# MGARCH Modeling of Inbound Tourism Demand Volatility in Turkey

**İnci Oya Coşkun, Lecturer**
School of Tourism and Hotel Management
Anadolu University
ioyazicilar@anadolu.edu.tr

**Mustafa Özer, Professor Doctor**
Faculty of Economics and Administrative Sciences, Department of Economics
Anadolu University
muozer@anadolu.edu.tr

***Abstract***

*Tourism has been one of the leading industries in the world economy for the last 50 years and has an outstanding importance for Turkey. Tourism industry mainly depends on demand, and analyzing the changes in tourism demand is essential for management purposes. Inbound tourism demand for Turkey has faced many challenges in the last three decades, such as terrorist attacks, epidemics, economic and financial crises, political turmoil and global downturns. Understanding the volatility of demand can help to develop appropriate solutions for recovery. In order to resolve volatility, this paper models the time series behavior of the four leading European tourism source countries, namely Germany, France, United Kingdom and Netherlands with multivariate GARCH models using monthly data for 1985:01-2009:09 period. The empirical results showed cross-country interdependent and dependent effects in the conditional correlations for all of the selected countries. The results of this paper indicate that -as the major source countries are dependent on each other- the demand volatility is caused by the economic conditions, preferences or other factors that originate from the source countries, rather than the internal dynamics of Turkey.*

Keywords: Tourism demand, volatility, multivariate GARCH models

JEL Classification: A12, C32

## Introduction

Tourism has become a leading industry in the world economy within the last 50 years. UN World Tourism Organization reports indicate that international tourist arrivals have reached to 880 million in 2009 by a 35 times increase since 1950s. International tourism receipts have increased from 2 billion US$ in 1950s to 850 billion with a 425 times increase in 2009 (UNWTO, 2010).

As is all over the world, Tourism is also one of the key sectors for Turkey. Turkish tourism industry began to grow in 1980s with the government's directive central planning model and supply-sided incentive macroeconomic policies. The industry has been growing in terms of international tourist arrivals and tourism receipts despite some challenging periods.

After the enactment of Tourism Incentive Law in 1982, that aimed to support the private sector investments in tourism, the accommodation capacity increased by 30%. After the increase in supply, number of tourist arrivals increased by 24% and the balance of international tourism receipts and expenditures increased by 106%. Incentives for investments created a structural change in Turkey.

Turkey's inbound tourism portfolio is very diverse, such as tourists from Europe, Middle East, Russia and some other countries overseas prefer Turkey for their holidays. The dominating market is Europe with a 55-60% average of the total tourist arrivals. Asia follows Europe by 11% average.

Almost half of the international visitors (48%) preferred Turkey for travel and entertainment/holiday purposes in 2008. The most important motivations in the other half is distributed among visiting friends and relatives (9%), culture (5%) and shopping (4%).

Turkey's share of the international tourism receipts is small when compared to its 'fame' as being a well-known tourist destination. There has been a debate that supply-sided tourism policies neither provide nor improve fulfilling tourism receipts, since the GDP is growing, but the share of tourism receipts is decreasing. Turkey's share in the world tourism receipts was 1.9% in 1990 and it steadily increased to 4.6% in 2008 (Development Bank of Turkey, 2008, p.6) and according to UNWTO it is one of the Top 10 Tourism Earners in tourism receipts. In 2008, Turkey was ranked number 8 in the list of world's top tourism destinations and number 9 in the list of world's top tourism earners. In 2009, despite the fact that tourist arrivals fell down by 6% worldwide, Turkey was one of the few countries that achieved a slight increase by 2% (UNWTO, 2009, p.5).

On the contrary of increasing world share, the share of tourism receipts in Turkey's export earnings and GDP has been decreasing since 2002. The share of tourism receipts in GDP was 5.2% in 2002 and fell down to 2.9% in 2008. Also, the share of tourism receipts in export earnings was 33% in 2002, and it steadily fell down to 16.6% in 2008. The reason for this decline is simply because of the fast growth in other industries and "cheap country" image of Turkey enforced by the last minute sales of the European tour operators. As Turkey still follows supply-sided tourism policies, this does not seem to change in near future. In fact, supply-sided policies should be supported and reinforced by demand-sided arrangements and policies.

Due to the devastating changes in the economy, the crises in 1991, 1994, 1999, 2001 and 2006 also adversely affected the economic contribution of tourism. The major downturn was in 1999; the tourism receipts decreased by 33%, and international tourism generated export earnings decreased by 9.3% within a year.

As is well known, since the two of the major problems of most of the developing nations is to have a substantial current account deficit and increase in foreign debt, tourism plays a key role especially for these countries. On one hand, tourism is an important tool for development with its direct effect on the balance of payments. On the other hand, tourism is highly dependent on tourism demand, which is extremely delicate to every kind of changes in the environment.

As we mentioned tourism industry mainly depends on demand, and analyzing the changes in tourism demand is essential for developing successful tourism policies. Turkish inbound tourism demand has faced many challenges in the last three decades including terrorist attacks, epidemics, economic and financial crises, political turmoil and global downturns. Despite this fact, the volatility of the international tourist arrivals has not been investigated fully in the literature. As Özer, Türkyılmaz, (2004, p.32) argued the cyclical fluctuations around the trend, namely the "volatility clusters" should be examined carefully for a better decision-making and strategic planning process and they must be considered as important as other managerial issues. Understanding volatility behavior can help to develop appropriate measures for solutions.

In order to resolve volatility problem, this paper aims to model the time series behavior of the four leading European tourism source countries, which are Germany, France, the United Kingdom and the Netherlands using multivariate GARCH models based on the monthly data for the period of 1985:01-2009:09. These countries comprise 41% average of total tourist arrivals in the last 10 years.

The organization of the paper is as follows: In section 2, some details about the inbound tourism demand from the selected countries are given. A literature review of multivariate GARCH models in tourism is presented in Section 3. Section 4 describes the data used for analysis and three alternative parameterizations for multivariate GARCH models. In section 5, the results of the empirical analysis are discussed. Finally, in Section 6 concluding remarks and policy implications are given.

## Inbound tourism to Turkey

Tourist arrivals to Turkey have increased more than 10 times from 2.6 million to 27.1 million between the years 1985 and 2009. In the last 10 years (2000-2009) international tourist arrivals have increased 360% (Turkish Ministry of Tourism and Culture, 2009).

The share of Europe in international tourist arrivals has been approximately around 55-60%, since 1985. Based on the last 10 years' average international tourist arrivals, 7 of the 10 leading source countries are from Europe namely Germany, the United Kingdom, Bulgaria, the Netherlands, France, Austria and Belgium.

Germany takes the first row for 2000-2009 periods with an average of 21% share in total arrivals and 33% share in European arrivals. Germany has also been the most important tourist generating country since 1980s. Russian Federation is following Germany with an 8.8% share as the second major source country.

The United Kingdom is the third leading market for international tourist arrivals to Turkey. It has an average share of 8.1% in total arrivals and 13% share in European arrivals for the same period. $4^{th}$ and $6^{th}$ countries are Bulgaria and Iran respectively. Although they have an important role, statistics are recorded for every foreigner as they cross the border. So, the entire visitors from these two countries cannot be considered as international tourists, because these countries are both neighbors and they usually visit Turkey for commercial or suitcase trading purposes on a daily basis.

The Netherlands is in the fifth row and France is in the $7^{th}$ row. The Netherland's share is 5.3% in the total arrivals and 8.4% in European arrivals. France receives a share of 3.5% of the total arrivals and 5.6% of European arrivals. Other three countries in the top 10 taking $8^{th}$, $9^{th}$ and $10^{th}$ rows are USA, Austria and Belgium respectively.

Arrivals from Europe has been resilient and made a peak in 2002 with a share of 70% in the total tourist arrivals. 1991 was the year of Gulf War, and total tourist arrivals showed a small increase of 2% and European arrivals followed the same cycle of growth with a 5% increase. 1994 was a year of an economic crisis in Turkey, with terrorist attacks on the background. In 1994, although there was an increase in the overall tourist arrivals, Europe's share fell down by 10%. There was another trough in 1999 because of the earthquake disaster and the political crisis caused by the capturing of leader of the separatist group. The overall tourist arrivals decreased by 23%, and European arrivals fell down by 29% in 1999. The last, but not the least, crisis was in 2006. The avian influenza and US invasion of Iraq brought about a new trough of 6% decrease in the overall international tourist arrivals and 12% decrease in the European arrivals.

Turkey's popularity in Europe is due to several reasons. The most important reason is that Turkey is a nearby country with natural and historical beauties, offering low prices. Also relaxed visa regime and attractive exchange rate in Turkey makes it a convenient alternative especially for Western European holidaymakers. Increasing recognition and awareness of Turkey in the European Union is also another advantage for Turkey.

The leading four European countries in the international tourist arrivals (Germany, UK, the Netherlands and France) show the same characteristics in terms of purpose of travel, length of stay, visitor profile and expenditure. Europeans generally prefer Turkey for holiday purposes and they choose to purchase inclusive tours from tour operators. They usually stay for 1 or 2 week holidays. As Turkey is known as a "cheap" country, people from the middle class with average income prefer Turkey.

The path of the selected countries' tourist arrivals follow the same path of the crises with peaks and troughs mentioned above. In 2009, the year of global crisis, the number of tourist arrivals increased, but the increase rate fell down by 3%, which is very consistent with the world average.

Europe is the most important tourist generating region for Turkish inbound tourism. As this paper aims to investigate the volatility of tourism demand, it is better to examine the important figures and countries for the Turkish tourism industry.

## Literature review on multivariate GARCH models in tourism

Multivariate GARCH models have mainly and commonly been used in financial market analysis for the last two decades (Bollerslev, 1990; Nelson, 1991; Engle and Ng, 1993; Engle and Kroner, 1995; Kroner and Ng, 1998; Lim, 2005). Tourism researchers have noticed the importance of these models in the last few years. In particular, using multivariate GARCH modeling, the studies of McAleer, Shareef and Hoti have an important influence on the tourism research. Unfortunately, the number of tourism studies using multivariate GARCH models is still very few, particularly in Turkey.

Table 1 shows a summary of the literature on multivariate GARCH models in tourism related researches.

**Table 1: Summary of literature review on multivariate GARCH models in tourism**

| Author | Publ. Year | Summary |
|---|---|---|
| Chan, Lim, McAleer | 2005 | - Tourism demand to Australia from 4 major source countries<br>- 1975-2000 monthly data, 3 different multivariate GARCH models<br>- Interdependencies of conditional variances and asymmetric effects of shocks. |
| Hoti, Leon, McAleer | 2005 | - Tourism demand to Canary Islands from 14 major source countries<br>- 1990-2003 monthly data, Multivariate CCC-GARCH model<br>- Source countries are independent to shocks |
| Shareef, McAleer | 2005 | - Tourism demand and growth rate to 6 different island economies<br>- Monthly data (different periods for each island, Multivariate ARMA-GARCH model<br>- Island economies are complementary in cross correlations but they differ according to tourist generating countries |
| Shareef, McAleer | 2007 | - Tourism demand to Maldives from 8 major source countries<br>- 1994-2003 monthly data, Multivariate ARMA-GARCH model<br>- Conditional correlations of 8 major source countries show independent effects to shocks |
| Hoti, McAleer, Shareef | 2007 | - Tourism growth, country risk ratings and their associated values for Cyprus and Malta<br>- 1986-2002 monthly data, VARMA-GARCH and VARMA-AGARCH models<br>- Cyprus and Malta re complementary destinations for international tourists |
| Alvarez, Hoti, McAleer | 2007a | - Tourism demand to 5 major tourist destinations in Spanish territory<br>- 1994-2006 monthly data, Multivariate CCC-GARCH model<br>- 5 destinations are substitutes and independent to shocks |
| Alvarez, Hoti, McAleer | 2007b | - Tourism demand to Spain from 5 major source countries<br>- 1994-2006 monthly data, Multivariate CCC-GARCH model<br>- Markets are independent and need different strategies |
| Shareef, McAleer | 2008 | - Tourism demand to Maldives and Seychelles from 5 major source countries<br>- 1994-2003 weekly data, Vector CCC-GARCH model<br>- Spillover effect from source countries to Maldives and Seychelles |
| Coshall | 2009 | - Outbound tourism demand of the UK to 12 major destinations<br>- To assess the forecasting capability of volatility models<br>- Quarterly data (different periods for each destination), GARCH and EGARCH models<br>- Volatility periods and effects change according to the structure of the shock and destination |
| Seo, Park, Yu | 2009 | - Determinants of Korean outbound tourism demand to Jeju Island and 3 other Asian islands<br>- 1980-2006 monthly data, Multivariate CCC-GARCH model<br>- Conditional correlations depend on time, 3 Asian islands are substitutes for Jeju Island |

## Empirical analysis

In this section, we fist introduce the data and models that we use in empirical analysis.

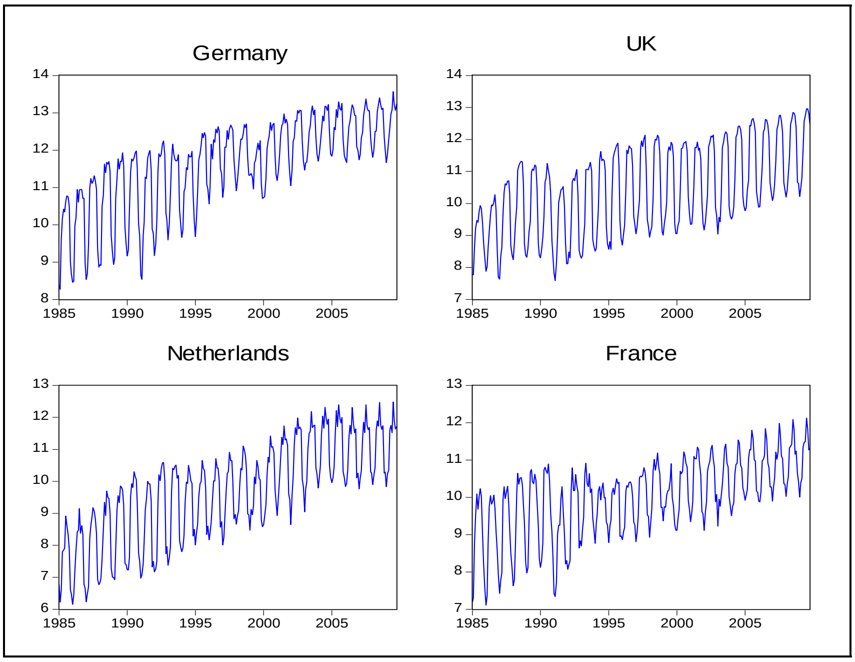
**Data**

Although tourism industry is one of the key industries in Turkey, especially as a source of exchange earnings and has faced many challenges in terms of tourist arrivals and tourism receipts in the last 30 years, it is hard to say that examining the demand volatility has been attractive to researchers significantly. Moreover, it is also true that such analysis may provide essential information about the strengths, weaknesses, opportunities and threats of a destination country. For that reasons, we will analyze the behavior of the logarithm of the monthly arrival rate from the four leading European source countries, namely Germany, the UK, France and the Netherlands using multivariate GARCH models.

We use monthly data for number of tourist arrivals over the period of January 1985 and September 2009. The data is obtained from the number of arriving-departing foreigners and citizens statistics of Turkish Ministry of Culture and Tourism (http://www.turizm.gov.tr).

Figure 1 shows the log arrival rate from the selected countries.

**Figure 1: Log arrival rate of selected countries**




As is seen clearly from figure 1 that all countries exhibit upward trend in the log arrival rate. They also show clear seasonal and cyclical patterns. To focus on the other components of the each series, we eliminate the seasonality by using Tramo/Seats method. All series share the same patterns for the same periods. High season is May-October period, and peaks are at July for each country. In addition, while all series exhibits a steady growth, there is a significant fall in 1991 due to the Gulf War. The worst crisis that affected tourist arrivals from Europe was in 1999. Tourist arrivals from all countries except the UK fell down approximately by 35%, but change in the UK arrivals was 18%.

Table 2 shows the correlation matrix of the seasonally adjusted log arrival rate for the four leading countries.

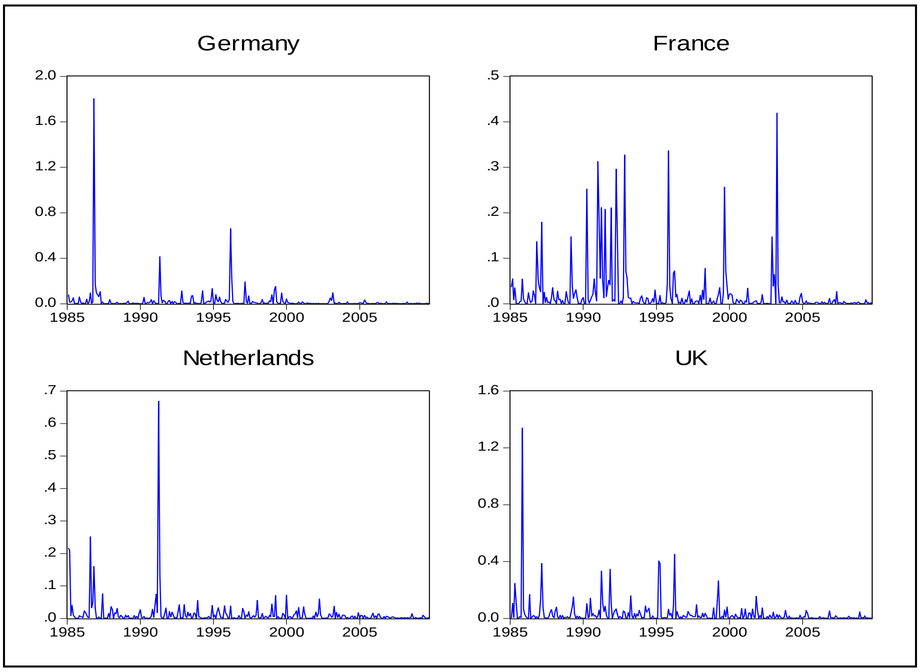
**Table 2: Correlation Coefficients of seasonally adjusted monthly log arrival rate for the selected countries**

| | Germany | France | The Netherlands | United Kingdom |
|---|---|---|---|---|
| Germany | 1.000000 | 0.926684 | 0.965393 | 0.931107 |
| France | | 1.000000 | 0.933267 | 0.927948 |
| The Netherlands | | | 1.000000 | 0.925029 |
| United Kingdom | | | | 1.000000 |

Germany and the Netherlands are ranked first with a correlation coefficient of 0.965393, followed by France and the Netherlands with a correlation coefficient of 0.933267, Germany and the United Kingdom with 0.931107, France and the United Kingdom with 0.927948, and Germany and France with a correlation coefficient of 0.926684. As the correlation coefficient shows the degree of relation between the variables, coefficients show a very strong relation between each selected country.

Figure 2 shows the volatility of the seasonally adjusted log arrival rates for the selected countries[1].

**Figure 2: Volatility of seasonally adjusted log arrivals rate for the selected countries**




The volatilities in Figure 2 have similar patterns for Germany, UK and Netherlands and they started to decrease after 2000. The volatilities for France exhibit different patterns. And also, there was a higher volatility before 2005 for France, but it decreased after 2005. The way that

[1] Volatility is calculated as the square of the estimated residuals from an ARMA (1,1) process with a deterministic time trend.

volatilities evolve indicates a structural shift in the volatilities for all countries.

The data should be stationary for modeling time series, thus testing for unit roots is essential for time series analysis with multivariate GARCH models. Taking the logarithm and seasonal adjustment sometimes provide stationary series, but it still has to be tested by unit root tests (Özer and Erdoğan, 2006, p. 98). Augmented Dickey-Fuller (ADF) unit root test models the structure of serial correlation (Dickey & Fuller, 1981, pp. 1057-1072), and Phillips-Perron (PP) unit root test models heteroskedasticity as well as serial correlation (Phillips & Perron, 1988, pp. 335-346). Table 3 shows the results of ADF and PP unit root tests for level and first difference values of the selected series.

**Table 3: ADF and PP test results**

| **ADF Test Statistics** | | | |
|---|---|---|---|
| Country | Levels | First Differences | Critical Values (*) |
| Germany | -1,743847 (4**) | -12,71058 (3) | -2,87 |
| France | -1,599573 (2) | -15,93760 (1) | -2,87 |
| Netherlands | -1,323002 (1) | -24,46114 (0) | -2,87 |
| UK | -1,112967 (2) | -17,40569 (1) | -2,87 |
| * MacKinnon (1996) one-sided p-values for 5% level of significance.<br>** Values in parentheses show lag length determined by SIC criteria. | | | |
| **PP Test Statistics** | | | |
| Country | Levels | First Differences | Critical Values(*) |
| Germany | -1.774581 | -41.24980 | -2,87 |
| France | -1.792175 | -23.28596 | -2,87 |
| Netherlands | -0.668423 | -30.68381 | -2,87 |
| UK | -1.388946 | -32.59659 | -2,87 |
| * MacKinnon (1996) one-sided p-values for 5% level of significance. | | | |

Since ADF and PP tests results indicate that all series are integrated of order one, that is they are stationary at their first differences; hence the presence of a cointegration relation should be analyzed. Cointegration analysis defines a stationary relationship between non-stationary series. Also it provides a common framework for the long and short run relationships. Johansen cointegration analysis is commonly used in empirical studies due to its advantages such as exterminating spurious regressions and eliminating the internal variable determination. To resolve the cointegration, first an unrestricted VAR model was estimated and the lag order was determined as 4 according to Akaike Information Criteria (AIC). Table 4 shows the results of Johansen cointegration analysis (Johansen, 1991, pp. 1551-1580).

**Table 4: Results for Johansen cointegration analysis**

| Null Hypothesis ($H_0$) | Alternative Hypothesis ($H_1$) | Trace Statistic | 5% Critical Value | Max-Eigen Value | 5% Critical Value |
|---|---|---|---|---|---|
| r=0 | r>0 | 56.76637 | 47.85613 | 36.01855 | 27.58434 |
| r≤1 | r>1 | 20.74782 | 29.79707 | 11.12961 | 21.13162 |
| | | | | | |
| Normalized Cointegration Coefficients | LALM_SA | LFRA_SA | LHOL_SA | LING_SA | |
| | 1.000000 | 1.824611 | -0.728050 | -1.531214 | |
| | | (0.36088)* | (0.16681) | (0.26996) | |
| * Values in parentheses are standard errors. | | | | | |

Johansen cointegration test results indicate a cointegration relation among the variables, therefore estimating multivariate GARCH models needs a pre-estimation of vector error correction (VECM) model, rather than a vector autoregressive (VAR) model.

Three different multivariate GARCH parameterizations are estimated in order to find the best model to analyze the conditional volatility of the seasonally adjusted log arrival rates of the selected countries and to investigate their conditional volatility. The selected three parameterizations are diagonal VECH, diagonal BEKK and CCC multivariate GARCH models. Before presenting the results of multivariate GARCH models, let's briefly introduce each model.

**Multivariate GARCH models**

Traditional methods for time series modeling based on the assumption of unconditional variances. However, this assumption may not be true because of the volatility clusters that affect the series. In that case, methods that include variance inequalities should be employed. ARCH/GARCH models work on the assumption of conditional variances that allows the variance to change over time.

Bollerslev, Engle and Wooldridge (1988) extended Bollerslev (1986)'s univariate GARCH model to multivariate models in which the variables are represented in matrix forms (Bollerslev, 1986, pp.307-308; Bollerslev, Engle, Wooldridge, 1988, pp. 119-122). There are numerous parameterizations introduced by many researchers. In this study, diagonal VECH, diagonal BEKK and CCC parameterizations are to be employed in analyses.

VECH parameterization illustrates variables in vector form and formulated by (1).

$$\begin{aligned} y_t &= b + \delta H_t \omega_{t-1} + \varepsilon_t \\ \boldsymbol{vech}\,(H_t) &= C + \sum_{i=1}^{q} A_i \boldsymbol{vech}\left(\varepsilon_{t-i}\varepsilon_{t-i}^{'}\right) + \sum_{j=1}^{p} B_j \boldsymbol{vech}\left(H_{t-j}\right) \\ \varepsilon_t|\psi_{t-1} &\sim N(0, H_t) \end{aligned} \tag{1}$$

Vech(.) is the matrix operator which stacks the lower triangle of a matrix into a column and $H_t$ is the variance-covariance matrix. $b$ is the Nx1 dimensional constants vector; $\varepsilon_t$ is the Nx1 dimensional error terms vector; $C$ is the ½ N(N+1)x1 dimensional coefficients vector. $A_i$ and $B_j$ are (i=1,…,q; j=1,…,p) ½ N(N+1)x½N(N+1) dimensional parameter matrices of the variables (Bollerslev, Engle, Wooldridge, 1988, pp. 119).

In diagonal VECH model, $A_i$ and $B_j$ are diagonal matrices (Engle and Kroner, 1995, p. 126). With this assumption, conditional variances of the individual matrices take the form of a GARCH (p,q) process. For N=2 and p=q=1, $\boldsymbol{vech}\,(H_t)$ is formulated as (2):

$$\begin{aligned} \boldsymbol{h}_t &= \begin{bmatrix} \boldsymbol{h}_{11,t} \\ \boldsymbol{h}_{12,t} \\ \boldsymbol{h}_{22,t} \end{bmatrix} \\ &= \begin{bmatrix} c_{01} \\ c_{02} \\ c_{03} \end{bmatrix} + \begin{bmatrix} a_{11} & 0 & 0 \\ 0 & a_{22} & 0 \\ 0 & 0 & a_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1}^2 \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}^2 \end{bmatrix} + \begin{bmatrix} b_{11} & 0 & 0 \\ 0 & b_{22} & 0 \\ 0 & 0 & b_{33} \end{bmatrix} \begin{bmatrix} \boldsymbol{h}_{11,t-1} \\ \boldsymbol{h}_{12,t-1} \\ \boldsymbol{h}_{22,t-1} \end{bmatrix} \end{aligned} \tag{2}$$

or;

$$h_{11,t} = c_{01} + a_{11}\varepsilon^2_{1,t-1} + b_{11}h_{11,t-1}$$
$$h_{12,t} = c_{02} + a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + b_{22}h_{12,t-1}$$
$$h_{22,t} = c_{03} + a_{33}\varepsilon^2_{2,t-1} + b_{22}h_{22,t-1}$$

$H_t$

In multivariate GARCH models, must be positively defined for every error term ($\varepsilon_t$) and information set ($x_t$). In VECH parameterization and diagonal representation, this restriction is not easy to control or apply.

BEKK parameterization was first introduced by Baba, Engle, Kraft and Kroner (1991) and was enhanced by Engle and Kroner (1995). This model is a solution for the restriction of positively defined variance-covariance matrix. The most important feature of BEKK model is that it ensures positive definition of $H_t$ by its quadratic nature (Billio, Caporin, Gobbo, 2003, p. 4; Kearney, Patton, 2000, p. 36).

BEKK parameterization of Engle and Kroner (1995) is formulated by (3) (Engle and Kroner, 1995, p. 127):

$$H_t = C_0C_0' + \sum_{k=1}^{K}\sum_{i=1}^{q}A_{ki}'\varepsilon_{t-i}\varepsilon_{t-i}'A_{ki} + \sum_{k=1}^{K}\sum_{i=1}^{p}B_{ki}'H_{t-i}B_{ki} \qquad (3)$$

Summation limit K determines the 'generality' of the process. $C_0$ is a triangular matrix, and $A_{ki}$ and $B_{ki}$ are NxN dimensional parameter matrices (Haffner and Herwartz, 2001, p. 5). For $N$ = 2 and $K$ = p = q = 1 BEKK formulation is given in (4):

(4)

Diagonal BEKK model is a specific case of VECH model and assumes that $A_{ki}$ and $B_{ki}$ are diagonal matrices.

VECH and BEKK parameterizations model the conditional variance-covariance matrix $H_t$ directly. Bollerslev (1990) introduced an alternative constant conditional correlation (CCC) parameterization. CCC model assumes the conditional correlations are constant over time and conditional covariance is simply related with the standard deviations. This model reduces the number of parameters to be estimated significantly (Bollerslev, 1990, p. 499). (5) shows the formulation for CCC model:

$$h_{ij,t} = \rho_{ij,t}\sqrt{h_{ii,t}h_{jj,t}} \qquad (5)$$

$j$= 1,…,$N$
$i$= $j$+1,…,$N$

$h_{ij,t}$, is the $ij^{th}$ element of $H_t$, $y_{it}$ and $\varepsilon_{it}$ are $i^{th}$ elements of $y_t$ and $\varepsilon_t$ respectively. Conditional correlation for $t$ – 1 that shows the constant measure of coherence between $y_{it}$ and $y_{jt}$ is calculated by (6);

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

$-1 \leq \rho_{ij,t} \leq 1$ condition is almost true for every *t*, and as $H_t$ changes over time, this measure of coherence will change over time. $h_{iit}$ is any univariate GARCH model and $R = (\rho_{ij})$ is a positively defined symmetrical matrix ($\rho_{ii} = 1, \forall i$) (Bauwens, Laurent, Rombouts, 2006, p. 88).

CCC parameterization matrix form is illustrated in (7):

$$\begin{gathered} H_t = D_t R D_t = \rho_{ij} \sqrt{h_{iit} h_{jjt}} \\ D_t = diag\left(h_{11t}^{\frac{1}{2}} \dots h_{NNt}^{\frac{1}{2}}\right) \\ R = \begin{bmatrix} 1 & \cdots & \rho_{1N} \\ \vdots & \ddots & \vdots \\ \rho_{N1} & \cdots & 1 \end{bmatrix} \\ H_t = diag\left(\sqrt{h_{11,t}}, \dots, \sqrt{h_{NN,t}}\right) R \; diag\left(\sqrt{h_{11,t}}, \dots, \sqrt{h_{NN,t}}\right) \end{gathered} \tag{7}$$

*diag* (.) is the operator that stacks the matrix elements to the main diagonal. If *N*=2 and *p*=*q*=1 $H_t$ is illustrated as (8):

$$H_t = \begin{bmatrix} \sqrt{h_{11,t}} & 0 \\ 0 & \sqrt{h_{22,t}} \end{bmatrix} \begin{bmatrix} 1 & \rho_{12} \\ \rho_{21} & 1 \end{bmatrix} \begin{bmatrix} \sqrt{h_{11,t}} & 0 \\ 0 & \sqrt{h_{22,t}} \end{bmatrix} \tag{8}$$

Under the assumption of conditional normality, a multivariate GARCH model can be estimated by maximizing a log-likelihood function (Brooks, 2002, p. 510). Log-likelihood function in (9) can be employed with the normal error distribution assumption (Kearney, Patton, 2000, p.36).

$$L(\theta) = -\frac{TN}{2} \ln(2\pi) - \frac{1}{2} \sum_{t=1}^{T} \left( ln|H_t| + \varepsilon_t' H_t^{-1} \varepsilon_t \right) \tag{9}$$

As the log-likelihood function is not linear in nature, some quantitative maximization techniques are used. Most common technique is the BHHH algorithm that gives the variance-covariance matrices for the estimated parameters (Berndt, Hall, Hall, Hausman, 1974, pp. 653-665).

## Empirical results of multivariate GARCH models

In order to analyze further conditional correlations, we first need to select the best multivariate GARCH model using some common model selection criteria, such as Akaike information criterion (AIC), Schwarz information criterion (SIC) and Hannan-Quinn (HQ) criterion in addition to log-likelihood values. Table 5 shows the results for the model selection criteria mentioned above.

**Table 5: Model selection criteria results for the selected models**

| | VAR (4) Diagonal VECH-MGARCH (1,1) | VAR (4) Diagonal BEKK-MGARCH (1,1) | VAR (4) CCC-MGARCH (1,1) |
|---|---|---|---|
| Log-Likelihood | 710.4153 | 758.4427 | 706.0478 |
| AIC | -4.153005 | -4.562749 | -4.205104 |
| SIC | -2.871853 | -3.432320 | -3.074676 |
| HQ | -3.639885 | -4.109995 | -3.752351 |

The results show that diagonal BEKK is the model that maximizes the log-likelihood function and gives the lowest scores in terms of the other information criteria. Consequently, diagonal BEKK model is selected to be used in further analysis. The results of the diagonal BEKK model estimation are given in Appendix A.

The conditional correlation matrix of BEKK-MGARCH (1,1) model is given in Table 6.

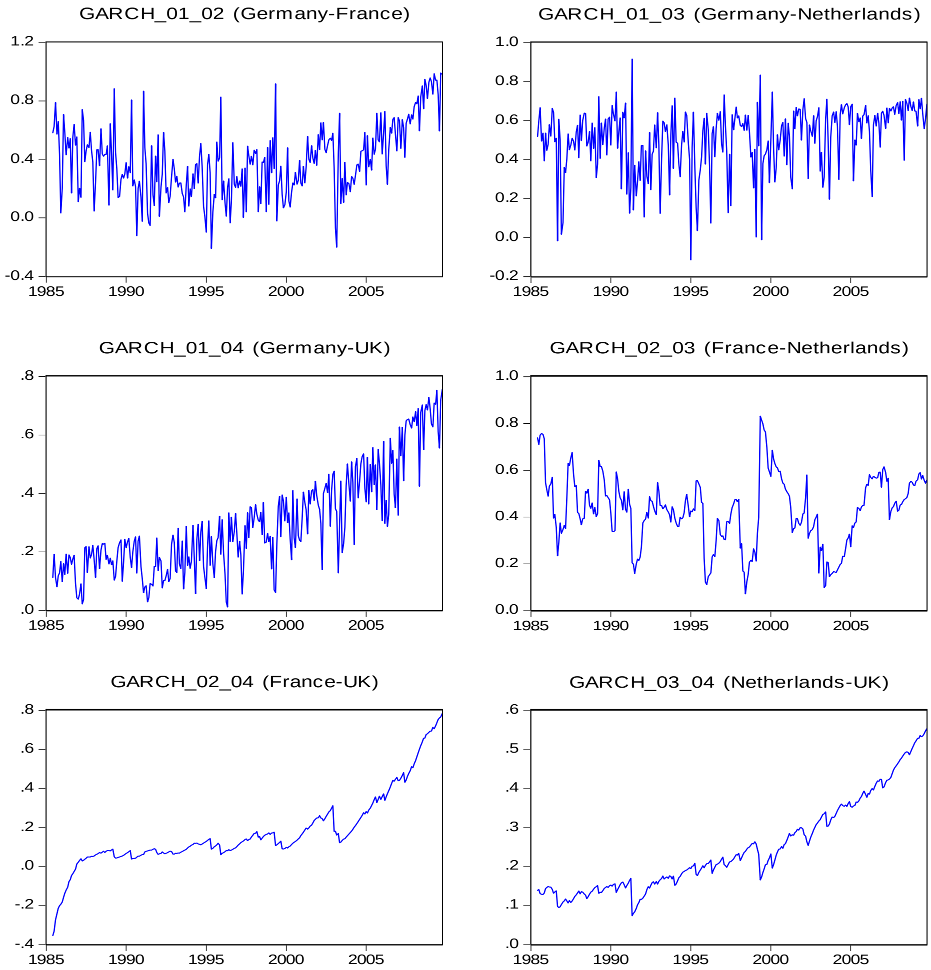
**Table 6: Conditional correlation matrix for BEKK-MGARCH (1,1) model**

| | Germany | France | Netherlands | UK |
|---|---|---|---|---|
| Germany | 1.000000 | 0.582513 | 0.519080 | 0.113240 |
| France | | 1.000000 | 0.738437 | -0.354481 |
| Netherlands | | | 1.000000 | 0.139473 |
| UK | | | | 1.000000 |

According to Table 6, the highest conditional correlation is between France and the Netherlands. Germany-France and Germany-Netherlands conditional correlations follow each other closely. France and the UK has the only negative pair-wise conditional correlation.

Figure 3 shows the dynamic paths of the conditional correlations for BEKK-MGARCH between the selected countries.

**Figure 3: Conditional correlation graphs for BEKK-MGARCH (1,1) model**




The conditional correlations between UK and other three countries exhibited upward trends. In addition, only the conditional correlation between France and the UK were negative at the beginning, but gradually become positive. Also, it is clear that conditional correlations for Germany and other three countries are highly volatile.

Table 7 summaries the cross-country interdependence and dependence.

**Table 7: Cross-country dependence and interdependence**

| | |
|---|---|
| **Germany ↔ France** | Interdependence between Germany and France |
| **Germany ↔ Netherlands** | Interdependence between Germany and the Netherlands |
| **Germany → UK** | Dependence between Germany and the UK |
| **France → UK** | Dependence between France and the UK |
| **Netherlands → France** | Dependence between the Netherlands and France |
| **UK ↔ Netherlands** | Interdependence between the UK and the Netherlands |

There are interdependent effects between Germany and France, Germany and Netherlands, UK and Netherlands. UK is affected by both Germany and France. Also, France is affected by Netherlands, but not affected by the UK.

## Conclusion

In this paper, we modeled the conditional variances and correlations of the seasonally adjusted logarithm of the monthly arrival rate from the four leading tourism source countries (Germany, France, Netherlands, UK) to Turkey using three different multivariate GARCH parameterizations for the period 1985:01-2009:09. The results of the diagonal BEKK parameterization were used for further analysis of tourism demand volatility in Turkey.

The empirical results indicated cross-country interdependent and dependent effects in the conditional correlations for all of the selected countries. The countries are dependent on one or the other, but not independent from each other. Specifically Germany comes forward by affecting all the other three countries. These results show that positive or negative shocks change the behavior of tourism demand from the selected countries. In addition, the tourism demand behavior of a country has an influence on another country. This influence might be very strong for some tourist generating countries. Therefore, along with demand analysis, policies and strategies considering the behavior of tourism demand has an important role in developing tourism in destination countries.

As tourism is one of the most important industries for Turkey, it is essential utilizing as much tools as possible in managerial decisions. Demand volatility analysis may provide a useful tool for evaluating demand fluctuations. In addition, volatility analysis may offer important results for public and private sector tourism decision-makers.

Turkey has been following supply-sided tourism policies since 1980s to encourage the tourism activities. But it is now a well known fact that increasing accommodation capacity is not enough to attract more tourists and generate more tourism receipts. Incentives for accommodation investments have been applied for the last three decades, and it certainly did not serve for better results. The increasing accommodation capacity forced the entrepreneurs to sell their rooms at any price, sometimes with very small profits and lower quality. Especially European tour operators triggered 'last minute sales' for very low prices, and as the operators took advantage of the situation, the hoteliers faced many administrative and economic problems. As a result, the image of Turkey was damaged by being labeled as a "cheap" country.

The results of this paper indicate that -as the major source countries are dependent on each other- the demand volatility is caused by the economic conditions, preferences or other factors that originate from the source countries, rather than the internal dynamics of Turkey. In that case, internal supply-sided tourism policies cannot be effective to overcome the problems caused by demand fluctuations. There are some efforts to control these problems by diversifying tourism products and extending the tourism season. But these efforts cannot be successful unless there is a comprehensive change in the overall tourism policy.

Turkey should start to pursue demand-sided tourism policies regarding the important source countries that affect others, like Germany. The promotion and advertisement campaigns should be designed specifically for the source countries' unique conditions. These unique conditions should be researched by scientific methods with a wide range of variables. The public sector may use incentives and supply-sided policies to change the image of Turkey and to reduce the effects of shocks and crises, but the applications and improvements must consider demand as a major problem.

The limitation of this paper is that the results indicate the conditions only for the selected countries. Further analysis of tourism demand from different source countries and regions may reflect the overall effects of shocks on tourism demand. In addition, comparisons with different models may also provide useful information about the nature and volatility of inbound tourism demand for Turkey.

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## Appendix A: Diagonal BEKK results

Variables: LALM_SA for Germany, LFRA_SA for France, LHOL_SA for the Netherlands and LING_SA for the UK.

| **Mean equations** |
|---|
| D(LALM_SA) = 0.434599965725*( LALM_SA(-1) + 1.82461061477*LFRA_SA(-1) - 0.728049680071*LHOL_SA(-1) - 1.53121441942*LING_SA(-1) - 6.85594552075 ) + 0.29170025144*D(LALM_SA(-1)) + 0.251218944256*D(LALM_SA(-2)) + 0.856883327581*D(LALM_SA(-3)) - 0.239728438707*D(LALM_SA(-4)) + 0.11243870527*D(LFRA_SA(-1)) + 0.17253001324*D(LFRA_SA(-2)) + 0.162056864392*D(LFRA_SA(-3)) + 0.0545669877986*D(LFRA_SA(-4)) - 0.0967333915722*D(LHOL_SA(-1)) + 0.0850411914424*D(LHOL_SA(-2)) - 0.0846243955297*D(LHOL_SA(-3)) + 0.0926571265091*D(LHOL_SA(-4)) - 0.243735353881*D(LING_SA(-1)) - 0.0536713460576*D(LING_SA(-2)) + 0.0310612906589*D(LING_SA(-3)) - 0.0111527505781*D(LING_SA(-4)) + 0.008867601943 |
| D(LFRA_SA) = -0.103419429526*( LALM_SA(-1) + 1.82461061477*LFRA_SA(-1) - 0.728049680071*LHOL_SA(-1) - 1.53121441942*LING_SA(-1) - 6.85594552075 ) + 0.238550100512*D(LALM_SA(-1)) + 0.201684319554*D(LALM_SA(-2)) + 0.212244727078*D(LALM_SA(-3)) - 0.186840765001*D(LALM_SA(-4)) - 0.382643977589*D(LFRA_SA(-1)) - 0.202716962553*D(LFRA_SA(-2)) - 0.0345141733556*D(LFRA_SA(-3)) + 0.132603538062*D(LFRA_SA(-4)) + 0.0325370718347*D(LHOL_SA(-1)) - 0.022870686789*D(LHOL_SA(-2)) - 0.125437185716*D(LHOL_SA(-3)) + 0.138612366636*D(LHOL_SA(-4)) - 0.151946294842*D(LING_SA(-1)) - 0.118130847616*D(LING_SA(-2)) - 0.0351964229992*D(LING_SA(-3)) - 0.084327132234*D(LING_SA(-4)) + 0.0103646374765 |
| D(LHOL_SA) = -0.0472606230986*( LALM_SA(-1) + 1.82461061477*LFRA_SA(-1) - 0.728049680071*LHOL_SA(-1) - 1.53121441942*LING_SA(-1) - 6.85594552075 ) + 0.140272849578*D(LALM_SA(-1)) + 0.0781958257144*D(LALM_SA(-2)) + 0.0537962362942*D(LALM_SA(-3)) - 0.0996895872451*D(LALM_SA(-4)) + 0.000717121785473*D(LFRA_SA(-1)) + 0.0927696918192*D(LFRA_SA(-2)) + 0.123249836925*D(LFRA_SA(-3)) + 0.117670848837*D(LFRA_SA(-4)) - 0.40084254304*D(LHOL_SA(-1)) - 0.16582686692*D(LHOL_SA(-2)) - 0.161766605023*D(LHOL_SA(-3)) + 0.0768721591379*D(LHOL_SA(-4)) - 0.0828038037286*D(LING_SA(-1)) - 0.0319028689243*D(LING_SA(-2)) + 0.100046409171*D(LING_SA(-3)) + 0.062881464521*D(LING_SA(-4)) + 0.0115482174519 |
| D(LING_SA) = 0.0310961425882*( LALM_SA(-1) + 1.82461061477*LFRA_SA(-1) - 0.728049680071*LHOL_SA(-1) - 1.53121441942*LING_SA(-1) - 6.85594552075 ) + 0.0406153059458*D(LALM_SA(-1)) - 0.0812180112902*D(LALM_SA(-2)) + 0.0382937684177*D(LALM_SA(-3)) - 0.134818481631*D(LALM_SA(-4)) - 0.118850915664*D(LFRA_SA(-1)) + 0.0888245601018*D(LFRA_SA(-2)) - 0.0373811684432*D(LFRA_SA(-3)) - 0.0470448681839*D(LFRA_SA(-4)) + 0.000142457159305*D(LHOL_SA(-1)) + 0.0778097682453*D(LHOL_SA(-2)) - 0.00131047875879*D(LHOL_SA(-3)) + 0.28379429371*D(LHOL_SA(-4)) - 0.430911044257*D(LING_SA(-1)) - 0.243754172971*D(LING_SA(-2)) - 0.0781371186226*D(LING_SA(-3)) + 0.00548624188137*D(LING_SA(-4)) + 0.0189491775879 |

| **Variance equations** |
|---|
| GARCH1 (Germany) = 0.00813298163666 + 1.19429302516*RESID1 (-1)^2 + 0.000139515517738 * GARCH1(-1) |
| GARCH2 (France)= 0.000266169110848 + 0.14538298142*RESID2 (-1)^2 + 0.87874541347 * GARCH2(-1) |
| GARCH3 (Netherlands)= 0.00198400704983 + 0.0673493868217*RESID3 (-1)^2 + 0.806754688006 * GARCH3(-1) |
| GARCH4 (UK)= -5.18743249698e-05 + 0.000212438080514*RESID4 (-1)^2 + 0.993149048915 * GARCH4(-1) |

| **Covariance equations** |
|---|
| COV1_2 (Germany-France) = 0.00505929068149 + 0.41668918955*RESID1(-1)* RESID2(-1)* RESID1(-1)* RESID2(-1)* RESID1(-1)* RESID2(-1) -0.0110724261714 * COV1_2(-1) * COV1_2(-1) * COV1_2(-1) |
| COV1_3(Germany-Netherlands) = 0.0066374281557 + 0.283610477469 * RESID1(-1) * RESID3(-1) * RESID1(-1) * RESID3(-1) -0.0106091846051 * COV1_3(-1) * COV1_3(-1) |
| COV1_4 (Germany-UK)= 0.0053146544272 + 0.0159283808919 * RESID1(-1) * RESID4(-1) - 0.0117711385919 * COV1_4(-1) |
| COV2_3 (France-Netherlands)= 0.000497056377533 * RESID2(-1) * RESID3(-1) + 0.098951779433 * RESID2(-1) * RESID3(-1) * RESID2(-1) * RESID3(-1)* COV2_3(-1) + 0.84198098665 * COV2_3(-1) * COV2_3(-1) |
| COV2_4 (France-UK) = 0.000204388495941 * RESID2(-1) * RESID4(-1) + 0.00555741680211 * RESID2(-1) * RESID4(-1) * COV2_4(-1) + 0.934197608446 * COV2_4(-1) |
| COV3_4 (Netherlands-UK) = 0.00044434980266 * RESID3(-1) * RESID4(-1) * RESID3(-1) * RESID4(-1) + 0.00378253545393 * RESID3(-1) * RESID4(-1) * COV3_4(-1) * COV3_4(-1) + 0.895113205746 * COV3_4(-1) |