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THE EFFECT OF EXCHANGE RATE AND OIL PRICE ON VOLATILITY OF INBOUND AND OUTBOUND TOURISM DEMAND

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Synopsis:

This study examined the volatility of inbound and outbound tourism demand and correlation between them using DCC(dynamic conditional correlation) - MGARCH (multivariate generalized autoregressive conditional heteroskedasticity) model. In addition, we analyze the effect of exchange rate, oil price on the volatility. The inbound and outbound tourism demand change rates have volatility, and there was interdependence between volatility. Oil prices and/or exchange rates affected volatility.

The Effect of Exchange Rate and Oil Price on Volatility of Inbound and Outbound Tourism Demand[*]

ABSTRACT

This study analyzes the volatility of inbound and outbound tourism demand and interdependence of their volatility. In addition, we analyze the effect of exchange rate and oil price on the volatility. The DCC (dynamic conditional correlation)-MGARCH (multivariate generalized autoregressive conditional heteroscedasticity) model was used to reflect their interaction and correlation over time. First, inbound and outbound tourism demand did not affect each other significantly, but were influenced only by autoregressive variables. Second, the inbound and outbound tourism demand change rates have time - varying conditional variance (volatility), and there was interdependence between volatility. Third, oil prices had a significant effect on the volatility of inbound and outbound tourism demand change rate, and the exchange rate had a significant effect on the volatility of outbound demand change rate. Government and tourism industry need to consider interdependence between volatility of inbound and outbound tourism demand and appropriately respond to the change in the exchange rate and international oil price to reduce risk in tourism industry.

KEYWORDS: Inbound, outbound, volatility, exchange rate, oil price, DCC-MGARCH

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INTRODUCTION

According to World Travel and Tourism (WTTC), the tourism industry accounts for 10% of the world's gross domestic product (GDP) by 2015, and 1.8% of Korea's tourism industry. If the added value of industry is applied, the share of GDP is 2.51%. The tourism industry is expected to continue to develop because of its high contribution to the economy, such as income increase and job creation, which will increase its importance in the Korean industry. The Korean outbound market is steadily expanding to over 30 million a year, but inbound tourism is stalling around 10 million a year due to the difficulty of diversification and diversification in China. Despite the importance of outbound tourism demand in terms of promoting the welfare of Koreans, attention has been focused on inbound tourism demand related to the balance of payments and job creation. Since inbound and outbound tourism demand can interact with each other, comprehensive research is needed.

Engle (1982) has introduced the autoregressive conditional heteroskedasticity (ARCH) model to estimate the volatility, and there have been many studies to analyze the volatility of the financial time series, but relatively little study (Chan, Lim & McAleer, 2005; .Shareef & McAleer, 2007) has been conducted on travel demand area, especially the interdependence between the volatility of inbound and outbound tourism demand and the process of change in correlation over factors that affect volatility.

This study estimates the volatility of inbound tourism demand and outbound tourism demand in Korea using DCC (dynamic conditional correlation) - MVARCH (multivariate generalized ARCH) model. We then examine the effects of exchange rate and oil price on their volatility. The DCC-MGARCH model may describe the interdependence of volatility and the change in correlation over time.

This study is significant that the DCC-GARCH model analyzes the interdependency between inbound and outbound tourism demand volatility and the change in correlation coefficient over time. Considering these interdependencies may reduce a serious error in analyzing the demand volatility of the tourism industry. This study is different from previous research in that the effect of exchange rate and oil price fluctuation on inbound and outbound tourism demand volatility is examined. Most studies are concerned with the estimation and prediction of volatility, but the analysis of the determinants of volatility has been disregarded. The analysis of the determinants of volatility may contribute to decision-making to cope with volatility appropriately.

LITERATURE REVIEW

Volatility is used as a measure of uncertainty in conditional variance. If volatility continues in some direction, volatility concentration phenomenon appears for a certain period. Various studies have been conducted to accurately estimate the change of volatility over time. Engle (1982) presented the ARCH (Autoregressive Conditional Heteroscedasticity) model, which shows the conditional variance as a shock function of the past, and Bollerslev (1986) extended it to the GARCH (Generalized ARCH) model of the past shock and conditional variance. Since volatility can react differently to good news and bad news, it has been extended to EGARCH (exponential GARCH), AGARCH (asymmetric GARCH), and GJR-GARCH (Glsten Jaganathan and Runkle) models reflecting these asymmetric effects. The multivariate GARCH model has been used consistently to reflect the transition of time series volatility.

Most studies on volatility have been conducted in the financial sector, and studies on the volatility of tourism demand have begun to appear gradually since 2000 by Chan, Lim & McAleer (2005), Shareef & McAleer (2007) and Seo, Park & Yu (2009).

Shareef & McAleer (2007) analyzed the volatility of inbound tourism demand of six small islands (Barbados, Cyprus, Dominica, Fiji, Maldives & Seychelles) through GARCH model and GJR-GARCH model. Dominica Inbound tourism demand volatility is asymmetric, but the rest of the island's inbound tourism demand volatility is symmetric.

Chan, Lim & McAleer (2005) estimated variability in the number of visitors to Australia from Japan, New Zealand, the United Kingdom and the United States through multivariate GARCH models as well as univariate GARCH and AGARCH models. They found the volatility of individual inbound tourism demand and their interdependency.

Seo, Park and Yu (2009) analyzed the relationship between the outbound tourism demand of three Asian countries (Thailand, Singapore, Philippines) and Jeju Island in Korea using VECM and MGARCH model. The conditional correlation between tourist demand for Jeju Island, Thailand, Singapore, and the Philippines has changed over time. The conditional correlation of tourist demand in Jeju and three Asian countries was replaced by negative sign for a certain period. Industrial production index and real exchange rate have a significant effect on the conditional correlation of tourism demand.

Methods

In order to simplify the concept of tourism demand between Korea and Japan, this study uses the number of foreign tourists in Korea as the inbound tourism demand (inbound) and the number of Korean tourists in Japan as the outbound tourism demand (outbound). Inbound tourism demand change ratio (inbound) and outbound tourism demand change rate (outbound) are expressed as follows.

$$rinbound_t = \ln(\frac{inbound_t}{inbound_{t-1}}) \times 100(\%) \tag{1}$$

$$routbound_t = \ln(\frac{outbound_t}{outbound_{t-1}}) \times 100(\%) \tag{2}$$

Here, $rinbound_t$ is the rate of change in the number of tourists visiting in Korea from Japan and $routbound_t$ is the rate of change in the number of tourists visiting Japan from Korea, respectively. The $inbound_t$ is the number of tourists visiting Korea from Japan in t, and $outbound_t$ is the number of Korean tourists visiting Japan.

The data used in this study are monthly data from January 2005 to March 2018. The tourism demand data were obtained from TOURGO (www.tourgo.com), the international oil prices from PETRONET (www.petronet.com), and the exchange rate from the monthly data of the e-country index (www.index.go.kr).

This study attempts to analyze the interrelation between the inbound and outbound tourism demand change rates and the transition effect between volatility. We then analyze the relationship between volatility and exogenous variables (exchange rate, oil price). The most commonly used models for estimating volatility are the ARCH model of Engle (1982) and the GARCH model of Bolerslev (1986). Since these methods estimate the variability of a single variable, there is a limit to explain the interdependence between variables. Considering these limitations, the MGARCH model is used to explain the interrelationships between variables. In the MGARCH model, as the number of variables increases, the number of parameters to be estimated becomes too large. Therefore, the MGARCH model often fails to derive a meaningful relationship because it does not converge or becomes difficult to identify in the estimation process. In this study, we use Engel and Sheppard (2001)'s Dynamical Conditional Correlation (DCC) MGARCH model. The DCC-MGARCH model has the advantage of improving the convergence and identification of the model by analyzing the interdependence of the variable lines through the time-varying conditional correlation coefficient matrix and decreasing the parameter to be estimated.

The VAR (1) model of inbound and outbound tourism demand with time variant conditional variance can be expressed as follows.

$$Y_t = CY_{t-1} + \sum_{m=1}^{11} \lambda_m M_m + \epsilon_t \tag{3}$$

$$\epsilon_t = H_t^{1/2} v_t$$

Here, Y_t is the vector of inbound tourism demand change rate (rinbound) and outbound tourism demand change rate (routbound). M_m is the monthly dummy variable for controlling the seasonal effect, and ε_t is the random error of the VAR model. The random error (ε_t) has the property of the time-variable conditional variance. H_t is a time-varying conditional variance matrix, and $v_t$is a probabilistic error vector.

The MGARCH model has a diagonal VECH, a Constant Conditional Correlation (CCC), and a DCC (Dyanmic Conditional Correlation) according to the method of using the conditional variance matrix (H_t). The DVECH-MGARCH model, the CCC-MGARCH model, and the DCC-MGARCH model reduce the number of parameters to be estimated by restricting the parameters and improve the convergence. The DVECH model improves the convergence by constraining the parameters to be estimated by diagonalizing the variance and covariance equations, but there is a limit that cannot consider the correlation between the variabilities. The CCC-MGARCH model and the DCC-MGARCH model are more realistic than the DVECH model because they take into account the correlation of volatility. The CCC-MGARCH of Bollersleve (1990) assumes constant conditional correlation over time, but the DCC-MGARCH model of Engle (2002), Engle, Sheppard (2001) allows a time-varying correlation coefficient.

Considering the correlation between inbound tourism demand and outbound tourism demand volatility, the DCC-MGARCH model of Engle (2002) is used as follows.

$$H_t = D_t R_t D_t \quad (4)$$

$$D_t = diag(h_{11,t}, h_{22,t}) = \begin{bmatrix} \sqrt{h_{11,t}} & 0 \\ 0 & \sqrt{h_{22,t}} \end{bmatrix} \quad (4\text{-a})$$

$$R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2} \quad (4\text{-b})$$

$$Q_t = (1 - \lambda_1 - \lambda_2)\overline{Q_t} + \lambda_1 \epsilon_{t-1}\epsilon_{t-1}' + \lambda_2 Q_{t-1} \quad (4\text{-c})$$

$$\epsilon_t = (\epsilon_{1t}, \epsilon_{2t}) \quad (4\text{-d})$$

Here, $H_t$is a conditional covariance matrix, R_t is a dynamic conditional correlation coefficient matrix, D_t is a conditional standard deviation diagonal matrix of residuals, Q_t is a conditional covariance matrix of normalized residuals, and $\overline{Q_t}$ is a covariance matrix of unconditional normalized error are respectively shown.

The adjustment factors λ_1, λ_2 control the dynamics of the conditional correlation and should be

$\lambda_1 > 0$, $\lambda_2 > 0$, $\lambda_1 + \lambda_2 < 1$. The parameter λ_1 shows the effect of past residual shock on conditional covariance, and λ_2 indicates the effect of past conditional covariance on conditional covariance.

International oil price and exchange rate are additionally considered factors of affecting conditional variance of tourism demand change rate as follows

$$h_{ii,t} = \alpha_i + \beta_i h_{ii,t-1} + \gamma_i \epsilon_{i,t-1}^2 + \mu X_t \qquad (5)$$

Here, X_t indicates exchange rates and international oil prices.

RESULTS

Table 1 shows the statistical characteristics of data. In the case of inbound tourism demand change rate (rinbound), the degree of deviation is shifted to the left with a negative sign, and the kurtosis is 7.450, which is much more acute than the regular normal distribution (3). The null hypothesis of the normal distribution is rejected and it can be confirmed that the rate of change of the inbound tourism demand is not normal distribution. Ljung-Box Q statistic rejects the null hypothesis that there is no serial correlation between the remaining residuals, and the ARCH-LM test rejects the null hypothesis that there is no ARCH effect. Therefore, the rate of change of inbound tourism demand may have serial correlation and ARCH effect. However, the ARCH-LM test did not reject the hypothesis of no ARCH effect.

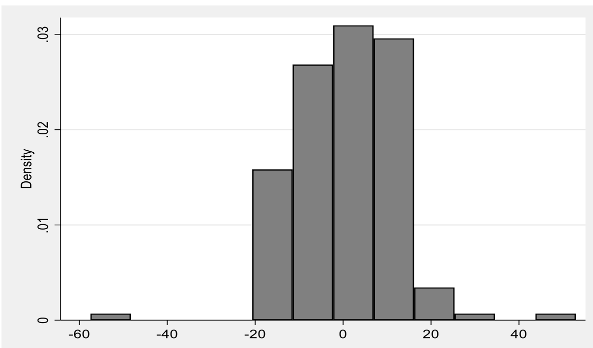
Table 1 Basic statistics of inbound and outbound tourism demand change rate

	rinbound	routbound
Mean	0.691	0.582
Standard deviation	11.834	13.18
Min	-57.479	-45.849
Max	52.947	30.984
Skewness	-0.257	-0.54
Kurtosis	7.45	3.463
Shapiro-Wilk Nomality Test (p-value)	0	0.005
Ljung-Box Q(10) (p-value)	0	0
ARCH LM Test (p-value)	0.01	0.68

Figure 1 shows the histogram of inbound and outbound tourism demand change rate. It can be seen that both of the variables have an acute distribution and there are observations at both ends, which follows the non-normal distribution. These characteristics are frequently seen when ARCH effect is present.

Figure 1 Histogram of rinbound and routbound

rinbound



routbound

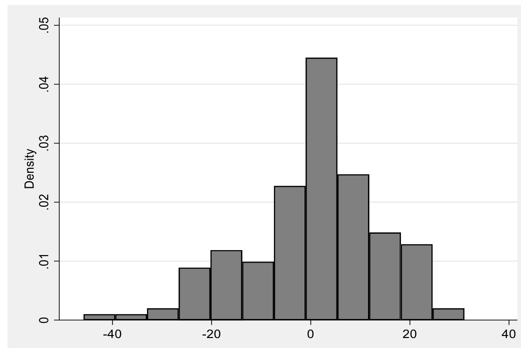
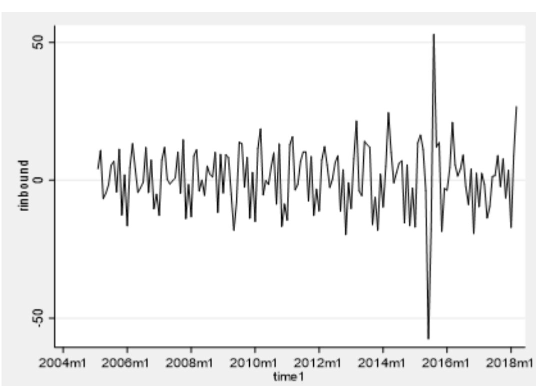


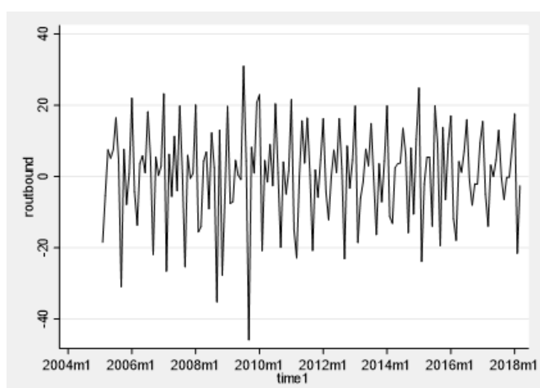
Figure 2 shows the transition of inbound and outbound tourism demand changes rate. It can be seen that the rate of change in the inbound tourism demand fluctuates more than the rate of change in the outbound tourism demand in a certain period.

Figure 2 Transition of rinbound and routbound

rinbound



routbound



The time series should be stationary because the MGARCH model can be used to estimate the conditional correlation between inbound and outbound tourism demand volatility, and conditional variance equation with exchange rate and international oil price change.

Augmented Dicky Fuller (Said & Dickey, 1984), PP (Phillip & Perron, 1988) and KPSS (Kwiatkowski et al., 1992) tests were conducted to examine the stationarity of the time series. The null hypothesis of the ADF test and the PP test is 'unit root exists', but the null hypothesis of KPSS test is 'no unit root exists'. The number of maximum lag lengths was set to 10, and the optimum lag lengh was determined based on the AIC standard. The rate of change moves around 0, and because there is no specific trend, the model with no intercepts and trends was chosen. For the ADF and PP tests, the null hypothesis was rejected for all variables, but the null hypothesis was not rejected for the KPSS test. Therefore, all time series can be concluded as I (0).

Table 3 Unit root test

	ADF	PP	KPSS
rinbound	-7.008(3)***	-12.422(3)***	0.0191
routbound	-11.092(2)***	-18.570(2)***	0.0273
rex	-13.615(0)***	-13.615(0)***	0.0394
roil	-6.472(1)***	-8.252(1)***	0.0834

Notes: *** indicates significance at 1% level.

<Table 4-a, b> show the estimation results of the DCC-MGARCH model. <Table 4-a> shows that dependent variable is inbound tourism demand change rate (rinbound) and <Table 4-b> is estimated simultaneously considering mutual relation as outbound tourism demand change rate (routbound). The DCC-1 model does not include the determinants of volatility but the others include explanatory variables. The DCC-2 model includes crude oil price, the DCC-3 model includes exchange rate, and the DCC-4 model has oil price and exchange rates.

The conditional average equation of Table 4-a shows that the rate of change of inbound tourism demand is influenced only by the autoregressive lagged variables and that it is not significantly influenced by the lagged variables of outbound tourism demand change rate.

Inbound tourism demand change rate is seasonal, monthly variables are significant except for May, June, and July. There was no significant difference in outbound tourism demand change before and after the Sard deployment. The estimation result of the conditional average equation of outbound tourism demand change rate in <Table 4-b> is similar to the inbound tourism demand change rate. The dummy variables except for June and August were significant. The Sadd dummy variable was not significant. No transitional effects were found between the inbound and outbound tourism demand change rates.

<Table 4-a, b> show that there is volatility of inbound tourism demand change rate and outbound tourism demand change rate in all cases. In the case of the DCC-3 model, the volatility of the inbound tourism demand change was more sensitive to the shock (ε_{t-1}^2) than the lagged volatility (h_{t-1}^2). It means that if the volatility increases, there is a high probability of a volatility clustering phenomenon to last for a while. Although exchange rate fluctuations do not have a significant effect on volatility of inbound tourism demand change, DCC-3 shows that oil price variability has a significant effect on volatility.

In the conditional variance equation of Table 4-b, the volatility of outbound tourism demand change rate in all models showed a greater response to lagged self-volatility than in the previous news. International oil price and exchange rate have a positive effect on the volatility of outbound tourism demand change rate. As oil prices and exchange rate changes increase, the volatility of outbound tourism demand change is increasing.

Table 4 DCC-MGARCH: rinbound

	DCC-1	DCC-2	DCC-3	DCC-4
$rinbound_{t-1}$	0.369***	0.357***	0.296***	0.357***
	(0.084)	(0.082)	(0.085)	(0.080)
$routbound_{t-1}$	-0.109	-0.109	-0.067	-0.136
	(0.066)	(0.071)	(0.061)	(0.070)
$thaad_t$	0.708	0.643	1.642	1.277
	(1.205)	(1.171)	(1.353)	(1.071)
m_{1t}	-15.567***	-15.222***	-14.671***	-15.344***
	(2.291)	(2.335)	(1.971)	(2.102)
m_{2t}	12.238***	11.934***	14.059***	14.505***
	(2.268)	(2.396)	(1.923)	(2.573)
m_{3t}	7.590**	7.594**	10.016***	7.647**
	(2.651)	(2.636)	(2.662)	(2.540)
m_{4t}	-10.601***	-10.484***	-6.166*	-10.921***
	(3.037)	(2.946)	(3.064)	(2.720)
m_{5t}	-2.765	-2.39	-4.736*	-1.513
	(2.384)	(2.335)	(2.358)	(2.192)
m_{6t}	-3.654	-3.79	1.436	-1.318
	(2.514)	(2.565)	(2.152)	(2.515)
m_{7t}	1.506	1.532	3.162	1.361
	(2.158)	(2.279)	(2.253)	(2.151)
m_{8t}	5.156	5.435	8.336**	6.801*
	(2.982)	(2.946)	(2.807)	(2.976)
m_{9t}	-13.944***	-13.678***	-11.788***	-13.675***
	(2.843)	(2.829)	(2.735)	(2.735)
m_{10t}	5.306**	5.341*	8.616***	5.281**
	(2.041)	(2.095)	(1.966)	(1.656)
m_{11t}	-20.703***	-20.458***	-18.876***	-20.144***
	(2.869)	(2.863)	(2.605)	(2.819)
$cons$	3.521	3.407	1.356	2.924
	(1.822)	(1.829)	(1.729)	(1.760)
ϵ^2_{t-1}	0.646***	0.658***	0.321***	0.627***
	(0.097)	(0.095)	(0.059)	(0.086)
h^2_{t-1}	0.354***	0.342***	0.679***	0.373***
	(0.097)	(0.095)	(0.059)	(0.086)
ex_t		-0.107		-0.116
		(0.078)		(0.130)
oil_t			0.627*	0.115
			(0.252)	(0.099)
$cons$	8.393**	2.124***	-5.656	1.418
	(2.831)	(0.345)	(4.719)	(0.822)

Table 5 DCC-MGARCH: routbound

	DCC-1	DCC-2	DCC-3	DCC-4
$rinbound_{t-1}$	0.150***	0.146***	0.463***	0.416**
	(0.036)	(0.033)	(0.124)	(0.130)
$routbound_{t-1}$	0.850***	0.854***	0.537***	0.584***
	(0.036)	(0.033)	(0.124)	(0.130)
$thaad_t$	-0.593	-0.616	0.757	0.465
	(1.329)	(1.281)	(1.208)	(1.092)
m_{1t}	17.017***	17.244***	18.820***	17.890***
	(1.873)	(1.796)	(2.021)	(2.207)
m_{2t}	-12.484***	-12.853***	-7.700**	-9.805**
	(2.628)	(2.558)	(2.935)	(3.636)
m_{3t}	-18.683***	-18.432***	-19.307***	-18.536***
	(1.995)	(1.948)	(2.149)	(1.909)
m_{4t}	-5.468**	-5.349**	-4.176	-5.043*
	(2.067)	(2.007)	(2.361)	(2.170)
m_{5t}	3.864*	3.957*	3.727*	4.409*
	(1.762)	(1.704)	(1.888)	(1.755)
m_{6t}	-1.949	-2.434	0.703	0.126
	(2.100)	(2.051)	(2.163)	(2.528)
m_{7t}	11.682***	11.249***	14.499***	13.482***
	(1.677)	(1.629)	(1.914)	(2.180)
m_{8t}	1.178	1.614	6.291*	3.718
	(2.362)	(2.324)	(2.703)	(3.514)
m_{9t}	-23.399***	-23.032***	-21.999***	-22.365***
	(1.922)	(1.890)	(2.236)	(2.205)
m_{10t}	-4.436*	-4.414*	-5.633*	-4.457*
	(1.943)	(1.903)	(2.238)	(2.065)
m_{11t}	-8.732***	-8.347***	-5.188*	-6.652*
	(2.102)	(2.043)	(2.127)	(2.629)
$cons$	4.601**	4.555**	2.777	3.370*
	(1.442)	(1.392)	(1.540)	(1.682)
ϵ^2_{t-1}	0.150***	0.146***	0.463***	0.416**
	(0.036)	(0.033)	(0.124)	(0.130)
h^2_{t-1}	0.850***	0.854***	0.537***	0.584***
	(0.036)	(0.033)	(0.124)	(0.130)
ex_t		0.433**		0.021
		(0.158)		(0.139)
oil_t			0.193***	0.202***
			(0.058)	(0.053)
$cons$	0.569	-1.483	0.692	0.551
	(0.480)	(1.513)	(0.652)	(0.642)

Table 6 shows the conditional correlation coefficients and adjustment coefficients of the DCC-MGARCH model. In the case of DCC-1 and DCC-2, the conditional correlation coefficients were 0.229 and 0.239, respectively, but the correlation coefficients were not significant for DCC-3 and DCC-4.

Table 6 DCC-MGARCH Model conditional coefficients and adjustment coefficients

	DCC-1	DCC-2	DCC-3	DCC-4
Conditional correlation coefficients	0.229*	0.239*	-0.016	0.160
	(0.114)	(0.122)	(0.158)	(0.141)
λ_1	0.607***	0.603***	0.426***	0.560***
	(0.116)	(0.118)	(0.112)	(0.162)
λ_2	0.028	0.035	0.331*	0.09
	(0.045)	(0.058)	(0.135)	(0.138)

CONCLUSIONS

This study employed DCC-MGARCH model to analyze the volatility of inbound and outbound tourism demand change rates and its interaction. Previous studies have used the GARCH model to estimate and predict the volatility of single variables. However, the GARCH model is limited in that it cannot analyze the mutual influence between variables. This study differs from the previous studies in that the change of conditional correlation coefficient over time and the response of volatility to exchange rate and oil price fluctuation are examined.

The results are summarized as follows. First, the DCC-MGARCH model well explains the volatility of inbound and outbound tourism demand change rate, and the DCC-2 model is particularly suitable for explaining the time-varying conditional correlation coefficients. The change in outbound tourism demand did not have the ARCH effect, but the DCC-MGARCH model had a volatility effect. Second, in the conditional average equation, the rate of change of inbound tourism demand and the rate of change of outbound tourism demand were influenced only by the autoregressive lagged variables and did not affect each other. Inbound and outbound tourism demand changes showed a monthly effect. Third, the rate of change in inbound tourism demand showed a stronger volatility than that of outbound tourism demand. Fourth, oil price changes have a significant effect on the volatility of inbound and outbound tourism demand change rate, and the exchange rate change has a significant effect only on the volatility of outbound tourism demand change rate.

Appropriate information on tourism demand volatility and information on the response of volatility to exchange rates and international oil price fluctuations could help the industry to develop measures to address the risks to volatility. Considering the interdependence and the change of conditional correlation coefficient over time, useful information that cannot be obtained when analyzing single variable volatility will be obtained.

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