant	0.00%	0.00%	0.00%	0.00%	0.00%	1.59%	4.76%	9.52%	15.87%	23.81%	34.92%	42.86%	Significant
	Unlucky	0.00%	0.00%	0.00%	0.00%	0.00%	1.59%	1.32%	2.65%	3.97%	5.29%	7.94%	10.58%	Lucky
	Unskilled	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	3.44%	6.88%	11.90%	18.52%	26.98%	32.28%	Skilled
7	Significant	0.00%	0.00%	1.59%	1.59%	3.17%	7.94%	0.00%	6.35%	9.52%	12.70%	20.63%	33.33%	Significant
	Unlucky	0.00%	0.00%	1.59%	1.59%	3.17%	7.94%	0.00%	4.23%	6.35%	8.47%	12.70%	16.93%	Lucky
	Unskilled	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.12%	3.17%	4.23%	7.94%	16.40%	Skilled
8	Significant	0.00%	1.59%	1.59%	1.59%	3.17%	4.76%	12.70%	25.40%	41.27%	47.62%	57.14%	71.43%	Significant
	Unlucky	0.00%	1.32%	1.59%	1.59%	3.17%	4.76%	0.66%	1.32%	1.98%	2.65%	3.97%	5.29%	Lucky
	Unskilled	0.00%	0.26%	0.00%	0.00%	0.00%	0.00%	12.04%	24.07%	39.29%	44.97%	53.17%	66.14%	Skilled
9	Significant	0.00%	0.00%	1.59%	1.59%	1.59%	4.76%	1.59%	4.76%	6.35%	6.35%	25.40%	33.33%	Significant
	Unlucky	0.00%	0.00%	1.59%	1.59%	1.59%	4.76%	0.74%	1.49%	2.23%	2.98%	4.46%	5.95%	Lucky
	Unskilled	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.84%	3.27%	4.12%	3.37%	20.93%	27.38%	Skilled
10	Significant	0.00%	0.00%	1.59%	4.76%	6.35%	12.70%	1.59%	3.17%	3.17%	3.17%	11.11%	20.63%	Significant
	Unlucky	0.00%	0.00%	1.59%	4.76%	6.35%	12.70%	1.59%	3.17%	3.17%	3.17%	10.71%	14.29%	Lucky
	Unskilled	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.40%	6.35%	Skilled

11	Significant	0.00%	0.00%	0.00%	0.00%	1.59%	3.17%	1.59%	6.35%	11.11%	14.29%	22.22%	34.92%	Significant
	Unlucky	0.00%	0.00%	0.00%	0.00%	1.59%	3.17%	0.66%	1.32%	1.98%	2.65%	3.97%	5.29%	Lucky
	Unskilled	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.93%	5.03%	9.13%	11.64%	18.25%	29.63%	Skilled
12	Significant	0.00%	0.00%	0.00%	1.59%	4.76%	6.35%	0.00%	4.76%	7.94%	11.11%	22.22%	30.16%	Significant
	Unlucky	0.00%	0.00%	0.00%	1.59%	4.76%	6.35%	0.00%	4.76%	7.33%	9.77%	14.65%	19.54%	Lucky
	Unskilled	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.61%	1.34%	7.57%	10.62%	Skilled
13	Significant	0.00%	1.59%	1.59%	1.59%	6.35%	7.94%	1.59%	3.17%	4.76%	6.35%	11.11%	23.81%	Significant
	Unlucky	0.00%	1.59%	1.59%	1.59%	6.35%	7.94%	1.59%	3.17%	4.76%	6.35%	11.11%	15.87%	Lucky
	Unskilled	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	7.94%	Skilled
14	Significant	0.00%	0.00%	3.17%	4.76%	9.52%	15.87%	0.00%	1.59%	1.59%	4.76%	9.52%	17.46%	Significant
	Unlucky	0.00%	0.00%	3.17%	4.76%	9.52%	15.87%	0.00%	1.59%	1.59%	4.76%	9.52%	15.87%	Lucky
	Unskilled	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1.59%	Skilled
15	Significant	0.00%	1.59%	1.59%	3.17%	3.17%	3.17%	3.17%	7.94%	12.70%	15.87%	33.33%	47.62%	Significant
	Unlucky	0.00%	1.59%	1.59%	3.17%	3.17%	3.17%	1.19%	2.38%	3.57%	4.76%	7.14%	9.52%	Lucky
	Unskilled	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1.98%	5.56%	9.13%	11.11%	26.19%	38.10%	Skilled
16	Significant	0.00%	0.00%	1.59%	1.59%	1.59%	1.59%	3.17%	4.76%	9.52%	12.70%	33.33%	41.27%	Significant
	Unlucky	0.00%	0.00%	1.59%	1.59%	1.59%	1.59%	1.16%	2.31%	3.47%	4.63%	6.94%	9.26%	Lucky
	Unskilled	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.02%	2.45%	6.05%	8.07%	26.39%	32.01%	Skilled
17	Significant	0.00%	1.59%	1.59%	1.59%	4.76%	4.76%	1.59%	3.17%	4.76%	4.76%	6.35%	19.05%	Significant
	Unlucky	0.00%	1.59%	1.59%	1.59%	4.76%	4.76%	1.59%	3.17%	4.76%	4.76%	6.35%	14.00%	Lucky
	Unskilled	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	5.05%	Skilled
18	Significant	0.00%	3.17%	7.94%	15.87%	19.05%	31.75%	0.00%	1.59%	1.59%	1.59%	4.76%	9.52%	Significant
	Unlucky	0.00%	1.32%	1.98%	2.65%	3.97%	5.29%	0.00%	1.32%	1.59%	1.59%	3.97%	5.29%	Lucky
	Unskilled	0.00%	1.85%	5.95%	13.23%	15.08%	26.46%	0.00%	0.26%	0.00%	0.00%	0.79%	4.23%	Skilled
19	Significant	0.00%	1.59%	1.59%	3.17%	3.17%	7.94%	3.17%	6.35%	7.94%	9.52%	11.11%	20.63%	Significant
	Unlucky	0.00%	1.59%	1.59%	3.17%	3.17%	7.94%	1.49%	2.98%	4.46%	5.95%	8.93%	11.90%	Lucky
	Unskilled	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1.69%	3.37%	3.47%	3.57%	2.18%	8.73%	Skilled
20	Significant	1.59%	1.59%	1.59%	1.59%	4.76%	4.76%	1.59%	7.94%	20.63%	26.98%	33.33%	44.44%	Significant
	Unlucky	1.59%	1.59%	1.59%	1.59%	4.76%	4.76%	1.59%	3.40%	5.10%	6.80%	10.20%	13.61%	Lucky
	Unskilled	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	4.54%	15.53%	20.18%	23.13%	30.84%	Skilled

References

Abdullah, F., Hassan, T., Mohamad, S., 2007. Investigation of performance of Malaysian Islamic unit trust funds: comparison with conventional unit trust funds. Manag. Financ. 33 (2), 142–153.

Afza, T., Rauf, A., 2009. Performance evaluation of Pakistani mutual funds. Pakistan Econ. Soc. Rev. 47 (2), 199–214.

Alam, N., Rajjaque, M.S., 2010. Shariah-compliant equities: empirical evaluation of performance in the European market during credit crunch. J. Financ. Serv. Mark. 15 (3), 228–240.

Annuar, M.N., Shamsher, M., Ngu, M.H., 1997. Selectivity and timing: evidence from the performance of Malaysian unit trusts. Pertanika J. Soc. Sci. Humanit. 5, 45–57.

Ayub, M., 2007. Understanding Islamic finance. Wiley, England.

Barras, L., Scaillet, O., Wermers, R., 2010. False discoveries in mutual fund performance: measuring luck in estimated alphas. J. Financ. 65, 179–216.

Bauer, R., Koedijk, K., Otten, R., 2005. International evidence on ethical mutual fund performance and investment style. J. Bank. Financ. 29 (7), 1751–1767.

Blanchett, D.M., 2010. Exploring the cost of investing in socially responsible mutual funds: an empirical study. J. Invest. 19 (3), 93–103.

Campbell, J.Y., Vuolteenaho, T., 2003. Bad beta good beta. NBER Working Paper (Retrieved 12 October 2012 from http://www.nber.org/papers/w9509).

Carhart, M.M., 1997. On persistence in mutual fund performance. J. Financ. 52, 57–82.

Elfakhani, S., Hassan, M.K., Sidani, Y., 2005. Comparative performance of Islamic versus secular mutual funds. 12th Economic Research Forum Conference, University of New Orleans, USA, November 2005.

Fama, E.F., French, K.R., 1992. The cross-section of expected stock returns. J. Financ. 47, 427–465.

Fama, E.F., French, K.R., 1993. Common risk factors in the returns on bonds and stocks. J. Financ. Econ. 33, 3–53.

Fama, E.F., French, K.R., 2010. Luck versus skill in the cross-section of mutual fund returns. J. Financ. 65, 1915–1947.

Forte, G., Miglietta, F., 2007. Islamic mutual funds as faith-based funds in a socially responsible context. Working Paper (Retrieved 12 October 2012 from http://ssrn.com/abstract=1012813).

Girard, E., Hassan, M.K., 2008. Is there a cost to faith-based investing: evidence from FTSE Islamic Indices. J. Invest. 17 (4), 112–121.

Hakim, S., Rashidian, M., 2004. How costly is investor's compliance to Sharia? Paper Presented at the 11th Economic Research Forum Annual Conference, Beirut, Lebanon, December 14–16, 2004.

Hayat, R., Kraeussl, R., 2011. Risk and return characteristics of Islamic equity funds. Working Paper (Retrieved 12 October 2012 from http://ssrn.com/abstract=1320712).

Hoepner, A.G.F., Rammal, H.G., Rezec, M., 2011. Islamic mutual funds' financial performance and international investment style: evidence from 20 countries. Eur. J. Financ. 17 (9–10), 829–850.

Hussein, K.A., 2004. Ethical investment: empirical evidence from FTSE Islamic index. Islam. Econ. Stud. 12 (1), 21–40.

Ismail, A.G., Shakrani, M.S., 2003. The conditional CAPM and cross-sectional evidence of return and beta for Islamic unit trusts in Malaysia. IIUM J. Econ. Manag. 11 (1), 1–31.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: implications for stock market efficiency. J. Financ. 48, 65–91.

Kosowski, R., Timmermann, A., Wermers, R., White, H., 2006. Can mutual fund “stars” really pick stocks? New evidence from a bootstrap analysis. J. Financ. 61, 2551–2595.

Lintner, J., 1965. The valuation of risk assets and the selection of risk investments in stock portfolios and capital budgets. Rev. Econ. Stat. 47, 13–37.

Lyn, E.O., Zychowicz, E.J., 2010. The impact of faith-based screens on investment performance. J. Invest. 19 (3), 136–143.

Mansor, F., Bhatti, M.I., 2011. Risk and return analysis on performance of the Islamic mutual funds: evidence from Malaysia. Glob. Econ. Financ. J. 4 (1), 19–31.

Merdad, H., Hassan, M.K., Alhenawi, Y., 2010. Islamic versus conventional mutual funds performance in Saudi Arabia: a case study. J. King Abdulaziz Univ. Islam. Econ. 23 (2), 157–193.

Obiyathulla, I.B., 1997. Adapting mudarabah financing to contemporary realities: a proposed financing structure. J. Account. Commer. Financ. Islam. Perspect. 1 (1), 26–54.

Ramasamy, B., Yeung, M.C.H., 2003. Evaluating mutual funds in an emerging market: factors that matter to financial advisors. Int. J. Bank Mark. 21 (3), 122–136.

Renneboog, L., Horst, J.T., Zhang, C., 2008a. Socially responsible investments: institutional aspects, performance, and investor behavior. J. Bank. Financ. 32, 1723–1742.

Renneboog, L., Horst, J.T., Zhang, C., 2008b. The price of ethics and stakeholder governance: the performance of socially responsible mutual funds. J. Corp. Financ. 14, 302–322.

Saad, N.M., Majid, M.S.A., Kassim, S., Hamid, Z., Yusof, R.M., 2010. A comparative analysis of the performance of conventional and Islamic unit trust companies in Malaysia. Int. J. Manag. Financ. 6 (1), 24–47.

Shamsher, M., Annuar, M.N., Taufiq, H., 2000. Investment in unit trusts: performance of active and passive funds. Proceedings of FEP Seminar 2000: Issues in Accounting and Finance 2. Universiti Putra Malaysia Press, Malaysia, pp. 129–141.

Sharpe, W.F., 1964. Capital asset prices: a theory of market equilibrium under conditions of risk. J. Financ. 19, 425–442.

Storey, J.D., 2002. A direct approach to false discovery rates. J. R. Stat. Soc. 64, 479–498.