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A Market Timing Strategy for the GCC Conventional and Shariah Stock Indices

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Abstract

This paper defines and assesses a market timing strategy for the Gulf Cooperation Council (GCC) stock indices, namely the Tadawul All Share Index, FTSE Abu Dhabi General Index, Qatar All Share Index and Qatar Al Rayan Islamic Index. The strategy intends to deliver a consistent reduction in volatility and better risk-adjusted performance. The present empirical study capitalises on the work by Colepand and Copeland (1999) on the US market, re-proposed recently by Bantwa (2020) on the Indian market, which resorts to implied volatility as the trigger to adjust the asset allocation. The strategy hereby proposed is modified considering the higher volatility of the GCC financial markets as well as its preeminent goal – risk-adjusted performance optimisation. Moreover, the implied volatility is unavailable for the GCC stock indices under assessment; therefore, it has been replaced with the forecasted volatility obtained through asymmetric GARCH models (GJR-GARCH), one for each stock index. The active strategy in question is backtested on both the conventional and Islamic stock indices to check whether it overperforms the passive strategy equally well on both types of indices. The empirical findings encourage the adoption of volatility-based market timing models in additional emerging markets and Islamic indices.

Keywords: Market Timing, Gulf Cooperation Council, Stock Indices, Shariah Stocks, GARCH, Volatility.

▪ INTRODUCTION

This paper represents the first attempt to define a market timing strategy suitable for the Gulf Cooperation Council (GCC) stock indices. A market timing strategy is developed aimed at containing volatility and simultaneously achieving a better risk profile, that is, better risk-adjusted performance metrics. An active strategy is expressly tailored for the stock indices of emerging markets as they are known to be more volatile than the indices of developed markets. GCC markets are no exception as their economies are dependent on the price of oil, which is itself volatile and impacts the variability of their stocks (Chebbi and Derbali, 2015; Muntazir and Ramiz, 2023).

In the context of asset management, a ‘market timing strategy’ is an active approach that entails switching from one asset class to another according to the currently detected market phase, which in this paper is determined based on the volatility estimated from historical data. This switch from one asset class to another is called ‘asset rotation’ or ‘rebalancing’ and may encompass either different sectors or types of stocks – small cap vs large cap – or various asset types, such as equity, fixed income or liquidity. The strategy formulated in this paper entails switching between equity and liquidity and vice-versa, which can easily be implemented using index-replicating ETFs.

Unlike the literature on market timing strategies (Bantwa, 2020; Copeland and Copeland, 1999), the strategy proposed herein adopts forecasted volatility instead of implied volatility as the rebalancing trigger. Forecasted volatility is estimated from the stock index time series (historical data), whereas implied volatility is disclosed by the derivative market where the call and put options of the given stock index are negotiated. For the GCC indices, the implied volatility is unavailable; thus, the forecasted volatility is the only possible choice. In this context, the present paper formulates non-linear GARCH models aimed at volatility forecasting regarding all involved GCC stock indices.

Regarding stock exchanges, the scope of the present study covers the three largest exchange markets in the GCC region in terms of market capitalisation: the Riyadh, Abu Dhabi and Doha stock exchanges. The first three stock indices subjected to the proposed market timing strategy are the following:

- FTSE Abu Dhabi General Index (FADGI)
- Tadawul All Share Index (TASI)
- Qatar All Share Index (QEAS)
- The indices listed above are qualified as 'conventional' (conventional indices) in that they encompass any kind of stock. By contrast, shariah indices are those encompassing only shariah-compliant stocks. The scope of this paper also encompasses an Islamic index:
- Al Rayan Islamic Index (QERI)
- The Al Rayan Islamic Index, launched by the Al Rayan Bank in 2013 but with historical data available from January 2007, is the only Islamic index in the GCC region characterised by sufficient historical depth to support active strategy backtesting.

According to a survey conducted by the Bahrain-based General Council for Islamic Banks and Financial Institutions in January 2022, the Islamic fund industry has reached nearly $200 billion in assets under management worldwide and has grown by more than 300% over the last decade. The outstanding growth of the Islamic funds is attributable to the compliance of these products to shariah principles, which are dear to Islamic investors. Moreover, the risk profiles of these funds are known to be less risky than their conventional peers during a major financial crisis. Extensive literature concerns the risk profile of Islamic securities compared to their conventional peers. Nevertheless, the present paper is the first to investigate the extent to which an active strategy works equally well on Islamic and conventional stocks.

LITERATURE REVIEW

Market Timing Strategies

Extensive empirical evidence has suggested that timing entries to and exits from equity markets can be profitable. The available academic contributions are first distinguished by the kind of trigger adopted to detect the market phase, then by determinations of whether to enter or to stay off the market:

- Wong *et al.*, (2001) and Shen (2003) adopted a trigger based on the earnings-to-price ratio differential against the Treasury yield.
- Resnick and Shoesmith (2002) adopted the yield spread as a trigger (i.e., the difference between the yields on 10-year US Treasury bonds and 3-month T-bills).
- Brooks and Katsaris (2005) focused on consistent departures of the market prices from fundamental values to detect market bubbles and trigger market exits.
- Recently, Bantwa (2020) adopted implied volatility (IV) as a market-timing trigger meant to switch from one equity class to another, namely large-cap to small-cap stocks.
- Bantwa's contribution is the most pertinent to the scope of the present paper in that it relates to an emerging market, namely the Indian stock market, whereas all the other cited works pertain to the US market. Bantwa separately computes the correlation between the CNX Nifty Index (NIFTY) and the India Volatility Index (India VIX) during bullish and bearish market years, highlighting the considerably strong inverse correlation observed in bear market years. The findings confirm the extent to which high implied volatility hints at forthcoming market downturns.

The market timing model formulated by Bantwa is derived from an earlier model by Copeland and Copeland (1999) focusing on the US market, where the market entry and exit triggers are characterised by the following volatility thresholds:

- Market entry trigger: volatility reading 30% lower than the 75-day moving average.
- Market exit trigger: volatility reading 30% higher than the 75-day moving average.
- Copeland and Copeland confirm that the market timing strategy could also be profitable by adopting different volatility thresholds. Nevertheless, the 30% threshold turns out to deliver the highest daily average return.

An implementation of the Copeland and Copeland (1999) strategy as-is for the GCC stock indices would face some hurdles, however:

a) Copeland and Copeland make use of implied volatility, whereas none of the stock exchanges covered in the present study – Riyadh, Abu Dhabi, Dubai, Doha – disclose the implied volatility of their stock indices. This non-disclosure is due to the unavailability of developed derivative exchanges where call and put options of the indices can be negotiated.
b) The equity classes involved in Copeland and Copeland's asset rotation are large-cap and mid-cap stocks because quite a number of futures and ETFs are available in the US financial markets to provide exposure to either of the asset classes. However, that is not the case for GCC financial markets. The Doha stock exchange, for instance, lists just two ETFs replicating the All Share Index and the Islamic Index, with no distinction between large- and small-cap stocks.

The hurdle related to the unavailability of the implied volatility is surmounted by the authors of the present paper by resorting to a volatility forecasting model. The difficulty related to the unavailability of either large- or mid-cap ETFs and futures has been addressed by reformulating the Copeland and Copeland (1999) strategy by encompassing a rotation from the equity market as a whole (the All Share Index) to liquidity and vice-versa. The volatility threshold defined by Copeland and Copeland has been adjusted accordingly, opting for absolute volatility thresholds instead of dynamic thresholds.

Regarding absolute thresholds, this study capitalises on the dichotomous rule of thumb formulated by Durand *et al.*, (2011) based on the investors' pools regarding the US stock market:

- Risk-averse investors pool (market uncertainty): IV reading ≥20%
- Bullish investors pool: IV reading <20%

Durand's threshold, referred to the US market, has been adjusted upwards for this empirical study considering the higher volatility of the GCC markets. The volatility differential between the GCC and US markets is structural in that it stems from the sensitivity of the GCC markets to oil prices. The most recent empirical study on the subject, conducted by Muntazir and Ramiz (2023), confirmed the connectedness of GCC stock markets returns and the S&P global oil index returns. Similar empirical evidence is provided by Chebbi and Derbali (2015) regarding the correlation between the volatility of oil prices and the Qatar stock indices.

Volatility Modelling & Forecasting for GCC Markets

As of March 2023, no academic contribution examines volatility modelling for the GCC markets, though there are few papers regarding the Saudi Arabia stock index and just one empirical study about the Qatar index. All the academic works in question adopt a GARCH-family model based on the daily log-return time series of the stock index. We refer to these models as 'forecasting' models as they estimate the volatility at time t based on the historical data up to day $t-1$ (1-step ahead forecasting). The difference between the various academic papers hereby reviewed pertains to the specific kind of GARCH model employed.

The first to address the subject for the Saudi stock index was Kalyanaraman (2014), who modelled the Saudi stock index time series from 2004 to 2013 with a basic GARCH model, the same model formulated by Bollerslev (1986).

Four years later, Al Rahahleh and Kao (2018) focused their analysis on more Saudi stock indices – the TASI and the Tadawul Industrial Petrochemical Industries Share Index (TIPISI) – finding evidence of the superiority of non-linear GARCH models compared to linear GARCH models. According to Al Rahahleh and Kao, the 'threshold' GARCH formulated by Glosten–Jagannathan–Runkle (GJR-GARCH; Glosten *et al.*, 1993) is the most performing model. Compared to the basic GARCH, the GJR-GARCH model relaxes the linear restriction on the conditional variance dynamics. GJR-GARCH accounts for asymmetry by allowing conditional volatility to depend on the sign of the lagged log-returns considering that negative shocks usually have a significant effect on conditional volatility.

Independently formulated by Zakoian (1994) a year after GJR-GARCH, another threshold GARCH model is 'TGARCH'. From 2003 to 2012, TGARCH has been employed by Banumathy and Azhagaiah (2015) as the forecasting model for the volatility of the Indian stock market – the CNX Nifty Index. The threshold GARCH models by Glosten–Jagannathan–Runkle and Zakoian are identical except the former expressly models conditional variance while the latter models conditional volatility (the squared root of the variance).

Finally, considering the Qatar financial market, the only academic paper available on the subject is by Derbal *et al.*, (2022), which targets the Qatar Stock Exchange index. Along with Kalyanaraman (2014), Derbal confirms that the basic GARCH model performs well even if it does not provide comparative analysis encompassing the remaining types of GARCH, namely the non-linear GARCH models.

Based on these findings, the authors of this study examine both the threshold and the basic GARCH models to identify the best-performing model for each stock index. Moreover, each model is assessed in two versions, assuming a normal distribution and a Student's *t*-distribution for the lagged innovations (log-returns). This double assessment is in accordance with the findings of Kovačić (2007), who assessed the Macedonian Stock Exchange. Kovačić suggested that the accuracy of threshold GARCH models can be improved by assuming non-Gaussian innovation distributions. Al Rahahleh and Kao (2018) concur with Kovačić, maintaining that non-Gaussian distributions, particularly the generalized error distribution and the Student's *t*-distribution, guarantee a good fit for Saudi Arabian stock indices.

Shariah vs Conventional Stock Indices

Islamic banking and finance (IBF) has been rising during the past decades with more countries becoming aware of the importance of this niche market. IBF principles are based on the *Quran* and by definition this financial system is more ethical, conservative, and less volatile compared to its conventional counterparts. Foundational empirical research by Girard and Hassan (2008) investigates the potential competitive disadvantage of the average Islamic mutual fund with respect to its average conventional peer since IBF institutions 'can't freely choose between debt-bearing investments and profit-bearing investments and can't invest across the full spectrum of all available industries' but are subjected to the qualitative and quantitative constraints set by the shariah guidelines.

Girard and Hassan (2008) examined Islamic funds by means of a multivariate regression analysis conducted on the FTSE Global Islamic Index Series (GIIS) data from 1999 to 2006 according to the Carhart (1997) four-factor pricing model, which is a refinement of the Fama and French (1993) three-factor model, which in turn extends the capital asset pricing model (CAPM; Sharpe, 1964). Girard and Hassan demonstrated that after controlling for the value, effect of the size and the momentum, the Islamic funds performed as well as their peers. Adopting a similar methodology, Camgöz *et al*

., (2018) analysed data from 2022 to 2017 related to the Dow Jones Islamic Index (DJII) and the MSCI index restrictions for four distinct countries – Turkey, Malaysia, the United States and the UK. The authors revealed that the Islamic indices performed not just as well as conventional indices but even delivered a better risk-adjusted performance. Hakim and Rashidian (2004) subjected the DJII and the Dow Jones World Index (DJWI) data from 2000 to 2004 to a regression analysis according to a revisited CAPM, namely the 'conditional CAPM' proposed by Jagannathan and Wang (1996). Hakim and Rashidian found evidence of competitive risk-adjusted returns of the DJII. Moreover, the DJII was found to have a diversification benefit due to its lower sensitivity to global systematic risk.

Mansor and Bhatti (2011) focused their empirical research toward emerging markets, namely Malaysia, assessing the performance of 128 Islamic mutual funds and 350 conventional peers from 1996 to 2009. The authors provide evidence of a better risk-adjusted performance of the Islamic funds, especially in terms of the Sortino ratio. In addition, this overperformance extends to the Kuala Lumpur Shariah Index stock index compared to its conventional counterpart, the Kuala Lumpur Composite Index. Sherif and Lusyana (2017) analysed the data of the Jakarta stock exchange from 2010 to 2014 and conclude that the holdings of the Indonesia Shariah-Compliant Stock Index performed slightly better than the average holding of the all-share Jakarta Composite Index regarding risk-adjusted performance, precisely in terms of the Sharpe ratio.

In addition, Ho *et al.,* (2014) conducted an analysis of the global Islamic index and the global conventional index restricted to eight distinct countries, including emerging markets such as Malaysia and Indonesia. The authors pointed out that based on outcomes, the Islamic indices are superior in terms of risk-adjusted performance in financial crisis periods. In particular, Islamic indices outperformed during the dotcom crisis (2000–2002) and the global financial crisis (2007–2008; Ho *et al.*, 2014). Mirza *et al.*, (2022) conducted an empirical study involving mutual funds of either an Islamic or conventional type with exposure to some GCC markets, including Saudi Arabia, UAE, Qatar and Kuwait. The authors provided evidence of an overperformance of the Islamic funds in risk-adjusted performance metrics during the four months when the COVID-19 pandemic financial crisis reached its peak.

In contrast, some studies found that Islamic stock indices were not totally immune to the global financial crisis, and were found to be more volatile compared to their conventional counterparts. For example, Rejeb and Arfaoui (2018) conducted a study investigating whether Islamic stocks outperformed conventional stocks in the 2018 financial turmoil. The results showed that the Islamic stock indices are more efficient than conventional stock indices regarding informational efficiency, but they are not less volatile. A similar finding was observed by Jabeen and Kausar (2022), who examined the performance of Islamic and conventional stocks listed at the Pakistan Stock Exchange using both parametric and non-parametric approaches. The study analysed the Karachi Meezan Index-30 and the Karachi Stock Exchange Index-30 as proxies for Islamic and conventional finance, respectively. Jabeen and Kausar (2022) used several measures of performance, including the Sharpe ratio, the Treynor ratio, Jensen's alpha, beta, generalised autoregressive conditional heteroskedasticity and stochastic dominance. The result showed that Karachi Meezan Index-30 performs better compared to the Karachi Stock Exchange Index-30, but the risk and volatility present similar results.

The authors of the present paper investigate whether an active strategy expressly devoted to improving risk-adjusted performance can over perform an Islamic index even though Islamic securities deliver a slight over performance in terms of risk-adjusted returns according to the literature. This over performance of Islamic indices is especially evident when the observation period encompasses a significant financial crisis, as is the case in the present study.

RESEARCH METHODOLOGY

Input Data

The input data for the present empirical study consist of the daily time series of the stock indices under assessment:

- FADGI time series, available from ADX from January 4, 2003, onwards,
- TASI time series, from January 4, 2003, onwards,
- QEAS time series, from January 3, 2007, onwards, and
- QERI time series, from January 3, 2007, onwards.

The observation period starting dates for the FADGI and the TASI are set equal to support a comparative analysis. The start date is set according to the FADGI, whose historical depth is shorter than TSAI. Regarding the QEAS and QERI, it is impossible to find historical data before January 3, 2007. The upper boundary of the observation period for all stock indices is March 31, 2023.

To estimate the volatility for the stock indices above, it is necessary to compute the log returns of the stock indices. The log return r_t for the given stock index on day t is computed based on the index value (price) at time t and $t-1$, namely P_t and P_{t-1}, respectively:

$$r_t = \ln(\frac{P_t}{P_{t-1}}) \quad \textbf{(1)}$$

Volatility Estimation Model

According to the GARCH(1,1) model formulated by Bollerslev (1986), the log-returns r_t, which are assumed to be normally distributed, can be modelled as follows:

$$r_t = \mu + \varepsilon_t \quad \textbf{(2)}$$

The term ε_t represents an 'innovation', that is, an error term, which in turn can be expressed as the product of the 'conditional volatility', σ_t, and an independent and identically distributed random variable of mean 0 and unitary variance, denoted with ϵ_t:

$$\varepsilon_t = \sigma_t \times \epsilon_t \quad \textbf{(3)}$$

$$\epsilon_t \sim \text{IN}(0,1) \quad \textbf{(4)}$$

The conditional variance, ${\sigma_t}^2$, is then expressed as a function of the lagged conditional variance itself and of the lagged squared error term:

$${\sigma_t}^2 = \omega + \beta \times {\sigma_{t-1}}^2 + \alpha \times {\varepsilon_{t-1}}^2 \quad \textbf{(5.a)}$$

The model defined thus far was adopted by Derbal *et al.*, (2022) to estimate the volatility of the Qatar Stock Exchange index. In the present paper the linear GARCH(1,1) model is compared to the GJR-GARCH model as it performs distinctly better than the basic GARCH on the Saudi stock indices TASI and TIPISI (Glosten *et al.*, 1993). According to Al Rahahleh and Kao (2018), the GJR-GARCH(1,1) model can be formulated by simply replacing equation (5.a) with equation (5.b):

$${\sigma_t}^2 = \omega + \beta \times {\sigma_{t-1}}^2 + \alpha \times {\varepsilon_{t-1}}^2 + \gamma \times I_{t-1}^{-} \times {\varepsilon_{t-1}}^2 \quad \textbf{(5.b)}$$

Where:

- $I_{t-1}^{-} = 1, if\ \varepsilon_{t-1} < 0$ or 0 otherwise
- The models formulated thus far are fitted by means of a maximum likelihood estimation (MLE). The volatility estimate of the best-fitting model – either GJR-GARCH(1,1) or GARCH(1,1) – is intended to feed the proposed market timing strategy. For each model above mentioned, two different versions are tested encompassing two distinct innovation distributions:
- Normal distribution
- Student's *t*
- The following goodness-of-fit metrics are adopted to choose between the GARCH models and the innovations distributions under assessment:
- MAPE (Mean Absolute Percentage Error) to be minimised.
- MSE (Mean Square Error) to be minimised.

The model with the lowest MAPE is preferred; in case of models with the same MAPE, the MSE is considered.

Market Timing Strategy Formulation

The proposed market timing strategy is driven by the annualised volatility, σ_{AN_t}, instead of σ_t, the daily conditional volatility estimated with the GARCH model. The latter can be converted into an annualised estimate by means of a proper multiplication factor with considers the number of market days per annum:

$$\sigma_{AN_t} = \sqrt{252} \times \sigma_t \quad \textbf{(6)}$$

Based on the dichotomous characterisation of the market sentiment by Durand *et al.*, (2011) regarding market uncertainty, a risk-averse investor should reduce exposure to the equity asset class when its implied volatility is greater than the 20% threshold. This threshold is adjusted in the context of this paper because the GCC indices, as well as most emerging market indices, are riskier than the S&P 500 – the stock index involved in the empirical research mentioned above. This consideration demands shifting the volatility threshold at least 5 or 10 percentage points upwards. The authors of this paper opt for a 10 percentage-point increase in the implied volatility threshold to 30% to make the strategy more selective and minimise the strategy turnover ratio, that is, the rebalancing rate. This rate in turn impacts the annualised transaction costs. Hence, the market timing strategy output signal, O_t, which equals either 1 or 0, respectively, when the assets are fully allocated to the equity market (stock index) or fully allocated to liquidity, is defined accordingly:

$$O_t = 1 \text{ if } \sigma_{AN_t} \geq 30\% \quad \textbf{(7)}$$

$$O_t = 0\ if\ \sigma_{AN_t} < 30\% \quad \textbf{(8)}$$

At inception of the holding period, the stock index is bought as the strategy does not encompass short selling.

Strategy Performance Assessment

With the term 'benchmark', we refer to a passive strategy consisting of a long position on the stock index held across the entire observation period. With the term 'active strategy', we instead refer to the market-timing strategy outlined thus far, which is implemented either by buying or selling the given stock index according to the volatility-based triggers. For the active strategy, the log-returns are calculated based on the benchmark log-returns r_t and the active strategy output signals, O_t, previously defined:

$$r_t\ (active\ strategy) = r_t \times O_t \qquad \textbf{(9)}$$

The following set of metrics is adopted for the performance assessment of both the active strategy and the benchmark:

- R = annualised return
- $STDEV$ = annualised standard deviation
- VaR = Value at Risk at the 99% confidence level referred to a 1-year holding period
- $CVaR$ = Conditional VaR at the 99% confidence level referred to a 1-year holding period
- MDD = (historical) maximum drawdown. The MDD gauges the largest price drop, in percentage, from an equity peak to a trough recorded across the overall observation period
- MDP = (historical) maximum drawdown period. Expressed in years, the MDP gauges the longer time taken within the observation period to recover from a drawdown (to reach the previous equity peak)
- RR = Return-risk ratio. The ratio gauges the annualised return per unit of risk (annualised standard deviation)
- RAP = Risk-adjusted performance. Introduced by Modigliani and Modigliani (1997), RAP is designed to adjust the annualised profitability R (annualised return) assuming that the risk (annualised standard deviation) of the active strategy is altered to match the risk of the benchmark. For the benchmark, RAP and R are equal.
- We also introduce the following notation:
- $STDEV_{BMK}$ = annualised standard deviation of the benchmark
- C_i = Capital (equity) at the inception of the observation period
- C_F = Capital (equity) at the end of the observation period
- T = Observation period length in days
- $\bar{r}$ = Mean return across the observation period
- ϕ^{-1} = Quantile function of the standard normal distribution
- φ = Probability density function (PDF) of the standard normal distribution
- $1-\alpha$ = level of confidence for the VaR and the CvaR calculation (α = 0.01)

The adopted performance metrics can be estimated as follows:

$$R = \left(\frac{C_F}{C_i}\right)^{\frac{365}{T}} - 1 \qquad \textbf{(10)}$$

$$STDEV = \sqrt{\sum_{t=1}^{T} \frac{252 \times (r_t - \bar{r})^2}{T-1}} \qquad \textbf{(11)}$$

$$VaR = -STDEV \times \phi^{-1}(1-\alpha) \qquad \textbf{(12)}$$

$$CVaR = -STDEV \times \frac{\varphi(\phi^{-1}(\alpha))}{1-\alpha} \qquad \textbf{(13)}$$

$$RR = \frac{R}{STDEV} \qquad \textbf{(14)}$$

$$RAP = R \times \frac{STDEV_{BMK}}{STDEV} \qquad \textbf{(15)}$$

For both the benchmark and the active strategy, C_i coincides with the stock index value at the begninng of the observation period, P_1.

$$C_i = P_1 \qquad \textbf{(16)}$$

For the benchmark, C_F coincides with the stock index value at the end of the observation period, whereas for the active strategy, C_F must be calculated resorting to the strategy log-returns already computed in (**9**):

$$C_F\ (benchmark) = P_T \qquad \textbf{(17)}$$

$$C_F\ (active\ strategy) = C_i \times \prod_{t=2}^{T} e^{r_t} \qquad \textbf{(18)}$$

The core set of performance metrics defined thus far does not consider transaction costs. To provide at least a rough estimate of the risk-adjusted profit net of transaction costs, the following metric must also be computed:

$TURN$ = turnover ratio, which in our case equals the frequency of rebalancing operations on an annual basis, computed based on Q, which represents the overall number of such identified operations across the entire observation period:

$$TURN = Q \times \frac{365}{T} \qquad \textbf{(19)}$$

Zakamulin (2014) points out the bias in the assessment of the academic market timing strategies due to the total lack of consideration of transaction costs. These costs may vary considerably depending on the liquidity of the market, the order size relative to the average daily trading volume and the investor type. For example, institutional investors pay 0.10% or less per transaction, whereas individual investors may incur a per-transaction cost of 0.50% or more. The assumptions of Zakamulin, which the present paper also adheres to, are the following:

- Assumption 1: The market timing strategy is implemented by an institutional investor who pays minimal commissions, which can be neglected.
- Assumption 2: The buy and sell orders are far below the overall daily trading volume for the involved security (the stock index in question).

Based on these assumptions, the only factor that matters in the cost estimation is the average BidAsk half-spread – the BidAsk spread divided by two – for the security involved. Hence, the annualised transaction cost, TC, can be estimated as follows:

$$TC = \frac{BidAsk}{2} \times TURN \qquad \textbf{(20)}$$

A rough estimate of the risk-adjusted performance net of the transaction cost can then be easily obtained by subtracting TC from the gross RAP:

$$Net\ RAP = RAP - TC \qquad \textbf{(21)}$$

For the benchmark, the Net RAP and the RAP are equal because a passive strategy does not entail rebalancing operations.

Instead of providing a point estimate for the input variable $BidAsk$ involved in equation (20), the authors of this paper opt for a sensitivity analysis intended to gauge the net performance downgrade caused by various potential readings of the variable. Additionally, the break-even $BidAsk$ value is estimated that makes the active strategy Net RAP and that of the benchmark equal.

FINDINGS AND DISCUSSION

Abu Dhabi Stock Exchange Index (FADGI)

Table 4.A.1 reports the goodness-of-fit statistics regarding to the FADGI index for the various GARCH models and innovation distributions (Distribution) encompassed in this empirical study. The lowest values are highlighted in green.

Table. 4.A.1 – FADGI GARCH Models Comparison [2003–2023]

Model	Distribution	MAPE	MSE
GARCH(1,1)	Normal	140.50	0.001255
	Student's *t*	132.32	0.001255
GJR-GARCH(1,1)	Normal	131.17	0.001255
	Student's *t*	129.05	0.001255

The GJR-GARCH model performs better than the linear model (GARCH) on the FADGI regardless of the adopted distribution. Additionally, the Student's *t*-distribution is preferable regarding the Gaussian distribution. Table 4.A.2 reports the parameter estimates of the selected model along with their statistical significance.

Table. 4.A.2 – FADGI GJR-GARCH Model Parameter Estimates [2003–2023]

Parameter	Estimate	p-Value
μ	390E-6	<0.0001
ω	3E-6	<0.0001
β	0.7653	<0.0001
α	0.2021	<0.0001
γ	0.0947	<0.0001

The GJR-GARCH model parameter estimates are extremely statistically significant. Figure 4.A.1 shows the time plot of the stock index price and of the volatility estimated in the selected model. The volatility in the plot is annualised according to equation (6), and the red dashed horizontal line shows the volatility threshold triggering the rebalancing operations.

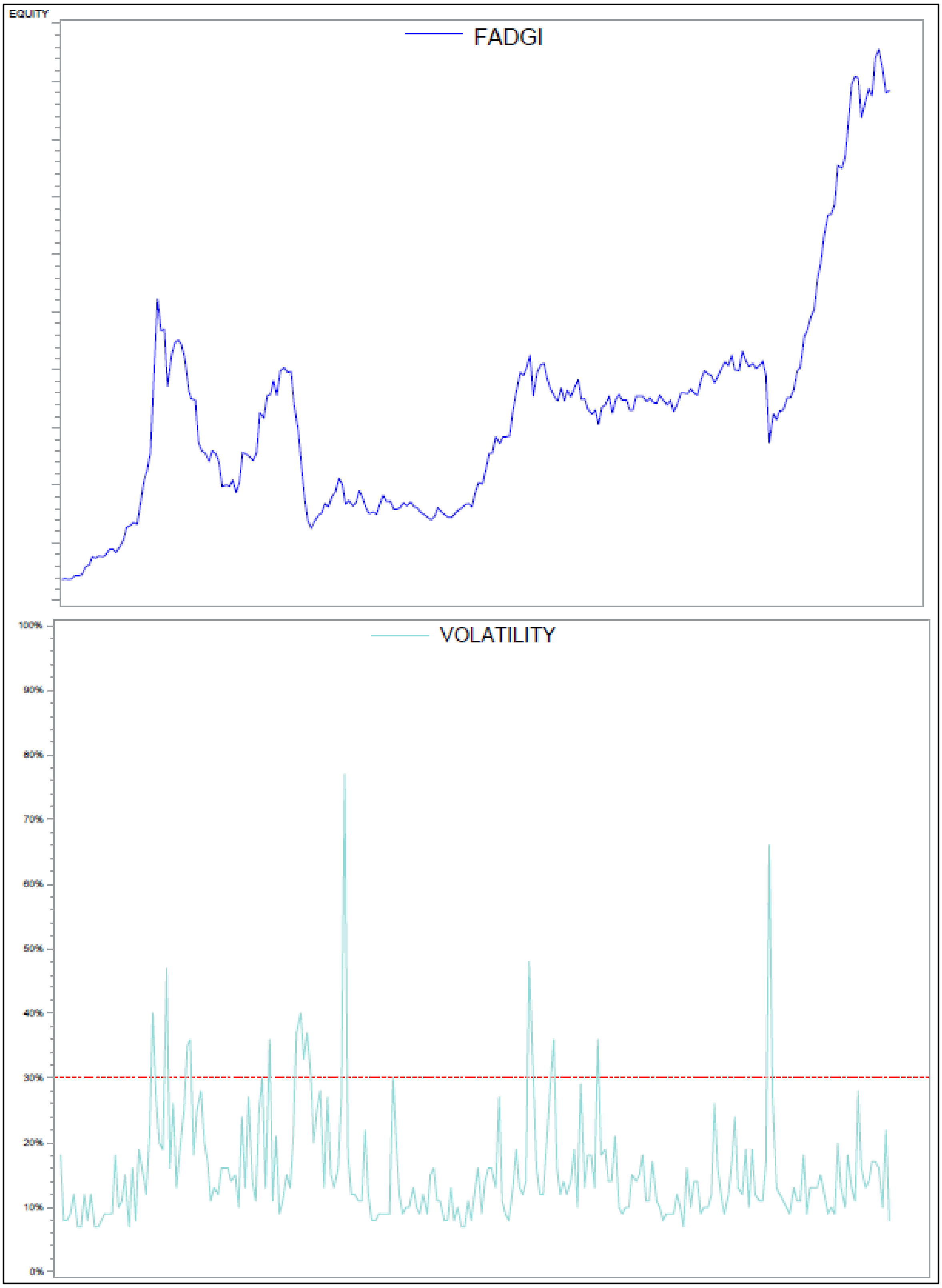

Figure 4.A.1 – FADGI Daily Price (top) and Annualised Volatility Timeplot (bottom) [2003–2023]

Figure 4.A.2 plots the equity curves of the active strategy and the benchmark. The active strategy is characterised by a much smoother equity curve and generates a slightly higher final capital at the end of the observation period, which hints at a better risk-adjusted performance.

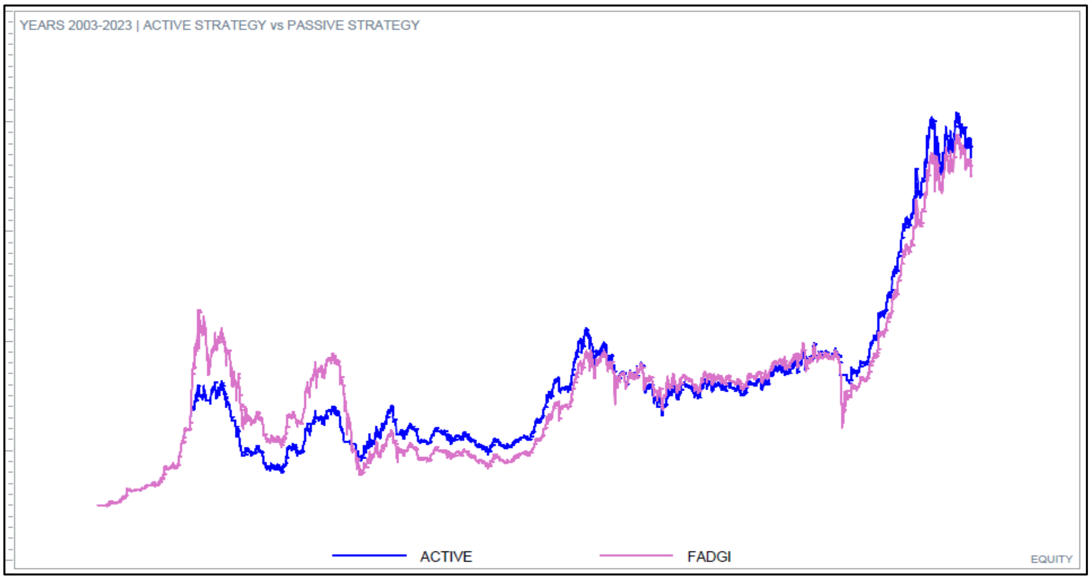

Figure 4.A.2 – FADGI Equity Curve Comparative Analysis: Active Strategy (blue) vs Benchmark (pink) [2003–2023]

Table 4.A.3 provides the performance metrics of the strategies under assessment. The metrics for which the active strategy outperforms the benchmark are highlighted in green. The active strategy delivers overperformance in all assessed metrics.

Table. 4.A.3 – FADGI Performance Comparative Analysis: Active Strategy vs Benchmark [2003–2023]

Metric	Active Strategy	Benchmark
R	10.40%	10.10%
RAP	13.80%	10.10%
$STDEV$	13.40%	17.80%
VaR	−31.10%	−41.40%
$CVaR$	−35.70%	−47.40%
MDD	−51.10%	−65.70%
RR	0.78	0.57

Table 4.A.4 shows the outcome of the sensitivity analysis for transaction costs conducted on the active strategy according to equation (21). This table confirms the cost-effectiveness of the active strategy because its break-even Bid Ask spread stands at 120 basis points, far above its feasible value (10 basis points).

Table. 4.A.4 – FADGI Active Strategy Sensitivity Analysis to Transaction Costs [2003–2023]

	Active Strategy		**Benchmark**	
ETF BidAsk [bp]	Turnover Ratio (TURN)	Net RAP	RAP	Break-even
5	6.34	13.64%	10.10%	
10		13.48%	10.10%	
20		13.17%	10.10%	
30		12.85%	10.10%	
50		12.22%	10.10%	
120		10.10%	10.10%	***

Tadawul All Share Index

Table 4.B.1 reports the goodness-of-fit statistics concerning the TASI index for the various GARCH models and innovation distributions (Distribution) encompassed in this empirical study. The lowest values are highlighted in green.

Table. 4.B.1 – TASI GJR-GARCH Models Comparison [2003-2023]

Model	**Distribution**	MAPE	MSE
GARCH(1,1)	Normal	165.91	0.002085
	Student's *t*	168.67	0.002085
GJR-GARCH(1,1)	Normal	151.91	0.002082
	Student's *t*	161.34	0.002084

The GJR-GARCH model performs better than the linear model (GARCH) on the TASI regardless of the adopted distribution. Additionally, the Gaussian distribution is preferable with respect to the Student's *t*-distribution. Table 4.B.2 reports the parameter estimates of the selected model along with their statistical significance.

Table. 4.B.2 – TASI GJR-GARCH Model Parameter Estimates [2003-2023]

Parameter	Estimate	p-Value
μ	872E-6	<0.0001
ω	4E-6	<0.0001
β	0.8138	<0.0001
α	0.0969	<0.0001
γ	0.1591	<0.0001

The GJR-GARCH model parameter estimates are extremely statistically significant. Figure 4.B.1 shows the time plot of the stock index price and of the volatility estimated through the selected model. The volatility in the plot is annualised according to equation (6), and the red dashed horizontal line shows the volatility threshold triggering the rebalancing operations.

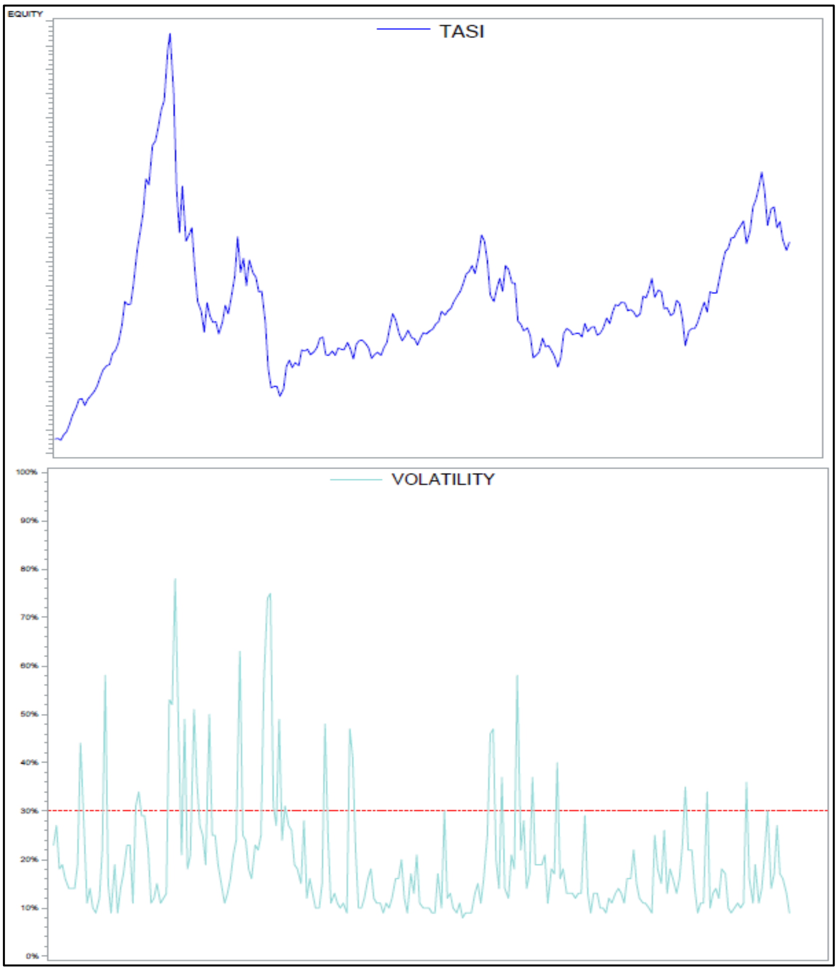

Fig. 4.B.1 – TASI Daily Price (Top) & Annualised Volatility Timeplot (Bottom) [2003-2023]

Figure 4.B.2 plots the equity curves of the benchmark and the active strategy. The active strategy is characterised by a much smoother equity curve and generates a much larger final capital at the end of the observation period, which indicates higher profitability and a better risk-adjusted performance.

Fig. 4.B.2 –TASI Equity Curve Comparative Analysis: Active Strategy vs Benchmark [2003-2023]

Table 4.B.3 provides the performance metrics of the strategies under assessment. The metrics for which the active strategy outperforms the benchmark are highlighted in green. The active strategy delivers an overperformance as regards all metrics involved.

Table. 4.B.3 – TASI Performance Comparative Analysis: Active Strategy vs Benchmark [2003-2023]

Metric	Active Strategy	Benchmark
R	12.30%	7.21%
RAP	18.20%	7.21%
$STDEV$	15.40%	22.90%
VaR	-35.90%	-53.20%
$CVaR$	-41.10%	-61.00%
MDD	-41.70%	-80.00%
RR	0.80	0.32

Table 4.B.4 shows the outcome of the sensitivity analysis to transaction costs conducted on the active strategy according to equation (21). This table confirms the cost-effectiveness of the active strategy since its break-even Bid Ask spread stands at 235 basis points, far above its feasible value (10 basis points).

Table. 4.B.4 – TASI Active Strategy Sensitivity Analysis to Transaction Costs [2003-2023]

	Active Strategy		**Benchmark**	
ETF BidAsk [bp]	Turnover Ratio (TURN)	Net RAP	RAP	Break-even
5	9.44	17.96%	7.21%	
10		17.73%	7.21%	
20		17.26%	7.21%	
30		16.78%	7.21%	
50		15.84%	7.21%	
235		7.11%	7.21%	***

Qatar All Share Index (QEAS)

Table 4.C.1 reports the goodness of-fit statistics with regards to the QEAS index for the various GARCH models and innovation distributions (Distribution) encompassed in this empirical study. The lowest values are highlighted in green.

Table. 4.C.1 – QEAS GARCH Models Comparison [2007-2023]

Model	**Distribution**	MAPE	MSE
GARCH(1,1)	Normal	116.62	0.001431
	’s *t*	132.46	0.001432
GJR-GARCH(1,1)	Normal	106.14	0.001431
	Student’s *t*	128.25	0.001431

The GJR-GARCH model performs better than the linear model (GARCH) on the QEAS regardless of the adopted distribution. Additionally, the Gaussian distribution is preferable considering the Student’s *t*-distribution. Table 4.C.2 reports the parameter estimates of the selected model along with their statistical significance.

Table. 4.C.2 – QEAS GJR-GARCH Model Parameter Estimates [2007-2023]

Parameter	Estimate	p-Value
μ	141E-6	<0.0001
ω	6E-6	<0.0001
β	0.7247	<0.0001
α	0.1927	<0.0001
γ	0.1404	<0.0001

The GJR-GARCH model parameter estimates are extremely statistically significant. Figure 4.A.1 shows the timeplot of the stock index price and of the volatility estimated through the selected model. The volatility in the plot is annualised according to equation (6), and the red dashed horizontal line shows the volatility threshold triggering the rebalancing operations.

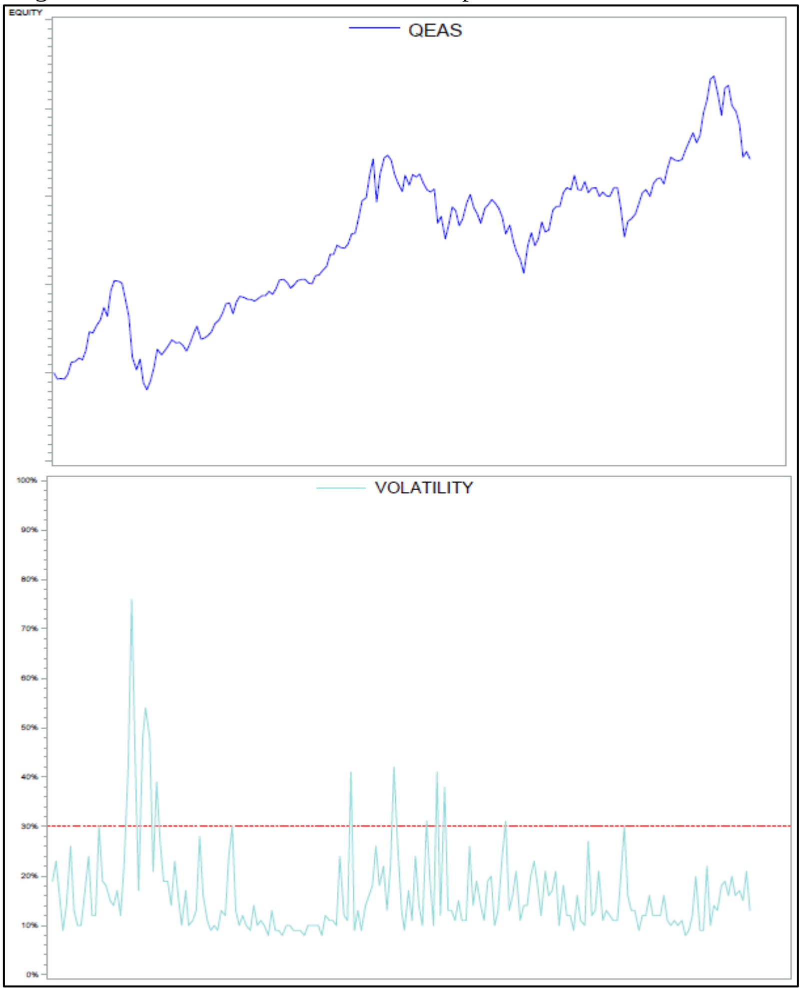

Fig. 4.C.1 – QEAS Daily Price (Top) & Annualised Volatility Timeplot (Bottom) [2007–2023]

Figure 4.C.2 plots the equity curves of the active strategy and the benchmark. The active strategy is characterised by a much smoother equity curve and generates nearly the same final capital at the end of the observation period, which suggests better risk-adjusted performance.

Fig. 4.C.2 –QEAS Equity Curve Comparative Analysis: Active Strategy vs Benchmark [2007–2023]

Table 4.C.3 provides the performance metrics of the strategies under assessment. The metrics for which the active strategy outperforms the benchmark are highlighted in green. The active strategy overperforms in all involved metrics except the annualised return.

Table. 4.C.3 – QEAS Performance Comparative Analysis: Active Strategy vs Benchmark [2007–2023]

Metric	Active Strategy	Benchmark
R	7.41%	7.54%
RAP	9.85%	7.54%
$STDEV$	14.30%	19.00%
VaR	−33.20%	−44.20%
$CVaR$	−38.10%	−50.60%
MDD	−51.70%	−63.20%
RR	0.52	0.40

Table 4.C.4 shows the outcome of the sensitivity analysis to transaction costs conducted on the active strategy according to equation (21). This table confirms the cost-effectiveness of the active strategy since its break-even Bid-Ask spread stands at 70 basis points, far above its feasible value (10 basis points).

Table. 4.C.4 – QEAS Active Strategy Sensitivity Analysis to Transaction Costs [2007–2023]

	Active Strategy		Benchmark	
ETF BidAsk [bp]	Turnover Ratio (TURN)	Net RAP	RAP	Break-even
5	7.03	9.67%	7.54%	
10		9.50%	7.54%	
20		9.15%	7.54%	
30		8.80%	7.54%	
50		8.09%	7.54%	
70		7.39%	7.54%	***

Al Rayan Islamic Index (QERI)

Table 4.D.1 reports the goodness of-fit statistics concerning the QERI index for the various GARCH models and innovation distributions (Distribution) in this research. The lowest values are highlighted in green.

Table. 4.D.1 – Comparison of QERI GARCH Models [2007–2023]

Model	Distribution	MAPE	MSE
GARCH(1,1)	Normal	134.44	0.001525
	Student's *t*	138.73	0.001526
GJR-GARCH(1,1)	Normal	122.09	0.001525
	Student's *t*	135.45	0.001526

The GJR-GARCH model performs better than the linear model (GARCH) on the QERI regardless of the adopted distribution. Furthermore, the Gaussian distribution is preferable to the Student's *t*-distribution. Table 4.D.2 displays estimates of the parameters for the selected model along with their statistical significance.

Table. 4.D.2 – QERI GJR-GARCH Model Parameter Estimates [2007–2023]

Parameter	Estimate	*p*-Value
μ	395E-6	<0.0001
ω	4E-6	<0.0001
β	0.8050	<0.0001
α	0.1103	<0.0001
γ	0.1391	<0.0001

The GJR-GARCH model parameter estimates are extremely statistically significant. Figure 4.D.1 shows the timeplot of the stock index price and of the volatility estimated through the selected model. The volatility in the plot is annualised according to equation (6), and the red dashed horizontal line shows the volatility threshold triggering the rebalancing operations.

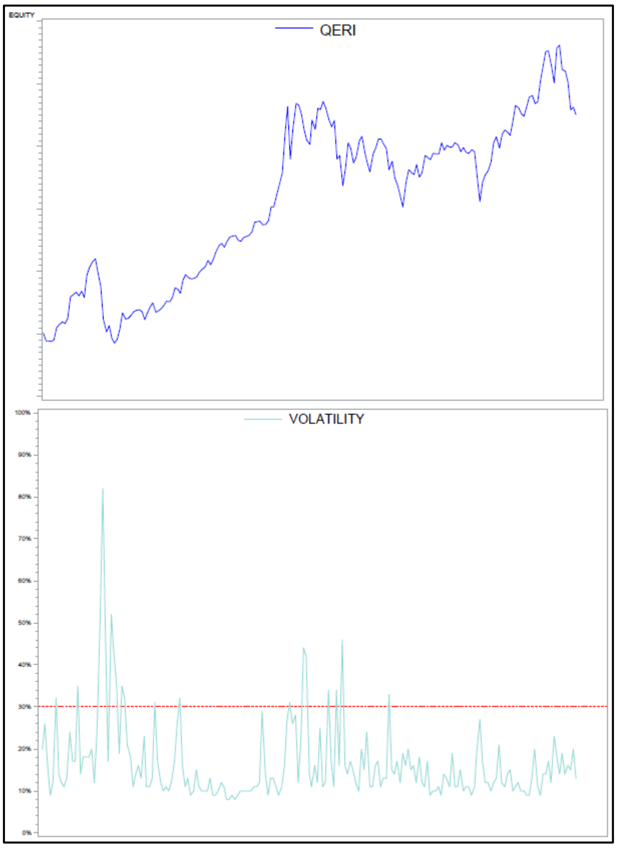

Fig. 4.D.1 – QERI Daily Price (top) & Annualised Volatility Timeplot (bottom) [2007–2023]

Figure 4.D.2 plots the equity curves of the active strategy and the benchmark. The active strategy is characterised by a much smoother equity curve but generates a smaller final capital at the end of the observation period. Thus, it is challenging to determine whether a better risk-adjusted performance has been achieved.

Fig. 4.D.2 –QERI Equity Curve Comparative Analysis: Active Strategy vs Benchmark [2007-2023]

Table 4.D.3 provides the performance metrics of the strategies under assessment. The metrics for which the active strategy outperforms the benchmark are highlighted in green. The active strategy delivers overperformance for all metrics except the annualised return.

Table. 4.D.3 – QERI Performance Comparative Analysis: Active Strategy vs Benchmark [2007- 2023]

	QERI	
Metric	**Active Strategy**	**Benchmark**
R	7.97%	9.39%
RAP	10.60%	9.39%
$STDEV$	14.70%	19.60%
VaR	−34.20%	−45.60%
$CVaR$	−39.20%	−52.30%
MDD	−47.20%	−64.60%
RR	0.54	0.48

Table 4.D.4 shows the outcome of the sensitivity analysis to transaction costs conducted on the active strategy according to equation (21). This table confirms the cost-effectiveness of the active strategy since its break-even Bid-Ask spread stands at 50 basis points, far above its feasible value (10 basis points).

Table. 4.D.4 – QERI Active Strategy Sensitivity Analysis to Transaction Costs [2007-2023]

	Active Strategy		**Benchmark**	
ETF BidAsk [bp]	Turnover Ratio (TURN)	Net RAP	RAP	Break-even
5	5.80	10.46%	9.39%	
10		10.31%	9.39%	
20		10.02%	9.39%	
30		9.73%	9.39%	
50		9.15%	9.39%	***

Overall GARCH Models Comparative Analysis

The proposed model for the TASI fits well as its accuracy is not only in line but even slightly better than that obtained by Al Rahahleh and Kao (2018) with an asymmetric GARCH model on the same stock index. The proposed model for TASI outperforms Al Rahahleh and Kao with a MAPE of 151.9 vs 167.73 and an MSE of 0.002082 vs 0.020179, respectively. It is impossible to compare the previous academic models to the other indices because Derbal *et al.*, (2022), who examined the Qatar stock indices, did not disclose any goodness-of-fit metrics except the Akaike information criterion, which does not allow for a comparative analysis across different samples. Nevertheless, all the goodness of-fit metrics for the remaining GCC stock indices, reported in Table 4.E.1, are in line if not better than that obtained on the TASI.

Table. 4.E.1 – Overall Accuracy of the JGR-GARCH Models

Metric	TASI GJR-GARCH	FADGI GJR-GARCH	QEAS GJR-GARCH	QERI GJR-GARCH
$MAPE$	151.90	129.05	106.14	122.09
MSE	0.002082	0.001255	0.001431	0.001525
History [Years]	20.25	20.25	16.26	16.25

Comparative Analysis of Overall Strategies

Table 4.F.1 provides a synoptic comparative analysis encompassing the active strategy against the benchmark regarding each conventional stock index under assessment. For RAP, the proposed market timing strategy outperforms the passive strategy on all GCC conventional stock indices. The active strategy in particular delivers a RAP differential greater than 2% on any stock index, having as extreme cases the QEAS and the TASI, with a RAP differential of 2.31% and 9.57%, respectively. This differential in RAP results from a drastic reduction of the volatility (STDEV) – on the order of 5% on average – which does not entail a downgrade in profitability (R). In two cases – FADGI and TASI – the profitability is even increased compared to the benchmark.

Table. 4.F.1 – Overall Performance Comparative Analysis: Conventional Indices

	FADGI [2003–2023]		TASI [2003–2023]		QEAS [2007–2023]	
Metric	**Active Strategy**	**Benchmark**	**Active Strategy**	**Benchmark**	**Active Strategy**	**Benchmark**
R	10.40%	10.10%	12.30%	8.63%	7.41%	7.54%
RAP	13.80%	10.10%	18.20%	8.63%	9.85%	7.54%
$STDEV$	13.40%	17.80%	15.40%	21.30%	14.30%	19.00%
VaR	−31.10%	−41.40%	−35.90%	−49.50%	−33.20%	−44.20%
$CVaR$	−35.70%	−47.40%	−41.10%	−56.70%	−38.10%	−50.60%
MDD	−51.10%	−65.70%	−41.70%	−80.00%	−51.70%	−63.20%
RR	0.78	0.57	0.80	0.41	0.52	0.40

Table 4.F.2 is similar to Table 4.5.1 but compares the conventional index to the Islamic index in the context of the Qatar stock exchange – the only exchange where such comparative analysis is possible. Table 4.F.2 shows that for RAP, the active strategy outperforms the passive strategy on both the conventional (QEAS) and the Islamic index (QERI).

Table. 4.F.2 – Overall Performance Comparative Analysis: Conventional vs Shariah Indices

	QEAS [2007–2023]		QERI [2007–2023]	
Metric	**Active Strategy**	**Benchmark**	**Active Strategy**	**Benchmark**
R	7.41%	7.54%	7.97%	9.39%
RAP	9.85%	7.54%	10.60%	9.39%
$STDEV$	14.30%	19.00%	14.70%	19.60%
VaR	−33.20%	−44.20%	−34.20%	−45.60%
$CVaR$	−38.10%	−50.60%	−39.20%	−52.30%
MDD	−51.70%	−63.20%	−47.20%	−64.60%
RR	0.52	0.40	0.54	0.48

Two considerations stem from these empirical data regarding the Islamic index and application of the active strategy to the index:

a) Sticking to the passive strategy, the Islamic index delivers a better RAP than its conventional peer as its return-risk ratio is higher, namely 0.48 vs 0.40, respectively.

b) The active strategy delivers a lower RAP differential on the Islamic index than on its conventional peer.

The first consideration (a) is in line with all the reviewed literature regarding comparative analysis of conventional and Islamic funds. In particular, Islamic funds hit on a better return-to-risk tradeoff, especially when the observation period encompasses a financial crisis. Regarding consideration (b), the RAP improvement from the active strategy being higher on the conventional index than the Islamic index may be attributed to the Islamic index's inherent superiority in risk-adjusted returns. Thus, the Islamic index has less room for improvement.

Overall Cost-Effectiveness of the Active Strategy

Table 4.G.1 provides a synoptic view on the cost-effectiveness of the active strategy, which recaps the outcomes of the 'sensitivity analysis to transaction costs' separately conducted on the four GCC stock indices. In a worst-case scenario simulation, even assuming a bid-ask spread of 0.50% (50 bp), which is five times bigger than the per-transaction cost deemed feasible by Zakamulin (2014) for institutional investors (0.10% or less), the downgrade of the active strategy in terms of 'net RAP' (net risk-adjusted performance) would still not make the passive strategy (benchmark) preferable. Hence, the proposed market timing strategy appears to be cost effective for the GCC financial markets as a whole.

Table. 4.G.1 – Overall Cost-Effectiveness of the Active Strategy

	FADGI		**TASI**		**QEAS**		**QERI**	
ETF BidAsk [bp]	Net RAP	Bench-mark	Net RAP	Bench-mark	Net RAP	Bench-mark	Net RAP	Bench-mark
10	13.48%	10.10%	17.73%	7.21%	9.50%	7.54%	10.31%	9.39%
15	13.32%	10.10%	17.49%	7.21%	9.32%	7.54%	10.17%	9.39%
20	13.17%	10.10%	17.26%	7.21%	9.15%	7.54%	10.02%	9.39%
25	13.01%	10.10%	17.02%	7.21%	8.97%	7.54%	9.88%	9.39%
30	12.85%	10.10%	16.78%	7.21%	8.80%	7.54%	9.73%	9.39%
50	12.22%	10.10%	15.84%	7.21%	8.09%	7.54%	9.15%	9.39%

CONCLUSION

Regarding volatility forecasting, the proposed GJR-GARCH model provides accurate estimates characterised by small goodness-of-fit metrics in line if not better than those obtained by other scholars (when comparable) on all GCC stock indices. Moreover, the forecasted volatility can replace the implied volatility as a market timing trigger. This property suggests that volatility-based market timing strategies can also be applied to markets for which the implied volatility data are unavailable, typically emerging markets.

For the market timing strategy, the strategy formulated and backtested in the present paper achieves its goals on all the GCC stock indices. The model in this study delivers significantly lower volatility – 5% lower, on average – and almost equal profitability (annualised return) – even higher profitability for FADGI and TASI. Consequently, the RAP of the strategy in this work overperforms not only in comparison to conventional stock indices but also Islamic peers (QERI). However, the active strategy performance differential is smallest for the Islamic index. This finding may be attributable to the passive replication of the Islamic index already delivering a good return-risk ratio, namely the second-best return-risk ratio among the four indices under assessment.

Unlike similar academic models that completely disregard the subject of rebalancing costs (Bantwa, 2020; Copeland and Copeland, 1999), the active strategy in this study shows distinctive cost-effectiveness properties that make it viable as a real asset management tool. This cost-effectiveness stems from the limited number of securities involved – just one index-replicating ETF – and the limited turnover ratio, which results from the sufficiently high volatility threshold adopted for the rebalancing.

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