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Forecasting the volatility of the Dow Jones Islamic Stock Market Index: Long memory vs. regime switching☆

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ABSTRACT

The financial crisis has fueled interest in alternatives to traditional asset classes that might be less affected by large market gyrations and, thus, provide for a less volatile development of a portfolio. One attempt at selecting stocks that are less prone to extreme risks is obeyance of Islamic Sharia rules. In this light, we investigate the statistical properties of the Dow Jones Islamic Stock Market Index (DJIM) and explore its volatility dynamics using a number of up-to-date statistical models allowing for long memory and regime-switching dynamics. We find that the DJIM shares all stylized facts of traditional asset classes, and estimation results and forecasting performance for various volatility models are also in line with prevalent findings in the literature. With this proximity to standard asset classes, investments in the DJIM could hardly provide a cushion against extreme market fluctuations. Among the various models, the relatively new Markov-switching multifractal model performs best under the majority of time horizons and loss criteria. Long memory GARCH-type models (FIGARCH and FITVGARCH) always improve upon the short-memory GARCH specification and additionally allowing for regime changes can further improve their performance, and also enhance the accuracy of value-at-risk forecast.

1. Introduction

In the wake of the recent global financial crisis, it is now well-established that enormous negative impacts have been felt by conventional institutions and markets. Understandably, a need has been felt for exploring alternatives to conventional financial practices that allow to reduce investment risks, increase returns, enhance financial stability, and reassure investors and financial markets. Herein one has observed a tremendous growth in Islamic Finance products and instruments. These services now sum up to a global industry amounting to around US $2 trillion in assets; 80% of which is accounted for by Islamic banks or Islamic

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windows of conventional banks, 15% *Sukuk* (Islamic bonds), 4% Islamic mutual funds, and 1% *Takaful* (Islamic insurance) (Abedifar, Ebrahim, Molyneux, & Tarazi, 2015). As indicated by Abedifar et al. (2015), even though Islamic banking and financial assets comprise less than 1% of total global financial assets, it has grown faster than conventional finance since the outbreak of the crisis. More importantly, this trend is expected to continue into the near future (Abedifar et al., 2015). In addition to the growth in banking assets, there is increasing competition between major financial centers like London, Kuala Lumpur and Dubai, to take the lead in the Islamic bonds issuance and to develop a broader array of Islamic investment products (Abedifar et al., 2015; Nazlioglu, Hammoudeh, & Gupta, 2015).

To understand this tremendous growth in Islamic Finance, following the crisis, one needs to understand the two underlying principles that define this market, namely the prohibition of interest (*Riba*) and adherence to other Islamic law (*Shariá*) requirements (Abedifar et al., 2015). As noted by Hammoudeh, Mensi, Reboredo, and Nguyen (2014), *Shariá* compliance imposes two types of restrictions on Islamic equity finance: (i) Any companies with involvement in alcohol, tobacco, pork-related products, gambling, entertainment, weapons, and conventional financial services are screened out, and (ii) Financial ratios are used to remove companies based on debt and interest income levels. The *Shariá*-based principle thus aims to prevent speculative financial transactions. For instance, Islamic finance prohibits financial derivatives (which do not have any underlying real transactions like futures and options), government debt issues with a fixed coupon rate, hedging by forward-sale, interest-rate swaps, and any other transactions,like short-sales, which involves items that are not in the ownership of the seller physically (Hammoudeh et al., 2014).

Against this backdrop, in this paper, we aim to model and forecast conditional volatility of the returns of the Dow Jones Islamic Market World Index (DJIM), accounting for both the possibility of long memory and structural changes in the volatility process. The choice of the DJIM is justified by the fact that it is the most widely used, and most comprehensive representative time series for the Islamic stock market (Hammoudeh et al., 2014). Appropriate modeling and forecasting of volatility of the DJIM is important due to the fact that, when volatility is interpreted as uncertainty, it becomes a key input to investment decisions and portfolio choices. The basic idea behind Islamic Finance rests on the belief that it is less riskier than conventional equity markets, given the type of investments it involves. However, the statistical evidence in the literature regarding this view is, at best, mixed (Abedifar et al., 2015). Hence, our analysis of volatility (if perceived as uncertainty) of the DJIM is of paramount importance, since based on our results relative to the widely-available evidence of volatility modeling and forecasting for the conventional equity markets based on the models we use here as well, we can determine whether Islamic Finance is indeed different from conventional markets or not. Understandably, if it tends to behave similarly to conventional equity markets, it too can have wide repercussions on the economy as a whole, via its effect on real economic activity and public confidence. Hence, estimates of market volatility can serve as a measure for the vulnerability of the DJIM. While there is a rich literature on volatility modeling and forecasting of conventional financial assets, not much evidence exists to date with respect to the Islamic stock market. We try to fill part of this gap using some of the most advanced tools available in contemporaneous econometric literature.

There exists a large literature on evidence of long memory in the conditional volatility of various financial time series (Baillie, Bollerslev, & Mikkelsen, 1996; Bollerslev & Mikkelsen, 1996; Davidson, 2004; Ding, Granger, Engle, & Engle, 1993; Lobato & Savin, 1998; Andersen & Bollerslev, 1997). At the same time, there is also another literature that finds evidence of structural changes in the volatility process of financial variables (Andreou & Ghysels, 2002; Bos, Franses, Ooms, & Ooms, 1999; Rapach, Strauss, & Wohar, 2008). Not surprisingly, a parallel literature exists that emphasizes the simultaneous role of both long memory and structural changes in characterizing financial returns volatility (Baillie & Morana, 2007; Beine & Laurent, 2000; Lobato & Savin, 1998; Martens, van Dijk, & de Pooter, 2004; Morana & Beltratti, 2004).

Given this line of research on the co-existence of both long memory and structural change in the volatility processes of financial market data, and following Ben Nasr, Boutahar, and Trabelsi (2010) and Ben Nasr, Ajmi, and Gupta (2014), we estimate a model for the DJIM returns that allows the volatility of the returns to accommodate for both these features. The idea is to allow for time-dependent parameters in the conditional variance equation of a Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity (FIGARCH) model. Specifically speaking, the change of the parameters is assumed to evolve smoothly over time using a logistic transition function, to yield a so-called Fractionally Integrated Time Varying Generalized Autoregressive Conditional Heteroskedasticity (FITVGARCH) model.

Further, a related line of research on long memory and structural changes in volatility discusses the connection between these phenomena. In fact, volatility persistence may be due to switching of regimes in the volatility process, as first suggested by Diebold (1986) and Lamoureux and Lastrapes (1990). This literature concludes that it could be very difficult to distinguish between true and spurious long memory processes. This ambiguity motivates us to include a relatively new type of Markov-switching model in addition to our array of volatility models (i.e., GARCH, FIGARCH, FITVGARCH) — the Markov-switching multifractal (MSM) model of Calvet and Fisher (2001). Despite allowing for a large number of regimes, this model is more parsimonious in parameterization than other regime-switching models. It is furthermore well-known to give rise to apparent long memory over a bounded interval of lags (Calvet & Fisher, 2004) and it has limiting cases in which it converges to a 'true' long memory process. To the best of our knowledge, this is the first attempt in forecasting the volatility process for the DJIM returns using a wide variety of advanced volatility models trying to capture long-memory, structural breaks and the fact that structural breaks can lead to the spurious impression of long-memory. The only closely related paper is that of Ben Nasr et al. (2014), which compared the in-sample fits of a FITVGARCH with a FIGARCH model, to show the superiority of the former. However, as is well-known, better in-sample fit does not guarantee superiority of a model based on out-of-sample forecasts, which is, more importantly, what is required for portfolio allocation. Further, unlike us Ben Nasr et al. (2014), did not include the powerful MSM