Journal of Empirical Finance 32 (2015) 63–79

Contents lists available at ScienceDirect

Journal of Empirical Finance

journal homepage: www.elsevier.com/locate/jempfin

The frequency of regime switching in financial market volatility

Ahmed BenSaïda

LaREMFiQ Laboratory, IHEC, Sousse University, B.P. 40, Route de la ceinture, Sahloul 3, Sousse 4054, Tunisia

ARTICLE INFO

Article history:
Received 30 May 2014
Received in revised form 11 January 2015
Accepted 16 March 2015
Available online 21 March 2015

JEL classification:
G17
C22
C58

Keywords:
Volatility
Risk response
Simulation
Skewed generalized *t*
Switching regime

ABSTRACT

The mechanism of risk responses to market shocks is considered as stagnant in recent financial literature, whether during normal or stress periods. Since the returns are heteroskedastic, a little consideration was given to volatility structural breaks and diverse states. In this study, we conduct extensive simulations to prove that the switching regime GARCH model, under the highly flexible skewed generalized *t* (SGT) distribution, is remarkably efficient in detecting different volatility states. Next, we examine the switching regime in the S&P 500 volatility for weekly, daily, 10-minute and 1-minute returns. Results show that the volatility switches regimes frequently, and differences between the distributions of the high and low volatility states become more accentuated as the frequency increases. Moreover, the SGT is highly preferable to the usually employed skewed *t* distribution.

1. Introduction

Financial market risk, usually measured by the volatility of the returns, is changing over time. Consequently, researchers have introduced a large variety of heteroskedastic GARCH-type models to investigate the ever fluctuating volatility. However, these models consider that the mechanism of risk responses to market's multiple shocks remains stagnant by fixing the coefficients generating the conditional volatility. Andreou & Ghysels (2002), among others, have argued that financial returns are known to exhibit sudden jumps in their volatility, a phenomenon caused essentially by structural breaks, and cannot be captured by regime-invariant parameters such as the single-state GARCH-type models. Abdymomunov (2013) and Augustyniak (2014) have confirmed that the volatility is indeed subject to two regimes: high and low (or normal), where the high risk regime is considered as a financial stress and closely related to periods of crisis. Alternatively, Hillebrand (2005) has affirmed that the nearly integrated behavior, generally observed in classical GARCH models, is the consequence of structural changes. Besides, structural breaks in volatility dynamics can be the consequence of changes in risk perception. In fact, given the same information to an investor, the risk is perceived differently during periods of crisis with higher risk, and during normal periods with lower risk (Hoffmann et al., 2013).

The literature dealing with structural changes in volatility has emerged since the seminal paper of Hamilton & Susmel (1994). Mainly, two branches exist; some researchers consider that the risk is changing over different pre-identified periods, yet its structure is invariant during the same period by applying a time varying GARCH model (TV-GARCH), where breaks in the volatility are known, and the coefficients of the conditional volatility are held constant during the same period (Ichiue & Koyama, 2011; Karanasos et al., 2014; Liu et al., 2012). The second branch, however, considers that the volatility is subject to multiple unobservable or hidden

E-mail address: ahmedbensaida@yahoo.com.

http://dx.doi.org/10.1016/j.jempfin.2015.03.005
0927-5398/

regimes – typically two regimes – and the transition between the different states is defined by a probability matrix, this approach applies a Markov-switching regime GARCH model, MS-GARCH henceforth (Bauwens et al., 2014; Geweke & Amisano, 2011; Marcucci, 2005). MS-GARCH models are more difficult to estimate due to the path-dependency or tractability problem explained by Cai (1994) and Hamilton & Susmel (1994). Indeed, since the regimes are unobservable, the conditional variance at time t depends on all paths engendered by the different regimes, owing to the recursive property of GARCH process. Thus, the sample likelihood function is computed by integrating over all possible regime paths, which increase exponentially with time t and the number of switching regimes, and its maximum becomes intractable. This problem is solved by Gray (1996) and improved by Klaassen (2002) by incorporating the conditional expectations of the lagged conditional variances into the GARCH formulation, therefore allowing the tractability of the MS-GARCH model. However, to our knowledge, all studies dealing with the switching regime volatility have merely considered weekly or at most daily returns under the normal or the Student's t distribution, a convenient assumption due to the simplicity and analytical tractability of these distributions (Ardia, 2009; Litimi & BenSaïda, 2014; Sun & Zhou, 2014; Wilfling, 2009). The asymmetry is usually captured by estimating the GJR model of Glosten et al. (1993) (Ardia, 2009; Daouk & Guo, 2004; Marcucci, 2005), although Alexander & Lazar (2009) have mentioned that the leverage effect has no influence when a skewed distribution is used. Moreover, low frequency data cannot adequately detect the rapidity of the volatility's regime shifting. Hence, for the various aforementioned reasons, the main objective of this study is to investigate the frequency of regime switching in the financial market risk over different time scales, and under the highly flexible skewed generalized t (SGT) distribution.

The contribution is threefold; first, we verify the efficiency of the MS-GARCH model under the highly flexible skewed generalized t distribution in capturing both high-stress regime and normal-stress regime through extensive simulations; second, we estimate a GARCH switching regime model for weekly, daily, and intra-daily financial returns, and corroborate the likelihood tractability of the used approach; and third, we illustrate the efficiency of the SGT over the skewed t distribution. The remainder of this paper is as follow: Section 2 describes the methodology to perform a tractable MS-GARCH estimation; in Section 3 we simulate SGT pseudorandom numbers to generate high-volatility and normal-volatility returns into one single sample to confirm the effectiveness of the MS-GARCH model; Section 4 presents the data and summary statistics; Section 5 discusses the results; and finally we conclude in Section 6.

2. Concepts and methodology

2.1. Switching regime GARCH model

In general, the volatility evolves according to two different regimes: a high-stress regime, where the risk tends to be higher — generally during periods of financial crisis, and a low-stress regime, where the risk tends to be normal. As pointed out by Hoffmann et al. (2013), investors' risk perception fluctuates significantly during financial crisis, more than it does during normal non-crisis periods. Consequently, and in alignment with Abdymomunov (2013) and Augustyniak (2014), we suspect that during these high-stress periods, the volatility tends to be higher than during normal periods; hence, we see no reason to extend our analysis for more than two regimes.

Our model is the MS-GARCH with orders (1,1). There are many alternatives in choosing other GARCH-type models; however, Hansen & Lunde (2005) found no evidence that the GARCH model with orders (1,1) is outperformed by other more sophisticated GARCH-type models.

Let $\{s_t\}$ be a state variable indicating a Markov chain, *i.e.*, s_t represents the diverse regimes for a time-dependent variable. The state variable is supposed to evolve according to a first-order Markov chain with a probability transition matrix P, which indicates the probability of being in state j at time t knowing that at time $t-1$ the state was i. For numerous regimes, each element of the transition matrix is defined in Eq. (1).

$$p_{i,j} = \Pr(s_t = j | s_{t-1} = i) \tag{1}$$

In the case of two regimes, $s_t = \{1,2\}$, the probability transition matrix is defined in Eq. (2), where each column sums up to one.

$$P = \begin{pmatrix} p_{1,1} & p_{2,1} \\ p_{1,2} & p_{2,2} \end{pmatrix} = \begin{pmatrix} p & 1-q \\ 1-p & q \end{pmatrix} \tag{2}$$

The ergodic probability, or the unconditional probability of being in state $s_t = 1$, is given by Eq. (3).

$$\pi_1 = \frac{1-q}{2-p-q} \tag{3}$$

The model to be estimated is a MS-GARCH(1,1) defined in Eq. (4).

$$\begin{cases} r_t = c_k + u_{t,s_t} \\ u_{t,s_t} = \varepsilon_{t,s_t}\sqrt{h_{t,s_t}} \\ h_{t,s_t} = \alpha_{0,k} + \alpha_{1,k} u^2_{t-1,s_t} + \beta_{1,k} h_{t-1} \end{cases} \tag{4}$$