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Modelling volatility persistence under stochasticity assumptions: evidence from common and alternative investments

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ABSTRACT

Long-range memory estimation is a functional statistical mechanics technique to assess predictability in time series. In our work, we scrutinize the long-range dependence structure of volatility in a plethora of alternative and common investments via the use of a fractionally integrated conditional heteroscedastic model. Particularly, we evaluate the fractional persistence parameter of the temporal dynamics for the volatility series of Islamic, socially responsible and common investment indices related to the world major international stock markets. Long-range memory in volatility is measured under different types of market randomness, namely distributional specifications wherein the stochastic error components follow Normal and non-Normal densities. Our empirical results show strong evidence of long-range dependence in the volatility of alternative and common investments under all stochasticity assumptions. Furthermore, we show that the randomness profile has no effect upon the variability of long-range memory. We indicate differences in the statistical significance of the long-range memory across the investigated markets as well as in the degree of persistence. Our findings yield serious implications in terms of quantitative portfolio management and optimization.

1. Introduction

According to the theory of market efficiency in financial markets, the latter cannot be predicted as asset prices fully adjust to reflect all available information and consequently exhibit martingale dynamics. Within this framework, past prices cannot be used to forecast future ones. Recently, the analysis of efficiency in alternative investments is receiving a growing interest, with significant works emerging in the relevant literature such as [1–5] wherein efficiency of Islamic stock markets was examined, [6–10] in which ecological investments were studied or [11–15] that presented new results on crypto-currencies. Additionally, a rolling-window based approach was employed to measure the time evolution of dependence in a large set of various alternative markets in [16]. Nevertheless, in the context of volatility modeling a small amount of academic works has been presented. Few paradigms include the investigation of long-range memory in conventional banks and in Islamic banks (*e.g.*, in [17]), where it was found that volatility is more persistent in conventional banks than in Islamic banks. Also, long-memory GARCH-type models were found to be more effective than short-memory conventional GARCH specifications in improving the prediction accuracy when applied to the volatility of Dow Jones Islamic stock market index [18]. Above and beyond, volatilities of Islamic Dow Jones indexes were found to be more dependent upon the West Texas Intermediate and Brent oil prices than variances of the conventional Dow Jones index [19]. Indeed, there is evidence of asymmetric shocks in the volatility of environmental markets suggesting that each one reacts to different news sources from different markets and adjusts accordingly [20].

The purpose of the current work is to assess the predictability - hence market efficiency- in the volatility time series of alternative and conventional investments based on measuring long-range memory, fractality and inherent randomness. Alternative investments include Islamic (Shariah), ecology, sustainability, and ethical investments. Particularly, Islamic (Shariah) investments obey to Islamic rules and guidelines, ecology investments follow long-term economic, environmental and social criteria, sustainability

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investments are committed to mitigating risks arising from climate change, and ethical investments exclude companies that generate revenue from alcohol, tobacco, gambling, armaments and firearms, and/or adult entertainment. On the other hand, common investments include world major stock markets.

We contribute to the existing literature [1–20] in the following ways: firstly, we empirically assess the differences between long-memory measures in volatility series of numerous distinctive categories of investments, *i.e.*, alternative (Islamic and socially responsible) and common investments. The socially responsible investments include ecology, sustainability and ethical market positions. Secondly, we explore the relative effect of distributional variations on the estimated long-range memory parameters of the fractional time series models employed. The long-range memory coefficient is estimated under four different assumption of randomness, namely normal, standard Student-*t*, generalized error distribution (GED) and skewed-*t*. Thirdly, a large set of market indices is considered for generalization of our empirical results as well toward a comprehensive attempt of robustness analysis. Fourthly, we check whether differences in long-range memory measures exist between alternative and common investments. In fact, such comparative investigation will shed light on volatility dynamics in order market agents to reach better investment decisions on volatility forecasting, derivative pricing, portfolio optimization and capital allocation.

We employ a fractionally integrated generalized autoregressive conditional heteroscedastic (FIGARCH) modeling [21] to each investment time series dataset so as to obtain the estimated long-range memory parameters under variant distributional assumptions. Moreover, a plethora of robustness statistical tests are applied to the estimated populations of long-range memory coefficients to verify if there are significant differences between alternative and conventional investments. The remainder of our paper is organized as follows: Section 2 presents the fractional IGARCH methodology in order to capture fractality and persistence dependence. In Section 3 we illustrate our empirical results in detail. Finally, Section 4 concludes with important economic implications.

2. Methodological framework

2.1. Conditional heteroscedastic fractality

The fractionally integrated generalized autoregressive conditional heteroscedastic (FIGARCH) model [21] captures memory in estimated volatility time series by incorporating lagging information features inside model specification. It is employed in our study to estimate volatility and to assess its corresponding memory structure under different distributional assumptions. We consider a general form of return series modeling denoted by $r_t = \log(p_t) - \log(p_{t-1})$ where t is the time script and p denotes prices. Then, the benchmark GARCH(1,1) model [22] of conditional standard deviation h_t, for simplicity herein, is given by:

$$r_t = \mu + \phi r_{t-1} + \varepsilon_t + \theta\varepsilon_{t-1} \tag{1}$$

where,

$$\varepsilon_t = h_t^{0.5}\eta_t \tag{2}$$

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \tag{3}$$

where μ is the conditional mean, ϕ and θ are coefficients of the autoregressive moving average (ARMA) specification utilized to incorporate the conditional mean μ, h is the conditional standard deviation used to represent volatility, and finally the stochastic component $\eta \sim N(0,1)$. Recall that Eq. (3) corresponds to the popular GARCH(1,1) model, which indeed is widely employed in the literature due to its effectiveness and simplicity. As opposed, the FIGARCH (1,d,1) model is given as follows:

$$h_t = \omega + \beta h_{t-1} + \left[1 - (1-\beta L)^{-1}(1-\phi L)(1-L)^d\right]\varepsilon_t^2 \tag{4}$$

where d is the fractional integration parameter to characterize long-range memory in volatility series h_t, with $0 \le d \le 1$, $\omega > 0$, ϕ, $\beta < 1$, and L the lag operator. When $0 < d < 1$ intermediate ranges of persistence are allowed. When $d = 1$ volatility shocks exhibit full integrated persistence. Finally, when $d = 0$ volatility shocks decay with a geometric rate. In our work, all parameters of the FIGARCH model are estimated via the use of the quasi-maximum likelihood method.

2.2. Distributional variations

Modeling conditional volatility h_t can entail various distributional assumptions for the stochastic market term ε_t *e.g.*, normal, standard Student-*t*, generalized error distribution (GED) or skewed-*t*. Recall that $\varepsilon_t = h_t^{0.5}\eta_t$and $\eta \sim N(0,1)$. Hereafter we present the descriptions of their respective density functions. For the normal distribution, the density function is represented by:

$$f(\eta_t) = \frac{1}{\sqrt{2\pi h_t}} e^{-\frac{\eta_t^2}{2h_t}} \tag{5}$$

Next, the density of the standard Student-*t*, is given by:

$$f(\eta_t) = \frac{\Gamma(\nu + 1/2)}{\Gamma(\nu/2)\sqrt{\pi(\nu-2)h_t}}\left[1 + \frac{\eta_t^2}{(\nu-2)h_t}\right]^{(\nu+1/2)} \tag{6}$$

where ν is the degree of freedom used to control fat-tailedness and the peakedness of the distribution, and Γ is the Gamma function. For the GED, the density function is expressed as:

$$f(\eta_t) = \frac{\nu e^{-0.5\left|\frac{\eta_t}{\lambda\sqrt{h_t}}\right|}}{\lambda 2^{(\nu+1/\nu)}\Gamma(1/\nu)} \tag{7}$$

where,

$$\lambda = \left[\frac{2^{(-2/\nu)}\Gamma(1/\nu)}{\Gamma(3/\nu)}\right]^{0.5} \tag{8}$$

Finally, the skewed-*t* density is described as:

$$\begin{aligned} f(\eta_t) &= (2/(k+1/k))\, sg(s\eta_t + m),\ if\ \eta_t < -m/s \\ f(\eta_t) &= (2/(k+1/k))\, sg((s\eta_t + m)/k),\ if\ \eta_t \ge -m/s \end{aligned} \tag{9}$$

where $g(\cdot)$ is the symmetric student density, k is the asymmetric coefficient, and m and s^2 are respectively the mean and variance of the non-standardized skewed Student function. These are given by:

$$m = \frac{\Gamma((\nu-1)/2)\sqrt{\nu-2}}{\sqrt{\pi}\,\Gamma(\nu/2)}\left(k - \frac{1}{k}\right) \tag{10}$$

$$s^2 = \left(k^2 + \frac{1}{k^2} - 1\right) - m^2 \tag{11}$$

The normal distribution is widely adopted in the literature as it represents the assumption of Gaussianity of the returns, yet with significant flaws. Alternative distributions are more suitable and desirable as returns series exhibit deviations from normality almost always in the financial markets. In this regard, the standard Student-*t* distribution integrates fat-tails, the skewed-*t* is capable to flexibly fit leptokurtic and skewed return distributions, while the generalized error distribution (GED) poses the property of flexible symmetry and tails as well. Hence, under each distribution assumption, a particular long memory parameter d is obtained for each of our investment segment market positions.