Economic Modelling 31 (2013) 87–93

Contents lists available at SciVerse ScienceDirect

Economic Modelling

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

Regime-switching in volatility and correlation structure using range-based models with Markov-switching

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ARTICLE INFO

Article history:
Accepted 8 November 2012

JEL classification:
C22
G01
G10

Keywords:
Range-based model
Markov-switching method
Volatility
Correlation

ABSTRACT

This study examines latent shifts in the conditional volatility and correlation for the U.S. stock and T-bond data using the two-state Markov-switching range-based volatility and correlation models. This paper comes up with clear evidence of volatility regime-switching in stock indices and T-bond over the crisis period. As regards the process of correlation, we also find evidence of regime changes in correlations between stock indices and T-bond over several financial crises. We conclude that the phenomena of both volatility and correlation regime-switching are triggered by these financial crises. In addition, the range-based volatility and correlation model with regime-switching method could explicitly point out the true date of structure changes in the data generating process for volatility and correlation variables.

1. Introduction

For the recent decade, global financial markets have suffered several devastating shocks. The period surrounding the WorldCom scandal in 2002, the beginning of subprime crisis in the fall of 2007, the Lehman collapse on September, 2008 and the 2009 European sovereign-debt crisis etc. These financial crises not only destroy the asset values but also implicitly change the volatility structure of asset returns and the correlation structure between two assets. Using a more flexible volatility and correlation model to reassess the related processes is essential for a major overhaul of bank legislation and bank regulation. This study uses a two-state Markov-switching range-based volatility and dynamic conditional correlation (DCC) model to explore the different financial turmoil triggered regime switches in volatilities and corresponding correlation structures. The classical Markov-switching approach proposed by Hamilton (1989, 1990) is developed to delineate the uncertain regime shifts in the data generating process about economic and financial variables. Therefore, it is natural to introduce the framework of the Markov-switching into the range-based volatility and correlation models to discuss the impact of unusual events on the patterns of volatility and correlation processes.

There are lots of related literatures about volatility and correlation models with the Markov-switching method. The idea of regime switches in stock return volatility has been documented by Lamoureux and Lastrapes (1990), Hamilton and Susmel (1994), Dueker (1997), and more recently by Liu et al. (2012). The foregoing studies presented that considering the Markov-switching method in model specification for stock market data can capture the richer dynamics volatility process and obtain accurately in data fitting and forecasts. Furthermore, Cai (1994), Gray (1996), Edwards and Susmel (2003), and Sun (2005) demonstrate the phenomenon of regime shifts in interest rate volatility process, too. According to their empirical results, they explicitly point out that the distinct volatility regimes are highly related to macroeconomic shocks. In terms of literature on the issue of dynamical correlation pattern, Billio and Caporin (2005) and Haas (2010) illustrate the phenomenon of regime-switching in correlation processes between global stock market indices and evidence that the Markov-switching DCC model is superior to those multivariate GARCH models. Generally speaking, the previous studies provide empirical supports that the volatility and correlation models with the Markov-switching method outperform the single-regime models in data fittings and statistic prediction. In the case of estimating the dynamical volatility and correlation models, some recent literature consider that using the range data to replace the return data can obtain many advantages in parameter

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0264-9993/$ – see front matter
http://dx.doi.org/10.1016/j.econmod.2012.11.013

Table 1
Descriptive statistics for the daily ranges of the Nasdaq, S&P 500 and T-bond (2002.1.3–2011.12.31).

	Nasdaq	S&P 500	T-bond
Mean	1.656	1.509	2.091
Median	1.383	1.192	1.739
Maximum	11.129	10.904	20.104
Minimum	0.252	0.239	0.207
Std. Dev.	1.074	1.158	1.341
Skewness	2.614	3.082	2.616
Kurtosis	14.729	17.963	20.693
Bera–Jarque	17,306.80	27,488.85	35,429.05
Observations	2519	2519	2498

Notes: The Bera–Jarque is the statistic for normality test.

Table 2
Range-based volatility model fitting for the Nasdaq, S&P 500 and T-bond (2002.1.3–2011.12.31).

$R_t = \lambda_t \varepsilon_t \quad R_t | I_{t-1} \sim \exp(1, \cdot)$
$\lambda_t = \omega + \alpha R_{t-1} + \beta \lambda_{t-1}$

	Nasdaq	S&P 500	T-bond
$\hat{\omega}$	0.003 (0.001)	0.003 (0.001)	0.001 (<0.001)
$\hat{\alpha}$	0.128 (0.020)	0.107 (0.015)	0.044 (0.006)
$\hat{\beta}$	0.838 (0.024)	0.857 (0.019)	0.948 (0.007)
$Q^2(10)$	12.068 [0.281]	9.636 [0.473]	8.058 [0.623]
LLF	−382.970	−398.718	−1355.670

Notes: λ_t and R_t are the range-based conditional volatility and range, respectively. *LLF* is the log likelihood function, p-values are in brackets and the numbers in parentheses are robust standard errors proposed by Bollerslev and Wooldridge (1992). $Q^2(10)$ is the statistics for serial correlation up to the 10th order in the squared standardized residuals.

estimates of models and out-of-sample prediction for dependent variable.[1] For this reason, we take both the range-based volatility and correlation models as the basic frameworks for our analysis then introduce the Markov-switching method into these two models, respectively. We expect that the estimation results of our proposed models can capture how financial market volatility and correlation processes respond to the impacts of financial turmoil.

Our contributions to the related literature are twofold. Firstly, we confirm definitely that the volatility regime-switching in both two stock indices and T-bond are salient. In particular, there is a specific corresponding relationship between volatility regime and financial turmoil for these market data. Namely, during the financial crisis period, the volatility process stays in the high volatility regime; but in the tranquil period, the volatility process moves to the low volatility state. Besides, we find that the impacts of these financial crises on T-bond volatility are usually more persistent than that on stock indices' volatility. This finding could be attributed to the expectation of a falling interest rate environment. According to the switching frequency, it seems that the influences of shocks to S&P 500 volatility are more sensitive than that to Nasdaq and T-bond volatility. Secondly, from empirical results, the regime-switching in dynamical correlation processes between stock indices and T-bond is an obvious phenomenon. Moreover, using the range-based DCC model without structure change consideration for data fitting is liable to underestimate the short-run effect of correlation process over the tranquil period.[2] In addition, the impacts of the 2002 WorldCom scandal on dynamical correlations between stock indices and T-bond are more persistent than the dynamical correlation between the stock indices of Nasdaq and S&P 500. A series of financial crises from 2007 to 2009 triggered the structure changes in correlation processes between stock indices and T-bond in advance.

The remainder of this paper is organized as follows. Section 2 describes the setting of the two-state Markov-switching range-based volatility and correlation models. Section 3 reports the empirical results and makes constructively discussions for these findings. Section 4 summarizes the results and presents the concluding remarks.

2. Methodology

The main purpose for this section is to express volatility and correlation models with the Markov-switching mechanism.

[1] The range data can be defined as the difference of the highest and lowest asset prices during a fixed time interval. Also see Parkinson (1980), Alizadeh et al. (2002), Brandt and Jones (2006), Chou (2005), Chou et al. (2009) and Chou and Liu (2010).

[2] The short-run effect of correlation process means that the estimated immediate impacts of shocks on dynamic correlation process from the DCC model, also see the empirical results in this study later.

2.1. Two-state Markov-switching range-based volatility model

Considering the two-state nonlinear structure in dynamical volatility process, we construct the two-state Markov-switching range-based volatility model as

$$R_t = \lambda_{s_t,t}\varepsilon_t, \quad \varepsilon_t | I_{t-1} \sim exp(1, .) \tag{1.1}$$

$$p_{ij} = Pr(s_t = j | s_{t-1} = i), \quad i, j = 1, 2 \tag{1.2}$$

$$\lambda_{s_t,t} = \omega_{s_t} + \alpha_{s_t} R_{t-1} + \beta_{s_t} \lambda_{s_t,t-1} \tag{1.3}$$

where R_t is the observed range in logarithm type during the time interval t, ε_t is assumed to follow the exponential distribution with a unit mean, and S_t follows a Markov chain with two-state space $\mathbf{S} = \{1,2\}$. The transition probability is presented in Eq. (1.2). According to the probability axiom, the sum of probabilities has to satisfy $\sum_{j=1}^{2} p_{ij} = 1$ for $i = 1$, 2, and

Table 3
Markov-switching range-based volatility model for the Nasdaq, S&P 500 and T-bond (2002.1.3–2011.12.31).

$R_t = \lambda_{s_t,t}\varepsilon_t \varepsilon_t | I_{t-1} \sim exp1, (\cdot)$
$\lambda_{s_t,t} = \omega_{s_t} + \alpha_{s_t} R_{t-1} + \beta_{s_t} \lambda_{s_t,t-1}$
$p_{ij} = \Pr(s_t = j | s_{t-1} = i) i, j = 1, 2.$

	Nasdaq	S&P 500	T-bond
Low volatility regime			
$\hat{\omega}_1$	0.001 (<0.001)	0.001 (0.001)	<0.001 (<0.001)
$\hat{\alpha}_1$	0.032 (0.015)	0.028 (0.020)	0.008 (0.005)
$\hat{\beta}_1$	0.949 (0.019)	0.949 (0.028)	0.985 (0.007)
$\hat{p}_{11}$	0.998 (0.120)	0.996 (0.176)	0.999 (0.117)
$\hat{\pi}^1_\infty$	0.732	0.556	0.574
High volatility regime			
$\hat{\omega}_2$	0.020 (0.006)	0.005 (0.003)	0.004 (0.002)
$\hat{\alpha}_2$	0.305 (0.140)	0.171 (0.065)	0.098 (0.027)
$\hat{\beta}_2$	0.596 (0.126)	0.790 (0.074)	0.883 (0.030)
$\hat{p}_{22}$	0.993 (0.117)	0.995 (0.245)	0.998 (0.158)
$\hat{\pi}^2_\infty$	0.268	0.444	0.426
LLF	−369.880	−392.205	−1340.835
LR-test statistic	26.180 [<0.001]	13.026 [0.011]	29.670 [<0.001]

Notes: λ_t and R_t are the range-based conditional volatility and range, respectively. *LLF* is the log likelihood function, p-values are in brackets and the numbers in parentheses are robust standard errors proposed by Bollerslev and Wooldridge (1992). The probability of staying in the low volatility state is p_{11}, and that of staying in the high volatility state is p_{22}. The stationary regime probabilities, π^1_∞ and π^2_∞, are computed by the expression: $\pi^1_\infty = (1-p_{22})/(2-p_{11}-p_{22})$ and $\pi^2_\infty = (1-p_{11})/(2-p_{11}-p_{22})$, respectively. The LR-test statistic is equal to twice the difference in the *LLF* of the Markov-switching and single-regime model. The null hypothesis is that single-regime specification against the alternative of two-regime case. The critical values are 13.277 ($\chi^2(4) = 1\%$), 9.488 ($\chi^2(4) = 5\%$) and 7.779 ($\chi^2(4) = 10\%$).