Chen and Malinda, Journal of International and Global Economic Studies, 8(1), June 2015, 51-67

Room Occupancy Rates of Hotels in Bali: Testing for Long Memory and Multiple Structural Breaks

Jo-Hui, Chen[a] and Maya Malinda[b]

Chung Yuan Christian University, Taiwan

Abstract: This research examines the behavior of room occupancy rates of hotels using long memory and multiple structural break analysis. The room occupancy rates in Bali are divided into five-types of hotels. Autoregressive fractionally integrated moving average and fractionally integrated generalized autoregressive conditional heteroskedasticity (ARFIMA-FIGARCH) model and the iterated cumulative sums of squares test (ICCS) method for multiple structural breaks are applied to examine the long memory process. Empirical findings indicate that almost all types of hotels in Bali have a long memory process with the same structural break time, thus suggesting an interconnection to the type of hotel. The room occupancy rates of 2-star, 3-star and 4-star hotels in Bali have discovered long memory.

Keywords: Bali, Long Memory, Multiple Structural Breaks, Room Occupancy Rates.
JEL Classification: G170, G15.

1. Introduction

In this paper, we focus on long memory and multiple structural breaks for room occupancy rates of hotels in Bali, Indonesia. Different from studies in the literature, we combine long memory with autoregressive fractionally integrated moving average and fractionally integrated generalized autoregressive conditional heteroskedasticity (ARFIMA-FIGARCH) model and structural break with the iterated cumulative sum of squares test (ICCS) method to capture long memory and asymmetry in the conditional variance and structural change in room occupancy rates.

Of the 34 provinces of Indonesia, Bali is one of the islands belonging to its provincial capital, Denpasar. Bali is becoming a favorite destination for international and local tourists of different ages. It has several beautiful beaches, great scenery, and a relatively more diverse culture. Bali is a wonderful place for people to travel, enjoy life, and has a good time with friends and family. In 2013, the Global Market Research Company released the 2011 Top 100 Cities Destination ranking, which is a list of the top cities in the world in terms of international tourist arrivals. Bali, ranked 52nd from 100th (in the previous year) with 2.6 million arrivals and 0.5% growth. Moreover, in 2010 Indonesia earned US$ 7,603.45 million from tourism, which is nearly twice the earning (US$ 4,037.02 million) in 2003 (Grant,2013). According to the updated economic figures released by Oxford Business Group in 2013, Bali, which has long been the prime tourism destination in Indonesia, recorded at least 2.9 million visitors in 2012, exceeding the targeted of 2.8 million visitors. For the last five years, Bali has also become a popular for destination for tourist from China with an annual growth of approximately 10 to 12%. The Indonesian government has targeted 3.5 million tourist arrivals in 2015.

The preceding information motivated us to understand international tourism and market behavior and conduct this study. Several variables used to measure tourism market behaviors such as tourist arrival, duration of stay and expenditure. (Chaitip et al., 2010; Eita et al., 2011; Görmüş and Göçer, 2010; Chokethaworn et al., 2010). Subsequently, the present paper uses room occupancy rates to measure tourism market behavior. Law (1998) forecasted room occupancy rates in the Hong Kong hotel industry using a neural network approach and reported that using this method outperforms two generally used forecasting approaches namely multiple regression and adolescent extrapolation.

The rest of this paper is organized as follows. Section 2 discusses literature survey, section 3 explains the theoretical model the data and methodology. Section 4 provides data sources and the empirical study. Finally, Section 5 presents the summary and conclusion.

2. Literature survey

A long memory is an important indicator in determining nonlinear dependence in the conditional mean and variance of financial time series. To measure long memory for international tourisms, Gil (2005) forecasted short-term arrivals at Auckland international airport and indicated that the ARFIMA models outperformed non-ARFIMA ones in practically all of the cases. Sriboonchitta et al. (2010) used ARFIMA and ARFIMA-FIGARCH in estimating the number of worldwide tourist arrivals in Thailand and establishing that long memory process performance exists in the model. However, Chaitip et al. (2010) identified no long memory performance in the worldwide tourism market in India. Chokethaworn et al. (2010) using ARFIMA-FIGARCH found that there was no long memory for international tourist expenditure in Thailand.

Structural change likewise influences the tourism industry. Galdini (2005) revealed that in European economy significantly affects the role of the tourism industry transforming service occupations and industries. Klaus (1995) indicated that structural change in education and training influences the tourism industry.

The current paper aims to predict room occupancy rate using ARFIMA-FIGARCH and examine whether FIGARCH model for long memory is the better model compared with GARCH model. Second, this paper identifies structural break processes in room occupancy rate using the iterated cumulative sum of squares test (ICCS) method. This study intends to predict room occupancy rate and provides valuable information to the Bali Government to better serve for upcoming foreign tourists.

This paper applies long memory and multiple structural breaks in hotel room occupancy rates in Bali hotels from 1996 to 2012. During this period, bombings occurred in Kuta, Bali in October 2002 and October 2005. This study points out the impact of the bombings on the structural change in room occupancy rates in Bali. This paper also finds long memory for 2-star, 3-star, and 4-star hotels, and such that occupancy rates can be predicted based on the three types of hotels.

3. Theoretical Model

The methodology designed was the estimation of a long memory using ARFIMA and FIGARCH models, and the examination of multiple structural breaks using ICCS method.

The autoregressive moving average model (ARMA; *p, q*) proposed by Box and Pierce (1970) illustrated the stationary time series, where *p* is the autoregressive item and *q* is the moving average item. The autoregressive integrated moving average model (ARIMA; *p, d, q*) used parameter *d* to differentiate time series variables to allow for the stationary of the variables (Box and Pierce, 1970).

Granger (1980), Granger and Joyeux (1980) and Hosking (1981) developed ARFIMA (p, d, q) to test the long memory of financial time series. This model reflects on the fractionally integrated process (d) in the conditional mean. ARFIMA (p, d, q) model can be expressed as a generalization of ARIMA as follows:

$$\Phi(L)(1-L)^d(y_t-\mu_t)=\Psi(L)\varepsilon_t, \tag{1}$$

$$\varepsilon_t = z_t\sigma_t, \ \ z_t \sim N(0,1), \tag{2}$$

where $\Phi(L) = 1 - \Phi_1 L - \cdots - \Phi_p L^p = 1 - \sum_{j=1}^{p} \Phi_j L^j$ and $\Psi(L)\varepsilon_t = 1 + \Psi_1 L + \Psi_2 L^2 + \cdots + \Psi_q L^q$ are autoregressive (AR) and moving average (MA), respectively, ε_t is independent and identically distributed (i-i-d) with a variance σ^2, denoted lag operator L and y_t , μ_t is mean of y_t.

Based on Hosking (1981), Paul et al. (2009), Hsieh and Lin (2004), when *-0.5 < d <0.5*, y_t process is stationary and invertible. For some certain processes the effect of shocks to ε_t on y_t decay is from a slow rate to zero. When *d* = 0 the process is stationary. This outcome implies that the variable has a short memory, and the effect of shocks to ε_t on y_t decay is geometrical. When *d = 1*, a unit root process is present, and the effect of shocks to ε_t decay faster. When *0 < d < 0.5,* the process exhibits positive dependence between distant observations, implying long memory. When -0.5 < *d* < 0, process exhibits negative dependence between distant observations, implying so called "anti-persistence". The empirical results express that ARFIMA improved presentation in predicting volatility. Sivakumar and Mohandas (2009) reported that the predictive power of ARFIMA is reasonably better than that of ARMA and ARIMA.

Fractional Integrated Generalized Autoregressive Conditional Heteroskedasticity model (FIGARCH) proposed by Baillie et al. (1996) and Kang and Yoon (2007) confines the long memory of volatility return. The FIGARCH *(*p, d, q*)* model is expressed as follows:

$$\phi(L)(1-L)^d\varepsilon_t^2 = \omega + [1-\beta(L)]\upsilon_{t,} \tag{3}$$

where $\phi(L) \equiv \phi\_1\ L + \phi\_2\ L\^2 + \cdots + \phi\_q\ L\^q, \beta(L) \equiv \beta\_1\ L + \beta\_2\ L\^2 + \cdots + \beta\_p\ L\^p$ and $\upsilon_t \equiv \varepsilon_t^2 - \sigma_t^2$. The υ_t process can be interpreted as innovations for conditional variance, has zero mean, and serially uncorrelated. All of the roots of $\phi(L)$ and $[1-\beta(L)]$ lie outside the unit root circle. FIGARCH explains that, 0 < *d* < 1 implies an intermediate range of persistence. When *-0.5 > d > 0.5*, the series is stationary, in which the effect of market shocks decays to zero at a gradual rate. If *d = 0*, the series has short memory and the effect of shocks decays geometrically. When *d = 1*, the presence of a unit root process exists.

Beine et al. (2002) and Lu (2007) established that the analytical power of FIGARCH is practically better compared with that of GARCH and IGARCH. GARCH accommodates the covariance *d=0* and the non-stationary IGARCH model for *d = 1*.

Cumulative sum (CUSUM) test is designed to test a single structural break and chow test is often used. However, in testing multiple structural breaks, we used the iterated cumulative sums of squares test (ICSS). Aggarwal et al. (1999) examined stock prices in emerging markets and suggested that volatility in these markets was subject to frequent rule shifts. A number of papers used ICSS, an algorithm to distinguish swift shift in unconditional variance and included these shifts into variance equations. Malik (2003) used ICSS to establish variance and determine volatility in foreign exchange markets. Law (2007) analyzed volatility in the Kuala Lumpur stock exchange that returned to pre-Asian financial crisis levels. Hammoudeh and Li (2008) established volatility in emerging markets. Patricia and Tsorakidis (2009) discussed that ICSS can identify periods of high and low exchange volatility. Charfeddine et al. (2011) revealed that the experimental long memory behavior is reproductive and induces existence of breaks in the data.

Inclán and Tiao (1994) proposed the ICSS model to identify unexpected changes in the unreserved volatility of a series. $C_{k} = \sum_{t=1}^{k} X_t^2$ is the cumulative sum of square of the series of uncorrelated random variables (X_t^2) with mean 0, variance σ_t^2, where

t= 1,2,3…T. Let $D_{k} = \left(\frac{C_{k}}{C_T}\right) - \frac{k}{T}$, $k = 1, \ldots, T$; $D_0 = D_T = 0$. (4)

where C_{k} and C_T denote the mean of the centered cumulative sums of squares designed in k and T observations. The series D_{k} oscillates around zero, if no variance changes occurs over the sample period.

Moreover, Inclán and Tiao (1994) proposed the quantity $(\left(\frac{T}{2}\right) D_{k})^{\frac{1}{2}}$ be converged in distribution to a standard Brownian motion. The change point of variance over interval t=1,…,T, is the point k_0 for which $(\left(\frac{T}{2}\right) D_{k})^{\frac{1}{2}}$ reaches its maximum and $(\left(\frac{T}{2}\right) D_{k})^{\frac{1}{2}}$ > C_α, where C_α at the 5% level, is a breaking value at 1.358. To detect the unconditional variance this paper used GARCH model. Glosten et al. (1993) and Lamoureux and Lastrapes (1990) combined GARCH and dummy variables representing various changes in variance. High persistence occurred when applying GARCH models due to incorrect specification, in which achievable deterministic changes in the unconditional variance were not considered. The adapting GARCH model was cited considering the detected changes in unconditional variance by Arago and Fernandez (2003). The equation is as follows:

$$h_t^2 = \alpha + \sum_{i=2}^{p} F_i D_i + \sum_{i=1}^{p} \beta_i h_{t-i}^2 + \sum_{i=1}^{q} \delta_i \varepsilon_{t-1}^2, \quad (5)$$

where F_i reflects the differences with respect to α (estimated value for the first regime of variance obtained), and D_i are dummy variables for breaks that reflect the changes in variance.

$$h_t^2 = \alpha + \sum_{i=2}^{p} F_i D_i + \sum_{i=1}^{p} \beta_i h_{t-i}^2 + \sum_{i=1}^{q} \delta_i \varepsilon_{t-i}^2 + \gamma S_{t-1}^{-} \varepsilon_{t-1}^2. \quad (6)$$

If γ>0, an asymmetrical effect is captured. The sign of innovation in t-1 explains the different effects on volatility. S_{t-1} is equal to the unit if ε_{t-1}<0 (innovation at t=1), and zero if ε_{t-1}>0.

4. Data Sources and Empirical Results

This paper used the monthly room occupancy rates of 1-star to 5-star hotels in Bali, from the Badan Pusat Statistik website (bpsbali.go.id). This study period was from January 1996 to November 2012. This period was selected because of two important and memorable events in Bali, Indonesia. The events were the aforementioned incidents in Kuta, Bali October 2002, the first bombing, and October 2006 the second bombing. This study proved that these two events influenced structural breaks in the room occupancy rates of hotels.

Table 1 demonstrates that all of the room occupancy rates of hotels in Bali have positive means and similar standard deviations except for 1-star and all-star hotels. With regard to skewness, class hotels are of either negative or positive values. Positive skewness implies that future data will be greater than the mean. For kurtosis most data have a platikurtic distribution because values are smaller than three. The Jarque-Bera Statistic for residual normality indicates that, excluding 3-star and 4-star hotels most data are significant at the 1% and 5% levels of abnormal distribution.

For unit root, this study employs the Augmented Dickey Fuller (ADF) proposed by Dickey and Fuller (1979) to examine whether the variable is stationary or non-stationary. Table 2 shows the outcome of the unit root test, from the best fitted ARMA model, LM test, the Lagrange Multiple test (ARCH-LM) (Engle, 1982) as well as GARCH model. For ADF test, all of the data significantly reject the null hypothesis suggesting that all are stationary and appropriate for further testing. The current paper uses the lowest Akaike Information Criterion (AIC) to obtain the best fitted ARMA models. After establishing the model, serial correlation with LM test is conducted to test the significance. A nonsignificant result implies lack of a serial correlation. LM test in Table 2 shows that, except 2-star and 3-star hotels, most of the variables are nonsignificant. After testing the serial correlation, this study continues to process the heteroscedastisity test. If the ARCH LM test is significant, then no ARCH effect exits, which can apply to GARCH model. ARCH-LM results indicate that almost all of the samples in the null hypothesis were significant and apply to the GARCH model for 1-star, 2-star, and 5-star and all-star hotels. ARCH-LM significantly rejects the null hypothesis, demonstrates the ARCH effect. This study further applies ARFIMA and ARFIMA-FIGARCH models.

To obtain the optimal model, ARFIMA (*0*, *d*, *1*) to ARFIMA (*3*, *d*, *3*) are based on the minimum AIC. This work measures parameter *d* to estimate the existence of long memory. Table 3 presents ARFIMA and ARFIMA -FIGARCH models, in which *d*-coefficient for ARFIMA model shows that all -star hotels have long memory. This finding indicates that in a span of 16 years, the room occupancy rate of hotels in Bali is positive. These signs reveal that room occupancy rate can be predicted, which are consistent with Nouira et al. (2004), Kang and Yoon (2007), Choi and Hammoudeh (2009), Tan and Khan (2010), and Chen and Diaz (2012), who found positive results for ARFIMA model.

However, *d*-coefficient for room occupancy rate is negative and significant for 5-star hotels, It implied that the room occupancy rate of 5-star hotels has anti-persistence or intermediate memory. This result is significant because only a few tourists will stay in 5-star hotels. Generally, tourists are interested in staying in 4-star, 3-star or 2-star hotels because they are relatively cheaper than 5-star hotels and provide comfortable facilities.

For 4-star, 3-star and 2-star hotels, *d*-coefficients ($0 < d < 0.5$) are 0.4260, 0.3597 and 0.4254, respectively at the 1 % significance level. This finding indicates that 4-star, 3-star, and 2-star hotels have long memory and can be estimated in the long run.

Table 4 illustrates the effects of multiple structural breaks. To recognize sudden changes to the unconditional volatility of a series, this study uses the iterated cumulative sums of squares test (ICSS) proposed by Inclán and Tiao (1994). The ICSS method detects multiple structural breaks by endogenous events. If the value calculated by $\max_k\left(\left(\frac{T}{2}\right)|D_k|\right)^{\frac{1}{2}}$ is higher than 1.358, then a structural break exists. As shown in Table 4, all of the variables have multiple structural breaks.

The 4-star and 3-star hotels had a structural break in November 2002, in which room occupancy may have been influenced by the first bombing at Kuta, Bali. During this period, foreign tourists may fear going to Bali, thinking that the destination was not safe anymore. However, as time went by, the willingness of the tourists had been recovered.

In October 2005 the second bombing occurred. This incident was also reflected in the structural break, for 3-star hotels in January 2006 and for 5-star, 4-star and all-star hotels in February 2006. The first bombing in Bali has a direct impact on Bali, but the second bombing Bali did not have as much impact as the first one. Nevertheless, a structural break during the second bombing in Bali directly affected 4-star and 3-star hotels.

Determined by the ICSS method, this study applies the GARCH model with dummy variable (F_i). Variables F_i reflect the differences with respect to variance F1 in the study period. If F_i is larger than the criteria value of 1.358, a structural break exists. Testing the asymmetrical effect, this study likewise uses r. The asymmetrical effect exists, if r is significant and positive based on AIC for selecting a better fitting model.

Table 5 shows the effect of structural breaks on room occupancy rates. Almost all of the stars are significant except for 2-star hotels. For instance, the coefficient of F1 for 4-star hotels, 1.0207 is significant, which indicates an increase in the value of unconditional variance. For 3-star hotels, the estimated value of F3= -2.2722 is significant, which indicates a decrease in the value of unconditional variance obtained in the third sub-period.

All room occupancy rates coefficients of F1 are positive and significant, suggesting an increase in the value of unconditional variance obtained in every star hotels. The r result for 3-star, 2-star and all-star hotels have positive r indicating an asymmetrical effect in class hotels.

Table 6 summarizes room occupancy rates and long memory test. Most types of hotels have long memory, whereas 5-star, 1-star and all-star hotels have intermediate memory. Multiple structural break tests indicate that all of the markets for hotel types have values that are larger than the criteria value of 1.358. This result could have been attributed to the impact from the Kuta, Bali bombings in October 2002 and October 2005. The first bombing, may have influenced 4-star and 3-star hotels. By contrast, the second bombing may have influenced 5-star, 3-star, and all-star hotels. The 3-star hotels, were influenced by both events. Logically, tourists prefer staying in 3-star hotels, because of the prices and facilities. This fact proves that foreign tourists who arrive in Bali come from the middle class. Evidences suggest that the government should pay more attention to developing and expanding 3-star hotels and promoting potential middle-class consumers.

5. Summary and Conclusions

First, the results from the ARFIMA model indicated that all of the classes of hotels have long memory. However, the ARFIMA–FIGARCH model showed that 5-star and all-star hotels have intermediate memory effects. These results prove that the occupancy rate for hotels can be predicted and confirm that ARFIMA–FIGARCH model is better than GARCH model (Kang and Yoon, 2007). Based on ICCS model, the current study revealed that most variables have structural breaks, and some have similar dates because of the two bombings in Kuta, Bali. This paper suggests that the government should protect and improve security systems. Political and security conditions in a place or country will affect the tourism industry. This study likewise indicated that 3-star hotels were influenced by both bombing events. This result implies that future promotion and development should focus on 3-star hotels because of the preferences of foreign visitors. Finally, the structural breaks for room occupancy rates in hotels, except 2-star hotels, have strong asymmetrical effects; this result suggests that, in general, all types of hotels are unstable. Therefore, stability and security in the political condition in places are critically important for the development of the tourism industry.

Endnotes

[a] Professor, Department of Finance, Chung Yuan Christian University, Chung-Li City, Taiwan. Email: johui@cycu.edu.tw.
[b] PhD Candidate, PhD Program in Business, Chung Yuan Christian University, Chung-Li City, Taiwan; lecturer at Maranatha Christian University, Bandung, Indonesia. Email:hmy.malinda@yahoo.com.

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Table 1. The Descriptive Statistics of Variables.

Class Hotel	Period	Obs.	Mean	Std. Dev.	Skew.	Kurt.	J-Bera
5-Star	1996/1/1	203	59.857	10.060	-0.549	0.549	12.739***
4-Star	1996/1/1	203	53.663	10.430	0.136	-0.381	1.849
3-Star	1996/1/1	203	50.975	10.383	-0.056	-0.678	3.994
2-Star	1996/1/1	203	48.425	10.223	0.369	0.541	7.083**
1-Star	1996/1/1	203	38.673	13.725	0.632	0.067	13.537***
All-Star	1996/1/1	203	55.499	8.952	-0.548	-0.289	10.873**

Note: *, ** and *** are significant at 10, 5 and 1% levels, respectively; p-values are in parentheses.

Table 2. Summary Statistics of Unit Root, ARMA, LM, ARCH-LM and GARCH.

Class Hotel	ADF	ARMA	AIC	LM	ARCH-LM	GARCH	AIC	ARCH-LM
5-Star	-5.499***	(2,1)	6.695	0.402	7.447 (0.024**)	(3,1)	6.588	0.924 (0.630)
4-Star	-4.220***	(2,3)	6.876	0.216	0.122 (0.941)			
3-Star	-4.836***	(3,3)	6.537	64.601***	3.634 (0.163)			
2-Star	-5.501***	(2,1)	6.719	57.201***	25.096 (0.00***)	(2,1)	6.649	3.307 (0.191)
1-Star	-4.039**	(1,3)	7.382	1.037	12.339 (0.002***)	(2,2)	7.236	2.993 (0.224)
All-Star	-4.453***	(2,1)	6.131	0.548	10.683 (0.005***)	(2,1)	6.052	0.075 (0.963)

Note: *, ** and *** are significant at 10, 5 and 1% levels, respectively; p-values are in parentheses.

Table 3. Summary Statistics of ARFIMA and ARFIMA-FIGARCH Models with all Period

Class	ARFIMA				ARFIMA-FIGARCH				
Hotel	Model	d-coeff.	AIC	ARCH-LM	d-coeff.	Model	d-coeff.	AIC	ARCH-LM
5-Star	(1,0)	0.3299	6.6602	46.3670	-0.1855	(0,2)	-0.0795	6.6400	0.6935
		(0.039**)		[0.0000]**	(0.0341**)		(0.0000***)		[0.6290]
4-Star	(2,0)	0.3300	6.8991	37.8003	0.4260	(0,1)	0.0075	6.8918	1.1536
		(0.022**)		[0.0000]**	(0.0094***)		(0.9491)		[0.3337]
3-Star	(1,0)	0.3058	6.5727	60.2450	0.3597	(1,0)	-0.0428	6.5779	0.5779
		(0.009***)		[0.0000]**	(0.0013***)		(0.6978)		[0.7169]
2-Star	(1,0)	0.4021	6.7305	44.5330	0.4254	(1,0)	0.1709	6.6521	0.6648
		(0.000***)		[0.0000]**	(0.0001***)		(0.2568)		[0.6506]
1-Star	(1,0)	0.4635	7.4029	42.7960	0.5238	(1,0)	0.2474	7.3111	1.2902
		(0.000***)		[0.0000]**	(0.0000***)		(0.1828)		[0.2697]
All-Star	(2,2)	0.4883	6.0778	84.9930	-0.4288	(1,1)	-0.1461	6.1110	0.8336
		(0.000***)		[0.0000]**	(0.4460)		(0.0094***)		[0.5273]

Note: *, ** and *** are significant at 10, 5 and 1% levels, respectively; p-values are in parentheses.

Table 4. The Result of Multiple Structural Breaks

Variables	Change Points	Interval	$\max_k\left(\left(\frac{T}{2}\right)\lvert D_k\rvert\right)^{\frac{1}{2}}$
5-Star	**2006/02**	1996/01-2012/11	3.1699
Period $_1$	1998/04	1996/01-1998/08	1.8963
Period $_2$	2001/09	1998/09-2005/09	2.8853
Period $_3$	2006/02	2005/10-2010/12	2.8880
Period $_4$	2011/10	2011/01-2012/11	1.9570
4-Star	***2002/11***	1996/01-2012/11	3.3257
Period $_1$	2002/11	1996/01-2005/07	3.3391
Period $_2$	**2006/02**	2005/08-2010/06	2.1810
Period $_3$	2011/10	2010/07-2012/11	2.0328
3-Star	2010/06	1996/01-2012/11	2.2722
Period $_1$	***2002/11***	1996/01-2003/09	1.9266
Period $_2$	**2006/01**	2003/10-2008/08	1.7066
Period $_3$	2010/06	2008/09-2012/11	2.2313
2-Star	2007/09	1996/01-2012/11	4.6308
Period $_1$	2002/09	1996/01-2002/11	3.2709
Period $_2$	2007/09	2002/12-2011/06	3.8724
Period $_3$	2011/11	2011/07-2012/11	1.6412
1-Star	2008/04	1996/01-2012/11	4.9955
Period $_1$	2002/06	1996/01-2002/11	3.3551
Period $_2$	2010/06	2002/12-2012/11	4.1699
All-Star	**2006/02**	1996/01-2012/11	4.3445
Period $_1$	2001/09	1996/01-2002/11	3.4637
Period $_2$	2006/02	2002/12-2012/11	3.7588

Source: Organized by the Authors.

Table 5. The Effect of Structural Breaks

Variables	GARCH	AIC	F_i & r
5-star	(2,1)	6.629733	F_1=0.7088(0.000***)
			F_2=-0.2048(0.9583)
			F_3=-4.2130(0.3107)
			r= -0.3840(0.0001***)
4-star	(2,1)	6.8206	F_1= 1.0207(0.000***)
			F_2= -0.7115(0.3429)
			F_3=-4.6019(0.0311**)
			r= -0.1493(0.000***)
3-star	(3,3)	6.5436	F_1= 1.0193(0.000***)
			F_2= 2.8696(0.1429)
			F_3=-2.2722(0.0176**)
			r= 0.0394(0.0896**)
2-star	(2,1)	6.7177	F_1= 0.2111(0.2336)
			F_2= 2.2975(0.7099)
			F_3=-6.7176(0.8813)
			r= 0.3150(0.2059)
1-star	(1,3)	7.3127	F_1= 0.8446(0.000***)
			F_2= 5.751(0.0503*)
			r= -0.3037(0.0049***)
All-star	(2,1)	6.0980	F_1= 0.0679(0.8654***)
			F_2= -12.9920(0.0896)
			r=0.1044(0.0435**)

Source: Organized by the Authors.

Table 6. The Result of Testing Long Memory and Structural Break Test

Class Hotel	Long Memory Effect	Structural Break Test
5-Star	Intermediate memory	**2006/02**
4-Star	Long memory	**2002/11**
3-Star	Long memory	**2002/11, 2006/01**
2-Star	Long memory	2007/09
1-Star	Intermediate memory	2008/04
All-Star	Intermediate memory	**2006/02**

Source: Organized by the Authors.