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Modeling Turkish Tourism Demand and the Exchange Rate: the Bivariate Garch Approach

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Abstract

The primary purpose of this study is to investigate the relationship between tourism demand in Turkey and the exchange rate. Engle's (2002) two stage dynamic conditional correlation GARCH (DCC-GARCH) model is used to estimate the conditional correlations. The analysis of tourism demand from the Eurozone and the USA to Turkey indicates that tourism demand and the exchange rate are positively related. The results also show no clear positive relationship for tourism demand from the UK. In conclusion, tourism destinations are more popular to people from countries when their currency is more valuable.

Keywords: Tourism demand, Turkey, Exchange rate, DCC-GARCH

1. Introduction

One of the most important decisions for international tourists is destination choice. Factors that impact destination choice include tourism prices, number in party, income, transportation cost, distance, neighbouring country, qualitative factors in the country of origin or at the destination, the exchange rate between the origin and destination countries, safety, availability of tourist activities, and natural and climatic factors (Eryiğit et al., 2010; Rossello et al., 2005; Dritsakis, 2004).

The exchange rate between the origin and destination countries, as a component of the cost of living, is a crucial determinant of tourism destination (Webber, 2001). Potential tourists may allocate parts of their income for their tourism expenditures and may want to spend this money effectively. Therefore, rational tourists may prefer to visit countries with a relatively less valuable currency, as compared to own currency (Kuo et al., 2009). Turkey is popular tourism destination for many source countries, due to its less valuable currency.

Tourism contributes significantly to the Turkish economy and has been increasing significantly over the last decade. The total number of foreign tourists arriving in Turkey in 2000 was about 10.43 million. In 2010, that number increased to 27.5 million. The Eurozone (50-60% of international tourists), the United Kingdom (UK) (7-10%), and the United States of America (USA) (2-3%) are important source countries for Turkish tourism.

Quantitative methods, especially time series models, are commonly used in the literature to model tourism demand. Song and Li (2008) reviewed post-2000 empirical studies on international tourism demand and illustrated that the number of empirical studies about tourism demand for Turkey was limited. More specifically, according to our knowledge, there have been no bivariate generalized autoregressive conditional heteroscedasticity (GARCH) models used to study the relationship between tourism demand for Turkey and the exchange rate. Therefore, this study will investigate the relationship between tourism demand for Turkey and the exchange rate by using bivariate GARCH models.

Monthly data for the period of 2001-2010 was analyzed. Data consists of the number of tourist arrivals from the Eurozone, the UK and the USA to Turkey and country exchange rates (Turkish Lira/Euro, Turkish Lira/Sterling and Turkish Lira/USA Dollar).

The remainder of this paper is organized as follows. Section 2 reviews the related literature about the relationship between tourism demand and the exchange rate. Section 3 introduces the quantitative methodology (bivariate GARCH) used in the study. Section 4 describes the data and illustrates the empirical results. Finally, Section 5 presents concluding remarks.

2. Literature

The effect of exchange rate volatility on tourism demand should be evaluated in two aspects. First, exchange rate volatility affects the value of the destination country's currency. Second, volatility in the exchange rate may indicate instability, or a disorder, such as an earthquake or terrorist attack. The response of tourists to the volatility in the exchange rate depends on their attitudes towards risk. While a risk-averse tourist may cancel their holiday, a risk-taking tourist may see the situation as an opportunity (Webber, 2001).

The results of the empirical studies that examine the impact of the exchange rate on tourism demand vary from study to study (Crouch, 1994a; Crouch, 1994b). Webber (2001) indicates that exchange rate volatility may cause tourists to change their destination choice. Kuo et al. (2009) analyzes the impact of the exchange rate on tourism demand in eight Asian countries by using panel data and proposes that if the currency from the person in the source country is more valuable than the currency in the tourism country, the destination country is an attractive tourism region. Similarly, Croes and Vanegas (2005) illustrate that the exchange rate is one of the most important competing factors for tourist arrivals from the USA, Netherlands and Venezuela to Aruba. Uysal and Crompton (1984) also find that the exchange rate significantly affects international tourist flow to Turkey.

On the other hand, some empirical studies in the tourist literature have not found any significant effects of the exchange rate on tourism demand. Vanegas and Croes (2000) examined tourism demand from the USA to Aruba. The coefficients on the exchange rates in their model were not statistically significant. Quayson and Var (1982) showed that the exchange rate was not a determinant of Okanagan tourism demand. Other studies that found insignificant exchange rate effects include Croes (2000), Lee et al. (1996), and Loeb (1982).

Multivariate GARCH models have generally been used in financial studies. In the tourism literature, the numbers of studies that use the multivariate GARCH models are limited. Seo et al. (2009) examined Korean outbound tourism demand with a dynamic conditional correlation multivariate GARCH (DCC-MGARCH) model. Hoti et al. (2007) estimated vector autoregressive moving average GARCH (VARMA-GARCH) models to analyze tourism demand and country risk returns for Cyprus and Malta. Shareef and McAleer (2007) applied multivariate GARCH techniques for tourist arrivals to the Small Island Tourism Economy (SITE), namely Maldives. Shareef and McAleer (2008) extended their 2007 study by including international tourist arrivals to Seychelles and investigated the spillover effects between Maldives and Seychelles. Chan et al. (2005) attempted to illustrate cross-country effects in conditional variances for tourism demand from Japan, New Zealand, the UK and the USA to Australia. They used constant conditional correlation (CCC), VARMA-GARCH and VARMA-AGARCH (asymmetric VARMA-GARCH) multivariate GARCH models in their study.

There are few studies using multivariate GARCH models for Turkish tourism data. Coşkun and Özer (2010) examined Turkish tourism demand volatility with multivariate GARCH models. They used monthly tourist arrival data from Germany, France, the UK and the Netherlands to Turkey. As a result, they show the interdependent and dependent effects for the source countries.

The contribution of this study is twofold. First, it attempts to investigate the relationship between tourism demand for Turkey and the exchange rate by using various source country tourists' arrival data. Second, it uses the bivariate GARCH techniques, rarely used in studies that examine Turkish tourism demand.

3. Bivariate GARCH Models

Studies about modelling conditional variance have gained momentum with the development of the autoregressive conditional heteroscedasticity (ARCH) model by Engle (1982). Although the ARCH model offers a useful framework for the analysis of the conditional variance of a time series, it has some limitations. The most important limitations are the violation of non-negativity constraints of the parameters of the variance equation and the requirement of very large lags of the squared error to fulfil all dependence of conditional variance (Brooks, 2002:452). To overcome such limitations, Bollersev (1986) proposed a generalized autoregressive conditional heteroscedastic (GARCH) model. The GARCH model extends the ARCH model by allowing for past conditional variances being placed into the variance equations.

The univariate GARCH models can be generalized to multivariate GARCH models by taking into consideration the covariance. The multivariate GARCH models allow time varying covariances, as well as variances. The primary practical problem of implementing the multivariate GARCH model is the high number of parameters that are necessary to be estimated. They have therefore tried to reduce the number of parameters by using various reparameterization techniques. The most popular reparameterization techniques are Bollerslev, Engle and Wooldridge's (1988) diagonal VECH, Bollerslev's (1990) constant conditional correlation (CCC) model, Engle's (2002) dynamic conditional correlation (DCC) model and Engle and Kroner's (1995) BEKK model (Kearney and Patton, 2000; Chan et al., 2005).

In this study, a bivariate version of the Engle's (2002) DCC specification of the multivariate GARCH (1, 1) model is used.

$$y_t=\phi(L)\, y_t+\Xi_t \qquad \Xi_t \sim N(0,H_t) \tag{1}$$

$$H_t = D_t R_t D_t \tag{2}$$

$$D_t = diag(\sqrt{h_{11,t}}, \sqrt{h_{22,t}} \ldots, \sqrt{h_{nn,t}}) \tag{3}$$

$$R_t = [diag(Q_t)]^{-1/2} Q_t [diag(Q_t)]^{-1/2} \tag{4}$$

$$Q_t = (1-\alpha-\beta)\bar{Q} + \alpha u_{t-1}u'_{t-1} + \beta Q_{t-1} \tag{5}$$

where: $h_{ii,t}$ follows the GARCH (1, 1) process, H_t is the conditional covariance matrix of the random vector Ξ_t and u_t is a vector that contains standardized values of Ξ_t. In Equation (1), $\varphi(L) = \sum_{i=1}^{p} \varphi_i L^i$, p is an integer that represents the autoregression order and $\boldsymbol{L}$ is a backshift operator. In Equation (4), R_t denotes the time varying correlation matrix and Q_t is the positive definite symmetric matrix. $\bar{Q}$ represents the unconditional variance matrix of u_t. The time varying elements of R_t , $\rho_{ij,t}$, are:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} \tag{6}$$

where: $q_{ij,t}$ is the element of Q_t. For the positive definiteness of R_t, Q_t needs to be positive definite. In Equation (5), if $\alpha \geq 0, \beta \geq 0$ and $\alpha+\beta<1$, conditions are satisfied and the conditional correlation matrix will be positive definite.

The parameter estimation of the DCC model is carried out using conditional maximum likelihood estimation. Under the assumption of normally distributed errors, parameters can be estimated by maximizing the following log likelihood function:

$$L(\theta) = -\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi) + 2\log(|D_t|) + \log(|R_t|) + u_t' R_t^{-1} u_t) \tag{7}$$

where: T is the number of observations and n is the number of the variables in the system. θ, denotes all parameters to be estimated in the system. Since the log-likelihood function is non-linear, it is maximized by an iterative numerical algorithm to estimate the parameters. The most commonly used maximization algorithms are Berndt, Hall, Hall, Hausman (BHHH), Broyden, Fletcher, Goldfarb, Shanno (BFGS) and Marquardt. In this study, BFGS is used for the estimation.

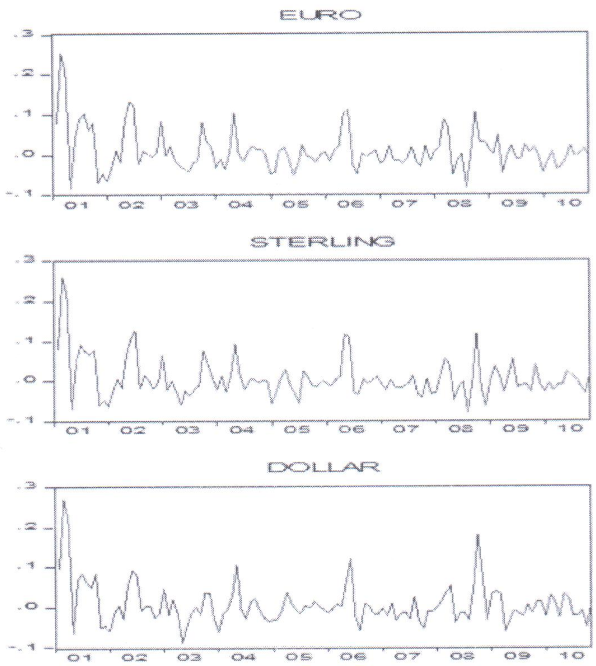
4. Data and Empirical Findings

The dataset used in this study contained monthly statistics about tourist arrivals from the Eurozone, the UK and the USA to Turkey. The Turkish Lira/Euro, Turkish Lira/Sterling, Turkish Lira/Dollar exchange rate series from January 2001 to November 2010 was followed. The data were gathered from the Turkish Ministry of Culture and Tourism (2010) statistics and Turkish Central Bank of Electronic Delivery System. In the study, logarithmic arrival rates and a logarithmic change of exchange rate series (Figure 1), calculated from Equation 8, were used instead of the level of the series, due to the presence of stationary problems.

$$y_t = \log(\frac{x_t}{x_{t-1}}) \tag{8}$$

In Equation (8), $\mathbf{y_t}$ represents the logarithmic change rate and x_t is the level of the corresponding variable at time **t**.

Figure 1: Logarithmic rate of change for TL/Euro, TL/Sterling and TL/Dollar



As can be seen in Figure 2, tourist arrival rates exhibited strong seasonality. The TRAMO/SEATS (Time Series Regression with ARIMA Noise, Missing Observations and Outliers/Signal Extraction in ARIMA Time Series) method was used to seasonally adjust arrival rates. TRAMO/SEATS programs are popular methods developed by Agustin Maravall and Victor Gomez at the Bank of Spain. TRAMO and SEATS are used together for the aim of seasonal adjustment.

TRAMO first preadjusts the series for SEATS. Next, the series is seasonally adjusted by SEATS (Gomez and Maravall, 1996).[1]

Figure 2: Tourist arrival rates and seasonally adjusted tourist arrival rates from the Eurozone, the UK and the USA to Turkey

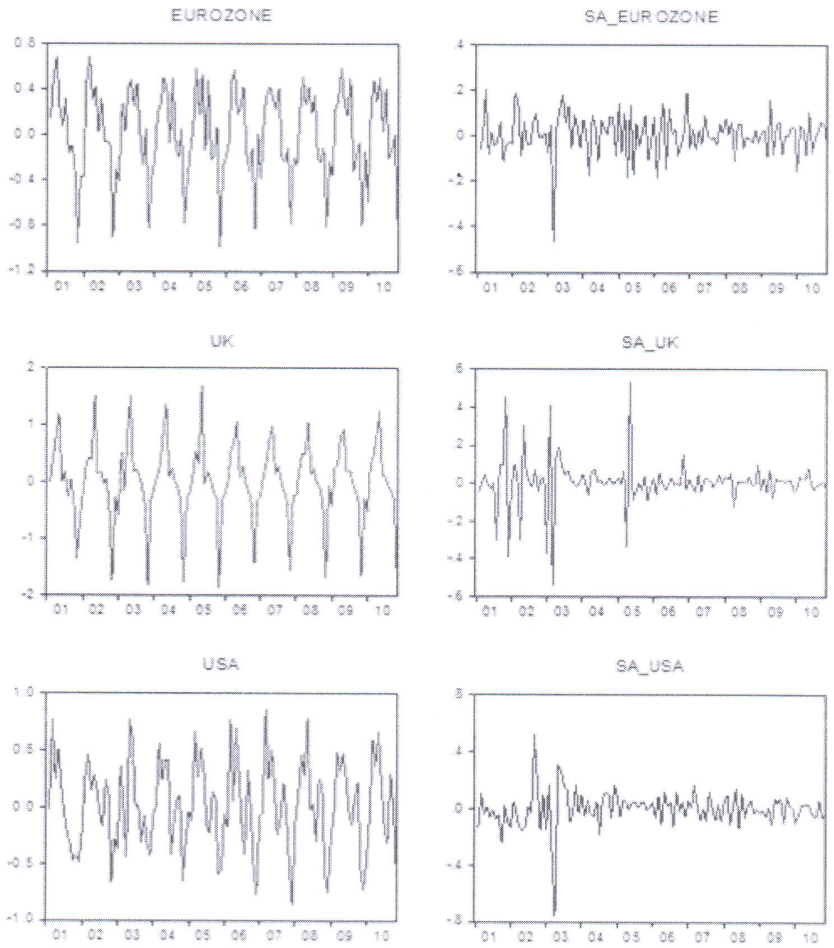


Table 1 presents the summary statistics of the data. The Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) tests for stationarity were conducted for the seasonally adjusted arrival rate to Turkey from the Eurozone (SA_EUROZONE), the UK(SA_UK) and the USA (SA_USA), along with the foreign exchange rate series (TL/euro, TL/sterling, TL/dollar). The lag length for the ADF was selected by the Schwarz Information Criterion (SIC). The test results show that the null hypothesis of the presence of the unit root for all monthly data is rejected. Therefore, it can be concluded that all series used in the study are stationary.

[1] Methodological details about TRAMO/SEATS can be obtained from Maravall and Gomez(1992), Gomez and Maravall(1992) and Gomez and Maravall (1996)

Table 1: Summary statistics for data

-	SA_EUROZONE	SA_UK	SA_USA	TL/EURO	TL/STERLING	TL/DOLLAR
Mean	0.006	0.009	0.001	0.010	0.007	0.006
Median	0.014	0.008	0.007	0.001	-0.005	-0.006
Maximum	0.201	0.537	0.512	0.254	0.261	0.270
Minimum	-0.464	-0.538	-0.761	-0.082	-0.079	-0.089
Std. Dev.	0.093	0.127	0.129	0.052	0.051	0.052
ADF	-14.934*	-11.715*	-10.877*	-8.473*	-8.894*	-8,549*
PP	-23.579*	-32.513*	-11.609	-6.876*	-7.324*	-7.017*

ADF: Augmented Dickey Fuller PP: Phillips-Perron * significant at 1%

The conditional mean equations for the models (Equation 1) were specified as autoregressive models. The lag length is selected by using the Schwarz Information Criterion (SIC). The SIC show that the autoregressive order for all variables is AR (1). Table 2 illustrates the maximum likelihood estimation results for DCC-GARCH (1,1). The conditions for the positive definiteness of R_t are satisfied ($\alpha \geq 0, \beta \geq 0$ and $\alpha + \beta < 1$). According to the results, α and β are significantly different from zero for all bivariate models. Thus, the conditional correlations are time varying, rather than constant in the sample period.

Table 2: Estimation results for bivariate DCC-GARCH models

	SA_Eurozone-Euro	SA_UK-Sterling	SA_USA-Dollar
α	0.197*	0.467*	0.194*
β	0.797*	0.518*	0.794*
$\alpha + \beta$	0.994	0.985	0.988
Likelihood	-322.27	-318.89	-321.70

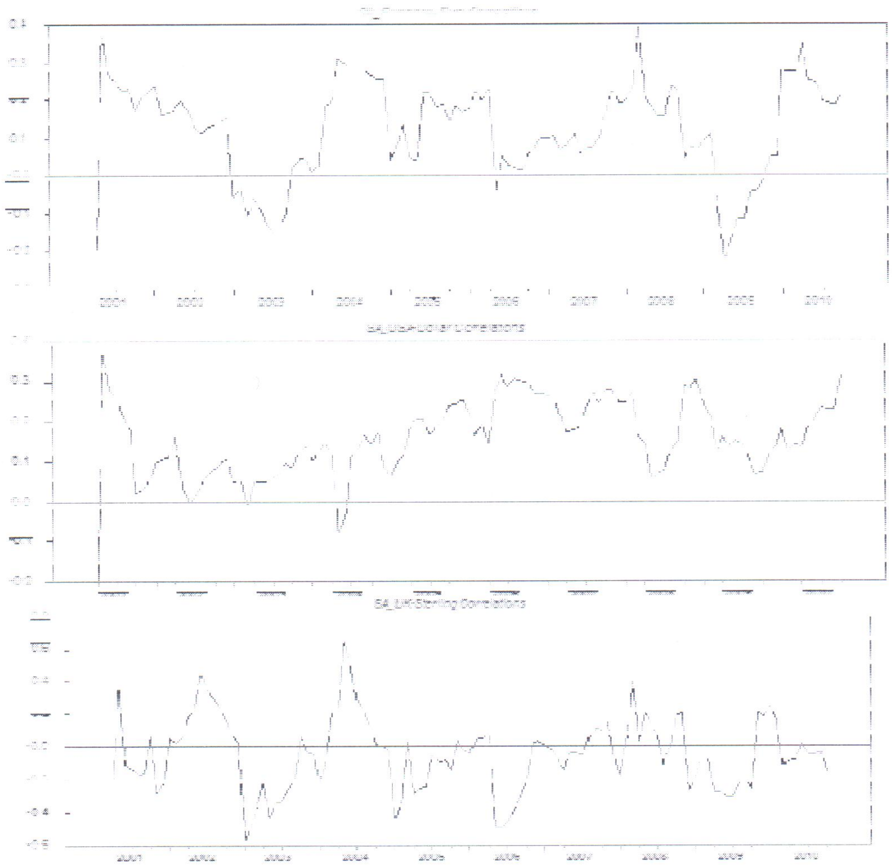
*significant at 1%

Figure 3 demonstrates the time varying correlations between the tourist arrivals rate and related exchange rate. The conditional correlations between tourist arrivals from the Eurozone and TL/Euro exchange rate exhibit strong volatility. There is a positive conditional correlation in the sample period, except for the years of 2003 and 2009. A similar pattern was observed for the conditional correlation between tourist arrivals from the USA and the TL/Dollar exchange rate. The conditional correlations are negative for 2004 and positive for all other time points. For the conditional correlations between tourist arrivals from the UK and the TL/Sterling, the situation is different. The conditional correlations are highly volatile around zero. There is no dominant structure about the sign of the conditional correlations. While the sign is positive for 2002, 2004 and 2008, it is negative for 2003, 2005 and 2009.

In summary, the exchange rate is an important determinant of Turkish tourism demand from the Eurozone and the USA. If the exchange rate increases, Turkey will be a more attractive tourism destination for the Eurozone and the USA. Tourists from the Eurozone and the USA may stay longer in Turkey than other tourism destinations with their tourism budget or they will stay in more qualified facilities. The results show that a high exchange rate may help the Turkish tourism industry to attract more tourists from the Eurozone and the USA.

Tourism demand from the UK to Turkey is not highly sensitive to the exchange rate. Tourists from the UK may not deal with the exchange rate. However, other tourism advantages of Turkey may affect the decisions of tourists from the UK. The geographic location, quality of facilities, various tourism alternatives (sun, sand, snow, nature, history, and health) of Turkey may be a powerful factor that attracts tourists from the UK.

Figure 3: Time-Varying Conditional Correlations



5. Conclusions

Turkey is an important tourism destination, because it is near many countries, has a lot of history and has a relatively less valuable currency than other countries. In this study, an investigation of the effects of the exchange rate on Turkish tourism demand is conducted. Engel's (2002) two stage procedure for the DCC-GARCH model is used to determine the conditional correlations over the monthly sample from January 2001 to November 2010. The data includes tourist arrivals from the Eurozone, the UK and the USA to Turkey, as well as TL/Euro, TL/Sterling and TL/Dollar exchange rates.

The empirical results show that tourism demand and the exchange rate for the Eurozone and the USA was positively correlated. The results for the UK did not indicate any conditional correlations between tourist arrivals and the exchange rate. The sign of the conditional correlations varied throughout the sample period.

The empirical results are beneficial, especially for tourism dependent countries. The policy-makers who make a decision about the exchange rate policy can benefit from the results.

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