Conditional forecasts of tourism exports and tourism export prices of the EU-15 within a global vector autoregression framework

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Abstract

Purpose – *The purpose of this paper is to analyze the ex ante projected future trajectories of real tourism exports and relative tourism export prices of the EU-15, conditional on expert real gross domestic product growth forecasts for the global economy provided by the Organisation for Economic Co-operation and Development for the years 2013-2017.*

Design/methodology/approach – *To this end, the global vector autoregression (GVAR) framework is applied to a comprehensive panel data set ranging from 1994Q1 to 2013Q3 for a cross-section of 45 countries. This approach allows for interdependencies between countries that are assumed to be equally affected by common global developments.*

Findings – *In line with economic theory, growing global tourist income combined with decreasing relative destination price ensures, in general, increasing tourism demand for the politically and macroeconomically distressed EU-15. However, the conditional forecast increases in tourism demand are under-proportional for some EU-15 member countries.*

Practical implications – *Rather than simply relying on increases in tourist income, the low price competitiveness of the EU-15 member countries should also be addressed by tourism planners and developers in order to counter the rising competition for global market shares and ensure future tourism export earnings.*

Originality/value – *One major contribution of this research is that it applies the novel GVAR framework to a research question in tourism demand analysis and forecasting. Furthermore, the analysis of the ex ante conditionally projected future trajectories of real tourism exports and relative tourism export prices of the EU-15 is a novel aspect in the tourism literature since conditional forecasting has rarely been performed in this discipline to date, in particular, in combination with ex ante forecasting.*

Keywords *Conditional forecasting, Ex ante forecasting, Global vector autoregression, Tourism export prices, Tourism exports*

Paper type *Research paper*

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1. Introduction

Tourism demand analysis and forecasting is one of the core areas of tourism economic research, since tourism demand is ultimately the basis of all business decisions in tourism (Song *et al.*, 2009). Given the perishable nature of tourism products and services, these business decisions require accurate forecasts that will reduce the risks in business decision making (Frechtling, 2001).

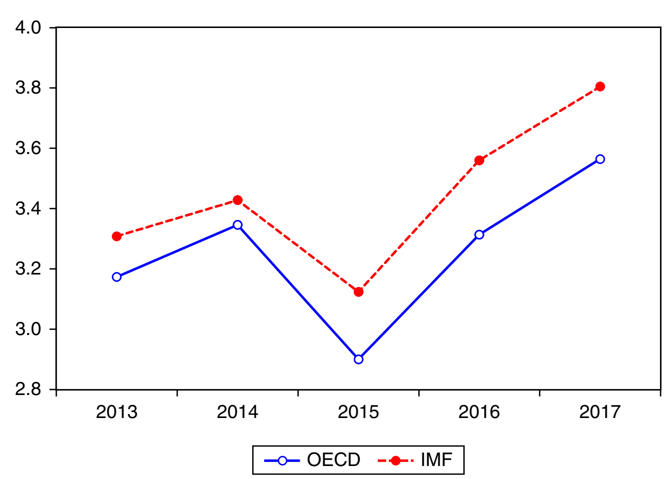
The aim of the present study is to analyze the projected future trajectories of real tourism exports (as a proxy for tourism demand) and relative tourism export prices (as a proxy for relative destination price) of the 15 member countries of European Union (the EU-15)[1], conditional on expert real gross domestic product (GDP) growth forecasts for the global economy provided by the Organisation for Economic Co-operation and Development (OECD, 2015) for the years 2013-2017, where real GDP serves as a proxy for global tourist income. Thus, this paper investigates how the income expectations of a "representative global tourist" are likely to materialize in the evolution of tourism demand for, and relative destination price of, the EU-15 compared to its global competitors.

Taking a closer look at the EU-15 is of particular interest for the following reasons. Tourism continues to be an important industry in the EU-15 contributing, on average, 8.1 percent to EU-15 countries' exports, 10.2 percent to their GDP, and 11.9 percent to their employment, according to the latest figures of the World Travel & Tourism Council (WTTC, 2016) as of 2015. However, tourism exports of the EU-15 relative to global tourism exports decreased by −20.8 percent (from 35.2 to 27.8 percent) between 1995 and 2015, while tourism exports from the EU-15 increased by +56.4 percent in absolute terms (from USD233 bn in 1995 to USD364 bn in 2015), which implies that the EU-15 is facing rising competition for market shares from other destinations around the world and reflects the continuing growth and increasing (geographic) diversification of global travel during the past decades. This increasing competition is exacerbated by the comparably low price competitiveness of the EU-15.

According to Pillar 8 of the Travel and Tourism Competiveness Report 2015 (World Economic Forum (WEF), 2015), all EU-15 countries are ranked in the lower third of the price competitiveness ranking with ranks ranging from 104 (PT) to 140 (GB) out of 141 ranked countries. Moreover, multiple crises (the global financial crisis, the European sovereign debt crisis, the rise of far right parties, and, more recently and not part of the sample employed in this study, the migration crisis, and Brexit) have put the EU-15 under macroeconomic and political distress during the past decade (see e.g. Gunter and Smeral, 2016), which may additionally deter potential travelers to the EU-15.

In light of a growing global economy (global real GDP is projected to grow at an annual average rate of around +3.3 percent from 2013 to 2017 according to OECD, 2015 forecasts, which is in line with the expert projection of +3.4 percent by the International Monetary Fund (IMF), 2015, see Figure 1), it is worthwhile investigating whether this predicted GDP growth also materializes in real tourism export increases at the EU-15 country level. In other words, is it sufficient for the comparably less price-competitive and politically and macroeconomically distressed EU-15 member countries to rely on the expected increases in global tourist income to ensure they can continue generating sufficient export earnings from international tourists in the future to, at least, defend their market share in the global travel market?

Figure 1 Annual global real GDP growth forecasts according to OECD (solid line) and IMF (dashed line)



Sources: OECD Economic Outlook No. 98 (OECD, 2015); IMF World Economic Outlook October 2015 (IMF, 2015); the author's own illustration

To this end, a comprehensive quarterly panel data set for these three variables comprising 3,555 observations for a cross-section of 45 countries and a time span ranging from 1994Q1 to 2013Q3 is employed (the list of the 45 countries can be found in Section 4 of this study). These additional countries from the rest of Europe and from all other world regions have been included in the present study to embed tourism demand for the EU-15 in an encompassing global tourism demand model.

While the data set accessible to the author does not cover each single country of the world, it can still be considered comprehensive in terms of tourism, since the 45 countries in the sample jointly account for around 69.0 percent of global tourism export earnings, 79.0 percent of global tourism import expenditures, as well as 89.1 percent of global domestic tourism spending as of 2015 (WTTC, 2016). Thus, the present model allows for the interdependence of travel to the EU-15 and to its competitors as well as for their dependence on the expected development of global tourist income. Since the sample accessible to the author ends in 2013Q3, the fourth quarter of 2013 marks the beginning of both the forecast and the restriction horizon for the conditional forecasting exercise.

Conditional (or contingency) forecasting implies making realistic assumptions regarding the development of one or more explanatory variables over a forecast horizon, conditional on which response of the forecast variable(s) is of interest. Therefore, conditional forecasting can also be interpreted as one way to carry out a policy or an impact analysis (Allen and Fildes, 2001). While there are various examples of conditional forecasting in the macroeconomic and monetary policy literature (see e.g. Bańbura *et al.*, 2015; Bloor and Matheson, 2011; Giannone *et al.*, 2014; Stock and Watson, 2012), not much attention has been given to this topic in tourism demand forecasting so far, although its importance is typically acknowledged (Scaglione, 2007): Smeral (2009) and the United Nations World Tourism Organization (2011) are two noteworthy exceptions.

According to microeconomic theory and reaffirmed by Song, Wong and Chon (2003) and Song *et al.* (2009), the most important variables influencing the demand for a specific destination are its own (relative) price, the (relative) prices of competing destinations (which could either be substitutes or complements to the destination under scrutiny), as well as tourist income. These variables are therefore part of virtually any standard (empirical) tourism demand model (see e.g. Crouch, 1995; Song and Witt, 2000; Stabler *et al.*, 2010). In addition, habit persistence and tourist expectations via the lagged dependent variable as a regressor were also shown to play an important role (Song, Wong and Chon, 2003), thus calling for a dynamic specification.

Now, the question is how to integrate these theoretical insights with panel-structured data for three variables, while allowing for interdependencies between countries to capture the impact of the relative prices of the relevant competing destinations per country. Furthermore, the dependency of all countries, including the EU-15, on the evolution of global real GDP, the presumably dynamic nature of the data-generating process, as well as the response of tourism demand and relative destination price conditional on the OECD global real GDP forecasts, need to be addressed at the same time. The global vector autoregression (GVAR) framework is able to deal with all of these issues within a unified setting and is hence utilized in the present study.

The GVAR framework is a relatively novel econometric model class which combines the properties of the well-known vector autoregression (VAR) model (Sims, 1980) with the characteristics of data that are available in panel format (i.e. data that possess both a time-series and a cross-sectional dimension). It was first introduced by Pesaran *et al.* (2004) with the purpose of investigating the impact of changing macroeconomic conditions at both national and global scales on the distribution of losses in credit portfolios of large banks and nonbank financial institutions in response to the Asian financial crisis of 1997.

Since then it has been further refined (see e.g. Dées, Holly, Pesaran and Smith, 2007; Dées, di Mauro, Pesaran and Smith, 2007; Garrat *et al.*, 2006) and successfully applied to various research questions. Its applications include the areas of shock transmission, policy analysis, and (conditional) forecasting where single entities are dependent on global developments and other entities over time (e.g. countries through trade or financial linkages; see Section 3 for an overview of past applications).

The ever-expanding usage of the GVAR model class in various areas of economics and finance can be explained by its advantageous properties, which are also relevant for tourism research:

1. It allows modeling of interdependencies between entities and incorporates the impact of common global factors, which are features of a globalized economy that need to be taken into consideration (di Mauro and Pesaran, 2013) and which are particularly important when addressing research questions in international tourism.
2. The GVAR model is comparatively easy to comprehend, especially for tourism researchers and practitioners already familiar with the standard VAR and vector error correction model (VECM) methodology and other particularities of (multivariate) time series (see e.g. Lütkepohl, 2005, for a standard reference) as well as with panel data approaches (see e.g. Baltagi, 2013a, for a standard reference), while not having higher requirements for the data compared to the existing models.
3. With the GVAR Toolbox 2.0, there is a ready-to-use Excel-based interface executing the GVAR-associated set of Matlab procedures (Smith and Galesi, 2014), which can be downloaded from https://sites.google.com/site/gvarmodelling/gvar-toolbox and which comes with a hands-on manual suitable for tourism researchers and practitioners alike.
4. The GVAR model has been shown to have greater forecast accuracy for inflation and GDP growth in Switzerland compared to simpler multivariate competitor models focusing on the time-series dimension of the data only (Assenmacher, 2013). Similar findings have been reported, for example, by Greenwood-Nimmo *et al.* (2012), Han and Ng (2011), and Pesaran *et al.* (2009). Improvements in forecast accuracy compared to the standard forecasting toolkit can therefore also be expected for the tourism forecasting discipline.
5. By estimating VAR models at the country level, the GVAR model circumvents the downside of estimating highly dimensional VAR models at the global level: a multitude of endogenous variables leading to over-parameterization, which may have a negative impact on (tourism) forecast accuracy (so-called curse of dimensionality; Bussière *et al.*, 2009; Cao, 2016).

These advantageous properties make the GVAR model class ideally suitable for addressing the present research question (analysis of the projected future trajectories of real tourism exports and relative tourism export prices of the EU-15 conditional on global real GDP growth forecasts) given a panel data structure, which is characterized by trade linkages. However, apart from the recent doctoral dissertation by Zheng Cao (2016), the GVAR methodology has not been employed so far in tourism demand analysis and forecasting (see Section 2 for a review of the literature on this topic).

The main contributions of this research therefore are that it applies the novel GVAR framework to a research question in tourism demand analysis and forecasting, while employing a comprehensive panel data set ranging from 1994Q1 to 2013Q3 for a cross-section of 45 countries. This approach allows for interdependencies between countries that are assumed to be equally affected by common global developments: which is a plausible assumption in a globalized economy. Thus, the GVAR framework can also be applied to other questions in tourism research, in particular to those with an international focus that require a realistic model of the global economy.

Furthermore, the analysis of the *ex ante* projected future trajectories of real tourism exports and relative tourism export prices of the EU-15 conditional on a global economy that is forecast to grow during the period 2013-2017 is a novel aspect in the tourism literature since conditional forecasting has rarely been performed in this discipline to date, in particular, in combination with *ex ante* forecasting.

While evaluating the accuracy of *ex post* forecasts (either of single forecast models or of various forecast models within a forecast competition) is a common option in the literature, it is not the topic of the present study. *Ex ante* tourism demand forecasts, in turn, have also been covered in the literature, yet much less frequently; only 15 out of 121 tourism demand modeling and forecasting studies published in the early 2000s dealt with this topic (see Song and Li, 2008, for a survey). Therefore, investigating the properties of *ex ante* tourism demand forecasts deserves researchers' attention.

The plan of the rest of this study is as follows: Section 2 reviews the models typically used in tourism demand analysis and forecasting, Section 3 briefly lays out the history and the setup of the GVAR framework; Section 4 describes the data set and reports about measures of data treatment; Section 5 highlights some properties of the estimated GVAR models; Section 6 presents and discusses the conditional forecasting results for the EU-15; and finally, Section 7 draws some overall conclusions.

2. Models used in tourism demand analysis and forecasting

Panel data analysis is a viable option given that the research focus is on tourism demand analysis and the tourism demand measure as well as the explanatory variables are available over time for a cross-section of destinations and/or source markets (e.g. Garín-Muñoz, 2006, 2007; Garín-Muñoz and Montero-Martín, 2007; Garín-Muñoz and Pérez-Amaral, 2000; Kuo *et al.*, 2009; Ledesma-Rodríguez *et al.*, 2001; Li *et al.*, 2017). One of the main advantages of panel data models when pooling the data across entities is the augmented number of observations compared to pure time-series or cross-sectional estimation, while fewer coefficients need to be estimated. Panel estimators based on pooled data are called homogeneous and return common coefficient estimates for the intercept and the slopes across entities. This parsimonious specification increases the degrees of freedom in estimation and mitigates potential collinearity issues while raising the efficiency and stability of the coefficient estimates (Baltagi, 2008; Song *et al.*, 2009).

On the other hand, when the research focus is on tourism demand forecasting, researchers typically use univariate and multivariate time-series models: the latter when data for explanatory variables are available and the forecast horizon is longer than two years (Frechtling, 2001). Univariate (or pure time-series) forecasting models draw on past observations of the forecast variable only and typically include members of the (seasonal) autoregressive integrated moving average model class ((S)ARIMA; Box and Jenkins, 1970; Kulendran and Witt, 2001; Li *et al.*, 2006; Song *et al.*, 2000; Witt *et al.*, 2003), the exponential smoothing model class which includes the error-trend-seasonal or exponential smoothing model class (Hyndman *et al.*, 2002, 2008; Athanasopoulos *et al.*, 2011; Cho, 2001; Law, 2000; Veloce, 2004), or the naïve model class: the latter usually serving as simple benchmarks.

Concerning multivariate, causal, or econometric forecasting models, (error-correction) autoregressive distributed lag models (Engle and Granger, 1987; Dritsakis and Athanasiadis, 2000; Ismail *et al.*, 2000; Kulendran and Witt, 2003; Roselló *et al.*, 2004) (Bayesian) vector autoregressive models (Doan *et al.*, 1984; Sims, 1981; Lim and McAleer, 2001; Oh, 2005; Song *et al.*, 2013; Wong *et al.*, 2006), and time-varying parameter models (Engle and Watson, 1987; Li *et al.*, 2006; Song, Witt, Jensen, 2003; Song, Wong and Chon, 2003; Song and Wong, 2003) have proven to produce quite accurate tourism demand forecasts in varying situations.

Interestingly, to date, panel data methods have not been used for forecasting tourism demand even when the data are available in panel format (Song and Li, 2008), although such forecasts have been employed quite frequently in other areas of economics. These include forecasting gasoline demand (Baltagi and Griffin, 1997), electricity and natural gas demand (Maddala *et al.*, 1997), GDP growth rates (Hoogstrate *et al.*, 2000), or migration to Germany (Brucker and Siliverstovs, 2006), just to name a few applications (see e.g. Baltagi, 2008, 2013b, for recent surveys of articles on panel data forecasting).

One common finding of the articles surveyed by Baltagi (2008) is that various homogeneous panel estimators such as traditional fixed effects and random effects estimation perform well in forecasting by taking advantage of the strengths of panel data estimation as mentioned above. Even though the GVAR model is estimated on an entity-by-entity basis drawing on the interdependencies between these entities, it is still solved as a whole since the variables are treated as endogenous from a global perspective, thus enabling the forecaster to (conditionally) predict all forecast variables jointly (Pesaran *et al.*, 2007).

3. The GVAR framework in brief

The GVAR framework is a parsimonious representation of a global aggregate of entities (typically: the global economy) characterized by interdependent entities (typically: countries that are connected through trade or financial linkages), which, in turn, are affected by the development of global variables (Crespo Cuaresma *et al.*, 2016). Before conditional forecasting can be performed with the GVAR model, multivariate time-series models must first be estimated at the country level. The GVAR has to be solved as a whole at the global level drawing on the estimation results at the country level, since all variables of the model are endogenous from a global perspective (di Mauro and Smith, 2013; Pesaran *et al.*, 2007).

Applications of the GVAR model are manifold and have included, for instance, investigating the impact of global food and oil price shocks on inflation and real GDP at the country level (Galesi and Lombardi, 2013), modeling global trade flows (Bussière *et al.*, 2009), forecasting economic and financial variables for a large number of countries (Smith, 2013), linking firm-level measures for systemic risk to global macroeconomic variables (Al-Haschimi and Dées, 2013), exploring the international linkages of the Euro Area (Dées, di Mauro, Pesaran, Smith, 2007), or analyzing the spillovers of macroeconomic shocks from China, the Euro Area, and the USA to the Middle East and North Africa region (Cashin *et al.*, 2012).

Recent methodological advances include the extension of dynamic stochastic general equilibrium models, macroeconomic models founded on microeconomic rationale, from modeling only one or two countries at a time to multi-country GVAR models characterized by theoretical constraints (Dées *et al.*, 2014) or Bayesian instead of frequentist estimation of the GVAR at the country level (Crespo Cuaresma *et al.*, 2016). The GVAR model is also related to the more generic model class of panel VARs (see e.g. Abrigo and Love, 2016; Koop and Korobilis, 2016; Love and Zicchino, 2006).

The subsequent brief description of the GVAR framework draws on the ideas laid out in Crespo Cuaresma *et al.* (2016), di Mauro and Smith (2013), and Pesaran *et al.* (2007).

It can be presupposed that the global economy consists of N+1 countries i with $i = 0, 1, \ldots, N$ that are observed over time t with $t = 1, 2, \ldots, T$, where country 0 is interpreted as the reference country or numeraire. For the present sample, N+1 = 45 (with country 0 corresponding to the USA) and $T = 79$ (from 1994Q1 to 2013Q3), thus $N \times T = 3{,}555$. The multivariate time-series models at the country level are VARs consisting of country-specific endogenous domestic variables, country-specific weakly exogenous foreign variables, weakly exogenous global variables, as well as deterministic components, the so-called VARX*(p_i, q_i) models. In these models, p_i corresponds to the country-specific lag order of the domestic, and q_i to the country-specific lag order of the foreign and global variables; these lag orders are determined by the use of information criteria such as the Akaike information criterion (AIC) or the Schwarz or Bayesian information criterion (BIC) (Lütkepohl, 2005).

The weak exogeneity assumption of the foreign and global variables implies that while there may be lagged short-run feedback from domestic to foreign and global variables, no long-run equilibrium impact of domestic on foreign and global variables is supposed to exist. Thus, the individual countries – except the USA – are modeled as small open economies (SMOPECs) (Granger and Lin, 1995; Johansen, 1992; Pesaran *et al.*, 2004).

Assuming that $p_i = q_i = 2$, a VARX*(2, 2) model for country i therefore reads:

$$x_{i,t} = \alpha_i + \beta_i t + \Gamma_{i1} x_{i,t-1} + \Gamma_{i2} x_{i,t-2} + \Phi_{i0} x^*_{i,t} + \Phi_{i1} x^*_{i,t-1} + \Phi_{i2} x^*_{i,t-2} + u_{i,t}. \tag{1}$$

In Equation (1), $x_{i,t}$ denotes a $k_i \times 1$ vector of domestic variables, $x^*_{i,t}$ represents a $k^*_i \times 1$ vector of foreign variables, Γ_{it} denote $k_i \times k_i$ coefficient matrices for the lagged domestic variables, and Φ_{it} represent $k^*_i \times k^*_i$ coefficient matrices for the current and lagged foreign variables. The deterministic components include a $k_i \times 1$ vector of intercept terms α_i as well as a linear deterministic time trend t. Finally, $u_{i,t}$ is a $k_i \times 1$ vector of idiosyncratic error terms with mean zero and the variance-covariance matrix $\Sigma_{u,i}$.

The foreign variables in Equation (1) are constructed as country-specific weighted averages in order to reflect the relative importance of the N remaining countries for country i, for instance in terms of their mutual trade or financial linkages. Thus, the foreign variables are constructed as follows:

$$x^*_{i,t} = \sum_{j=0}^{N} w_{i,j} x_{j,t}. \tag{2}$$

$w_{i,j}$, in Equation (2), with $j = 0, 1, \ldots, N$ denotes the weights with the properties $w_{ii} = 0$ and $\sum_{j=0}^{N} w_{i,j} = 1$. The entirety of these weights forms the weight matrix, which is time-constant and exogenous to the model (see Section 4).

In line with Dées, di Mauro, Pesaran, Smith (2007), the global variables are included as foreign and weakly exogenous for all countries except for country 0 (the USA), where they are included as domestic and endogenous. Since global variables reflect common global developments assumed to equally effect individual countries, these variables also attain the same realizations for each country for a given point in time. Constructing "country-specific" global variables according to Equation (2) therefore results again in the global variables attaining the same realizations for each country (Pesaran *et al.*, 2004).

Pertaining to the standard dynamic tourism demand model (Crouch, 1995; Song and Witt, 2000; Stabler *et al.*, 2010; Song, Wong and Chon, 2003; Song *et al.*, 2009), the vector of domestic variables $x_{i,t}$ in the present study consists of domestic real tourism exports and domestic relative tourism export prices, hence $k_i = 2$. The vector of foreign variables $x^*_{i,t}$, in turn, comprises foreign real tourism exports, foreign relative tourism export prices (representing real tourism exports and relative tourism export prices of competing destinations), as well as global real GDP (representing global tourist income) as the only global variable, hence $k^*_i = 3$.

In order to accommodate potential cointegration relationships between the variables, Equation (1) is not estimated in levels, but is reformulated to obtain its vector error correction form in first differences, which is then labeled VECMX*(p_i, q_i). This vector error correction form allows investigating jointly the short-run dynamics and the long-run equilibrium relationships of the variables, as well as convergence to the latter. The VECMX*(2, 2) form of Equation (1) for country i, for instance, reads:

$$\Delta x_{i,t} = c_i - a_i b_i' \left[z_{i,t-1} - \delta_i (t-1) \right] + \Phi_{i0} \Delta x^*_{i,t} + Y_i \Delta z_{i,t-1} + u_{i,t}. \tag{3}$$

In Equation (3), Δ denotes the first difference operator, $z_{i,t} = (x'_{i,t}, x^{*\prime}_{i,t})'$ is a $(k_i + k^*_i) \times 1$ vector stacking the vectors $x_{i,t}$ and $x^*_{i,t}$, a_i is a $k_i \times r_i$ matrix of speed of adjustment coefficients of rank r_i, and b_i is a $(k_i + k^*_i) \times r_i$ matrix of cointegration vectors of rank r_i, whereby r_i represents the number of cointegration relations. Equation (3) can be adequately reformulated to show that cointegration relations within $x_{i,t}$ and between $x_{i,t}$ and $x^*_{i,t}$ are possible and thus between countries i and j with $i \neq j$. Conditional on $x^*_{i,t}$ being treated as weakly exogenous and integrated of order $I(1)$, Equation (3) is then estimated on a country-by-country basis. The number of cointegration relations r_i, the matrix of speed of adjustment coefficients a_i, and the matrix of cointegration vectors b_i are estimated using reduced rank regression (Izenman, 1975), while for a given estimate of b_i, the remaining parameters of Equation (3) can be consistently estimated applying ordinary least squares (OLS) regression to the subsequent equation:

$$\Delta x_{i,t} = c_i - \delta_i ECM_{i,t-1} + \Phi_{i0} \Delta x^*_{i,t} + Y_i \Delta z_{i,t-1} + u_{i,t}, \tag{4}$$

where the error correction term $ECM_{i,\,t-1}$ in Equation (4) represents the r_i cointegration relations of country i (see Smith and Galesi, 2014, for further details).

Drawing on the property of the GVAR model that all variables are treated as endogenous from a global perspective (which includes the global variables as long as they are treated as domestic and endogenous in one country; Dées, di Mauro, Pesaran, Smith, 2007), the estimated country-specific models can be "stacked" so that a $k \times 1$ vector x_t comprising all endogenous variables with $k = \sum_{i=0}^{N} k_i$ and $x_t = (x'_{0,t}, x'_{1,t}, \ldots, x'_{N,t})'$ can be formed. This allows solving the GVAR model at the global level (see Pesaran *et al.*, 2004, for further details).

4. The data

The data used in this study have both a time-series and a cross-sectional dimension (panel data) and are taken from quarterly IMF and OECD databases. The variables employed in this study are real tourism exports per country (stated in million US dollars, base year for prices and exchanges rates: 2,000; source: IMF), tourism export prices per country relative to a global tourism export price (US dollar-based, 2,000 = 100; source: IMF), and global real GDP (stated in million US dollars, base year for prices and exchanges rates: 2,000; source: OECD). The three variables were available for the period 1994Q1-2013Q3 for 45 countries. Since tourism export prices per country and global tourism export price are both given in US dollars, the relative price ratio can also be interpreted as the real multilateral or real effective exchange rate in tourism terms, which is a measure for competitiveness of a country's tourism goods and services relative to the global market.

Although other explanatory variables such as qualitative factors, marketing expenditure, or transportation cost may be relevant drivers of real tourism exports, it was not possible to obtain consistently defined and measured time series for the set of 45 countries considered in the present study. Moreover, including transportation cost in a model that already contains a more comprehensive price index makes the model prone to multicollinearity (Song *et al.*, 2009).

The 45 countries are listed in the continuation (the corresponding country codes of the International Organization for Standardization according to the ISO 3166-1 alpha-2 standard are given in parentheses; countries in italics are the EU-15 member countries): Australia (AU), *Austria (AT)*, *Belgium and Luxembourg (BELU)*[2], Brazil (BR), Bulgaria (BG), Canada (CA), China (CN), Croatia (HR), Cyprus (CY), the Czech Republic (CZ), *Denmark (DK)*, Estonia (EE), *Finland (FI)*, *France (FR)*, *Germany (DE)*, *Greece (GR)*, Hungary (HU), Iceland (IS), India (IN), Indonesia (ID), *Ireland (IE)*, Israel (IA), *Italy (IT)*, Japan (JP), Latvia (LV), Lithuania (LT), Malta (MT), Mexico (MX), *the Netherlands (NL)*, New Zealand (NZ), Norway (NO), Poland (PL), *Portugal (PT)*, Romania (RO), Russia (RU), Slovakia (SK), Slovenia (SI), South Africa (ZA), South Korea (KR), *Spain (ES), Sweden (SE)*, Switzerland (CH), Turkey (TR), the *United Kingdom (GB)*, and the United States (US).

The "global" data are to be understood as follows: global real GDP denotes the aggregate (i.e. the unweighted sum) of the 45 available country GDPs for each quarter, whereas global tourism export price denotes the real-tourism-export-weighted average of the tourism export prices of the 45 countries in the sample for each quarter[3].

Consumer price indices are used as a proxy for the tourism export prices. Natural logarithms are taken of all variables before they are used for estimation to ensure linear relationships. In addition, individual seasonal patterns in the data are removed by taking seasonal differences, thus making all variables conveniently interpretable as annual growth rates. All calculations are performed using the GVAR Toolbox 2.0 for Excel and Matlab.

While global real GDP represents the only weakly exogenous global variable of the GVAR model, real tourism exports and relative tourism export prices as described above represent the country-specific endogenous domestic variables (see Section 3). Similar to di Mauro and Smith (2013), global real GDP is treated as an endogenous variable for the reference country: the USA. Hence, the USA is not modeled as a small, but as a large open economy. This not only accommodates the technical requirement of the GVAR model to treat all variables as endogenous from a global perspective, but with around 33 percent throughout the sample (1994-2003), the USA constitutes by far the most important contributor to the present measure of global real GDP. Thus, modeling the USA as a SMOPEC would be at odds with the empirical evidence (Galesi and Lombardi, 2013). As mentioned in Section 3, treating global real GDP as domestic and endogenous for the USA results in all variables being endogenous from a global perspective (Dées, di Mauro, Pesaran, Smith, 2007).

To complete the GVAR model, the country-specific weakly exogenous foreign variables still need to be constructed. There are two foreign variables for each country: real tourism exports and relative tourism export prices of competing destinations. Hence, the two country-specific foreign variables are calculated as country-specific weighted averages of real tourism exports and relative tourism export prices, respectively, of all other countries. The weight matrix used for the construction of the foreign variables is calculated by aggregating annual merchandise export data per trading partner (measured "free on board" and averaged over the period 1994-2013) of the 45 countries in the sample by drawing on the Direction of Trade Statistics database of the IMF (2016), thus following the "classic" suggestion by Dées, di Mauro, Pesaran and Smith (2007). Hence, if country B is a relatively more important trading partner of country A compared to country C, country B will receive a relatively higher weight than country C when calculating the country-specific weighted averages for country A. In principle, other types of weights are also possible depending on the nature of the study (Eickmeier and Ng, 2015; Feldkircher and Huber, 2016).

Finally, the forecasts for global real GDP growth for the period 2013-2017, conditional on which real tourism exports and relative tourism export prices are forecast, are taken from the OECD Economic Outlook database (OECD, 2015). Since the data for real GDP in GVAR estimation are sourced from the OECD, this organization's expert global real GDP growth forecast data constitute a natural candidate for the conditional forecasting exercise. These expert forecasts are employed as a realistic assumption regarding the development of one of the explanatory variables over the forecast horizon. This is a requirement for a conditional forecasting exercise as laid out in Section 1.

Descriptive statistics of all variables as well as the weight matrix representing the trade linkages between the countries in the sample are not presented in the study due to space constraints. They are, however, available from the author on request.

5. The estimated GVAR models at the country level

Before conditional forecasts of real tourism exports and relative tourism export prices can be calculated with the GVAR model, the country-specific VARX*(p_i, q_i) models according to Equation (1) first have to be specified and estimated. By automatically estimating the country-level models in vector error correction form (VECMX*(p_i, q_i) according to Equation (3), see Section 3), the GVAR model can easily deal with both stationary (integrated of order $I(0)$) and non-stationary variables (integrated of order $I(1)$ or higher, which includes the possibility of cointegration between variables provided that their degree of integration is identical; di Mauro and Smith, 2013).

Prior to OLS estimation of Equation (4), the country-specific optimal lag orders p_i^* (of the $k_i = 2$ country-specific domestic variables) and q_i^* (of the $k_i^* = 3$ country-specific foreign variables and the global variable) of the VARX$^*(p_i^*, q_i^*)$ models and the country-specific number of cointegration relations r_i have to be determined. p_i^* and q_i^* are determined by BIC (Lütkepohl, 2005), while the maximum lag orders are equal to 4 because of the quarterly frequency of the data ($p_i^{\max} = q_i^{\max} = 4$). r_i, in turn, is computed according to the Johansen procedure in the presence of weakly exogenous $I(1)$ regressors (here: $x_{i,t}^*$; Johansen, 1991, 1995; MacKinnon *et al.*, 1999; Pesaran *et al.*, 2000), while $r_{US} \in \{0, 1, 2, 3\}$ (due to the endogeneity of global real GDP from the US perspective) and $r_i \in \{0, 1, 2\}$ for all other countries since $k_i = 2$.

As shown in Table I, p_i^* and q_i^* as well as r_i differ between countries, which underlines the importance of taking country-specific characteristics of the data into account in order to obtain a correctly specified forecast model. For 17 out of 45 countries, there is cointegration between the two domestic variables ($r_i = 1$; given in italics in Table I), whereas for 26 countries the matrix of cointegration vectors b_i has full rank ($r_i = 3$ for the USA, $r_i = 2$ for the remaining countries), meaning that the already seasonally differenced variables are stationary. For the remaining two countries (IL and NZ) no statistically significant cointegration relation could be found ($r_i = 0$). Moreover, q_i^*, which represents the impact of the foreign and the global variables on the domestic economies, is never equal to zero; thus underlining the importance of allowing for interdependencies between the countries, in particular in terms of competing destinations' prices in a tourism context, as well as for the impact of common global developments. This result also underlines the importance of accounting for the competitors of the EU-15 in a comprehensive global tourism demand model.

While the detailed estimation results of the VECMX$^*(p_i^*, q_i^*)$ models are not presented in the study due to space constraints, they are, however, available from the author on request. Table I includes information about two important goodness of fit measures of the estimated VECMX$^*(p_i^*, q_i^*)$ models: the adjusted coefficient of determination (adjusted R^2) and the results of the weak exogeneity tests of the country-specific foreign variables and the global variable. The null hypothesis of the weak exogeneity test by Johansen (1992) and Harbo *et al.* (1998) is that there is no long-run equilibrium impact of domestic on foreign and global variables.

As can be seen from Table I, the adjusted R^2 is greater than 0.5 in most instances (71 out of 90; numbers that are given in italics) for the $k_i = 2$ domestic variables, which indicates an adequate goodness of fit for the individual country models. Furthermore, for the vast majority of cases (107 out of 128; numbers that are given in italics), the F-test statistics of the weak exogeneity test are below their 5 percent critical values so that the null hypothesis of weak exogeneity of the country-specific foreign variables (LNXRSA_FOR, LNXPRELSA_FOR) and the global variable (LNGDPRSA) cannot be rejected.

Table I Optimal lag orders, number of cointegration relations, and goodness of fit of the estimated VECMX* models

	Optimal lag orders		*No. of coint. rel.*	*Adjusted R^2*			*Weak exogeneity test results*		
Country	*p^**	*q^**	*r_i*	*LNXRSA*	*LNXPRELSA*	*5% crit. val*	*LNXRSA_FOR*	*LNXPRELSA_FOR*	*LNGDPRSA*
AT	2	2	*1*	0.1687	*0.9630*	4.0012	*0.1379*	*1.8966*	*0.0161*
AU	2	1	*1*	0.3803	*0.6430*	4.0130	8.5783	*0.1095*	*1.2665*
BELU	3	2	2	*0.5898*	*0.9633*	3.1478	*0.1766*	*2.4083*	6.2576
BG	2	2	2	*0.7527*	*0.7967*	3.1478	*0.9095*	*2.3193*	5.2657
BR	2	1	*1*	0.2308	*0.5357*	4.0012	*0.5301*	*0.8702*	*0.3378*
CA	2	2	2	*0.6708*	*0.7857*	3.1531	*0.2335*	*0.2866*	*0.1944*
CH	4	2	2	*0.5520*	*0.8114*	3.1478	*2.1527*	*1.1786*	*2.1066*
CN	2	1	2	*0.6508*	*0.8361*	3.1404	*2.3001*	*0.0541*	5.5327
CY	4	2	2	0.3807	*0.8385*	3.1428	6.4590	*1.2527*	*2.0920*
CZ	2	2	*1*	0.3748	*0.8408*	3.9959	*1.5935*	*0.9498*	*0.0592*
DE	2	2	2	*0.7583*	*0.9148*	3.1404	*0.1125*	*0.4370*	3.5451
DK	2	2	*1*	0.0451	*0.9122*	4.0012	*0.1183*	*1.6899*	*0.6941*
EE	2	1	*1*	*0.8029*	*0.8417*	3.9959	*0.0418*	4.3964	4.5630
ES	4	2	2	*0.7281*	*0.9369*	3.1478	*1.5733*	*0.4457*	*2.0034*
FI	2	1	2	0.4647	*0.8143*	3.1531	*1.7189*	*0.7198*	*0.8753*
FR	2	2	*1*	0.2752	*0.9432*	4.0040	*3.6249*	4.1863	*1.9496*
GB	2	2	2	*0.6071*	*0.7735*	3.1478	*1.9552*	5.5585	*0.6619*
GR	2	2	*1*	0.0141	*0.8411*	4.0130	*2.7263*	*0.4842*	*2.3927*
HR	1	1	*1*	−0.0035	*0.8580*	4.0012	*3.1554*	*2.8899*	*0.0123*
HU	2	1	2	*0.5313*	*0.6698*	3.1531	*2.6858*	*0.1958*	*0.3770*
ID	3	2	2	*0.6903*	*0.8216*	3.1478	*0.1391*	*2.4068*	*0.0771*
IE	2	1	2	0.4117	*0.6976*	3.1531	*1.2734*	*3.0157*	*0.1130*
IL	2	2	0	*0.5173*	*0.6093*	NC	NC	NC	NC
IN	4	2	2	0.4793	*0.7234*	3.1531	*0.0295*	*0.1994*	*0.5857*
IS	2	1	*1*	0.3455	*0.6767*	3.9959	*1.2261*	*2.7686*	*1.3123*
IT	2	2	2	*0.6007*	*0.7910*	3.1478	*0.7105*	3.3094	*2.1919*
JP	2	1	*1*	0.4127	*0.6778*	4.0012	*1.7999*	*0.0553*	5.0443
KR	2	1	2	*0.7461*	*0.6466*	3.1531	*1.0910*	*1.0663*	*0.3286*
LT	3	1	*1*	*0.6209*	*0.9168*	4.0012	*0.4882*	*1.3214*	*0.0030*
LV	3	1	*1*	*0.6887*	*0.8192*	3.9959	7.4565	20.6098	*1.3273*
MT	2	4	2	*0.9065*	*0.8489*	3.1478	*1.0059*	*0.3553*	*1.9400*
MX	2	4	2	*0.6605*	*0.8437*	3.1478	9.0690	4.1007	*1.7200*
NL	4	2	2	*0.6450*	*0.9770*	3.1478	*0.0905*	*0.5642*	*1.0008*
NO	2	1	2	0.3373	*0.6550*	3.1531	*0.5630*	*0.1506*	*0.7448*
NZ	4	1	0	0.2084	*0.7225*	NC	NC	NC	NC
PL	2	1	*1*	0.3420	*0.7247*	3.9909	*1.2061*	*0.1136*	*1.9003*
PT	2	2	2	*0.5648*	*0.9692*	3.1559	*1.5343*	*2.3002*	*1.2949*
RO	2	1	*1*	0.3414	*0.7400*	3.9959	*0.7208*	*2.9132*	*0.1152*
RU	4	1	2	*0.9945*	*0.8938*	3.1338	3.8108	*0.6763*	*0.7743*
SE	3	1	2	*0.5823*	*0.7531*	3.1650	5.3162	*1.0669*	*0.1716*
SI	4	2	2	*0.7321*	*0.9788*	3.1404	*1.9645*	4.7260	9.0014
SK	2	1	*1*	*0.5750*	*0.7300*	3.9959	*0.0024*	*1.3496*	*0.0169*
TR	2	1	2	*0.5003*	*0.7429*	3.1428	*2.3180*	*0.5739*	*0.2569*
US	2	3	3	*0.7256*	*0.8531*	2.7437	*0.8590*	3.8871	ND
ZA	2	1	*1*	0.1180	*0.6649*	4.0012	*0.4617*	*0.6815*	*2.9233*

Notes: "NC" denotes that the weak exogeneity test statistic could not be calculated for IL and NZ, while "ND" denotes that this test statistic is not defined for LNRGDPSA for the USA since this variable is assumed to be endogenous for this country. p^* and q^* are determined by BIC (Lütkepohl, 2005). r_i corresponds to the number of hypothesized cointegration relations that cannot be rejected anymore by the cointegration trace statistic at the 5 percent significance level (Johansen, 1991, 1995; MacKinnon *et al.*, 1999; Pesaran *et al.*, 2000), while italic r_i values denote the presence of cointegration. Adjusted R^2 values greater than 0.5 are given in italics. Weak exogeneity *F*-test statistics in italics denote that they are below their 5 percent critical values (Harbo *et al.*, 1998; Johansen, 1992)
Sources: IMF, OECD and own calculations

6. Conditional forecasting results

Based on the estimated and solved GVAR model, dynamic out-of-sample mean forecasts of real tourism exports and relative tourism export prices at the country level are calculated for the EU-15, conditional on expert real GDP growth forecasts for the global economy provided by the OECD for the years 2013-2017, with global real GDP being the only restricted variable.

Given the quarterly frequency of the data and 2013Q3 as the forecast origin T, the forecast horizon H is equal to 17 quarters between 2013Q4 and 2017Q4 ($H = 17$). Since global real GDP is not forecast, but assumed to be given for the entire forecast horizon, the restriction horizon $\underline{H}$ is equal to 17 quarters as well ($\underline{H} = 17$).

Algebraically, the restrictions are treated as known constants with d_{T+j} denoting the $m \times 1$ vector summarizing these constants, where m corresponds to the number of restricted variables (here: $m = 1$) and $j = 1, 2, \ldots, \underline{H}$. Thus, GVAR forecasts conditional on d_{T+j} can be written as (Pesaran *et al.*, 2007; Smith and Galesi, 2014):

$$\Psi x_{T+j} = d_{T+j}. \tag{5}$$

Ψ in Equation (5) is an $m \times k$ matrix relating the model variables x_{T+j} to be forecast to the restrictions over the restriction horizon. Hence, conditional dynamic out-of-sample mean forecasts f_h^* are expected values of the model variables over the forecast horizon restricted by the information set available at the forecast origin $\mathcal{I}_T$ and by Equation (5):

$$f_h^* = E_T\left(x_{T+h} | \mathcal{I}_T, \Psi x_{T+j} = d_{T+j}, j = 1, 2, \ldots, \underline{H}\right), \quad h = 1, 2, \ldots, H, H \leqslant \underline{H}. \tag{6}$$

Figure 2 displays the conditional real tourism export forecasts (LNXRSA; solid lines) as well as conditional relative tourism export price forecasts (LNXPRELSA; dashed lines) for each EU-15 member country for the forecast and restriction horizon 2013Q4 to 2017Q4. Since these conditional forecasts are purely *ex ante*, they have to be interpreted with a grain of salt. As noted by Clements and Hendry (1998) and Ericsson (2003), there are sources of forecast uncertainty beyond the forecast origin (2013Q3 in the present case) such as future structural changes in the economy that are beyond the control of the forecaster. These could include, for example, the impact of the onset of the migration crisis in 2015 on tourism demand in Western vs Eastern Mediterranean countries. This is also the reason why the subsequent interpretation of the conditional forecasting results focuses solely on whether the direction of the projected future trajectories of the variables is in line with the expectations from microeconomic theory instead of specific numerical mean forecast values, which naturally become less accurate as the forecast horizon gets longer.

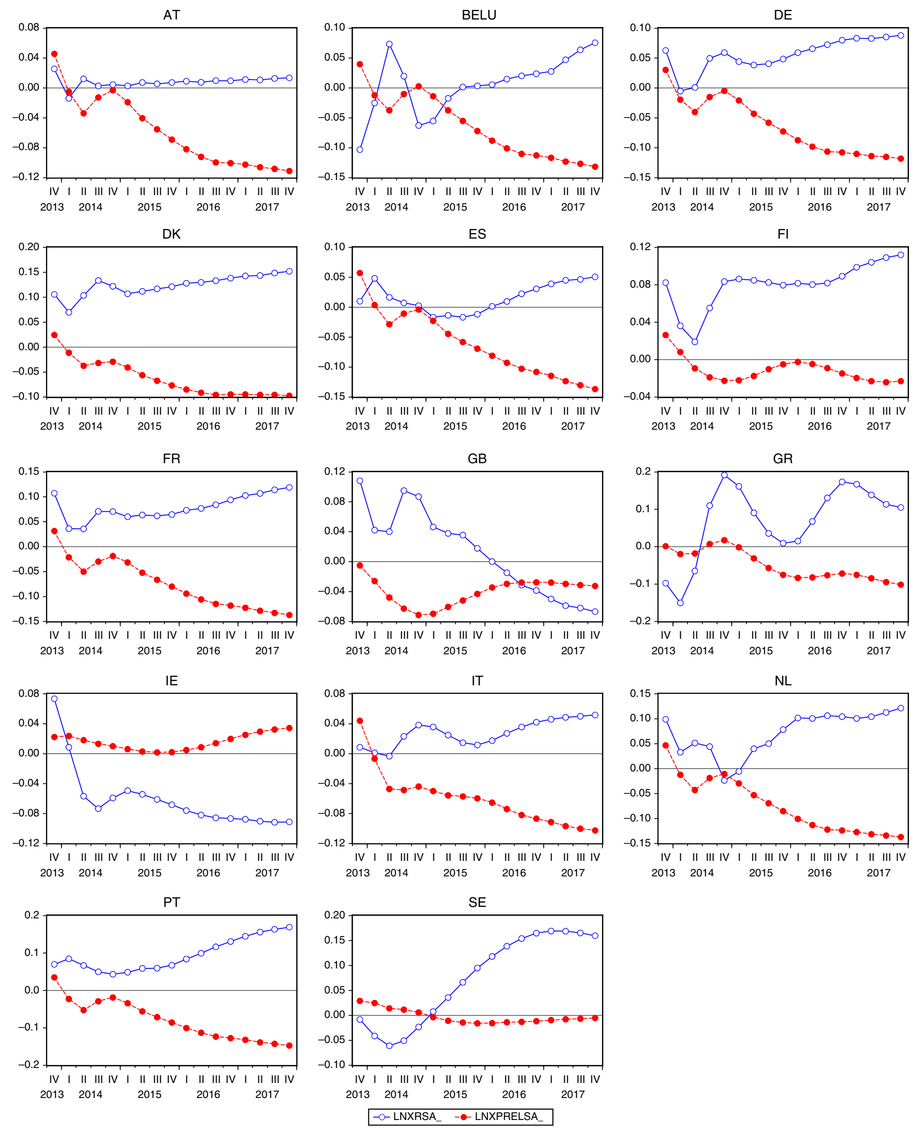
As can be obtained from Section 5 (therein notably from Table I), the estimated GVAR models at the country level are characterized by quite complex country-specific dynamics, which include the influence of past realizations of domestic variables on their current realizations, the influence of current and past realizations of foreign and global variables on current realizations of domestic variables, and even lagged short-run feedback from domestic to foreign and global variables[4].

Moreover, conditional forecasting *ex ante* precludes the evaluation of these forecasts in terms of traditional forecast accuracy measures such as the mean square error, the mean absolute error, or some of their variants, which would only be possible with *ex post* forecasts that are not part of this study.

Standard microeconomic theory implies that a growing global economy should be positively correlated with growing real tourism exports, while real tourism exports should be negatively correlated with relative tourism export prices as long as tourism can be seen as a normal good (Pindyck and Rubinfeld, 2015; Song, Wong and Chon, 2003; Song *et al.*, 2009).

As can be seen from Figure 2, all EU-15 countries adhere to microeconomic theory for the greater part of the forecast and the restriction horizon, except for GB from 2016Q2 onward. Thus, the direction of the projected future trajectories is as expected. Even though for most countries, notably AT, DE, DK, ES, FI, FR, IE, IT, NL, and PT, the immediate one-quarter-ahead forecasts of LNXRSA and LNXPRELSA are both positive, positive global real GDP growth results in positive conditional forecast LNXRSA trajectories after short adaptation periods lasting approximately until 2014Q4. Negative conditional forecast LNXPRELSA trajectories, which are characterized by short adaptation periods as well, support this development. These short adaptation periods are defined by more or less pronounced fluctuations according to the aforementioned country-specific dynamics of the estimated GVAR models.

Figure 2 Conditional forecasts of real tourism exports (LNXRSA; solid lines) and relative tourism export prices (LNXPRELSA; dashed lines) per EU-15 member country for the forecast and restriction horizons 2013Q4 to 2017Q4



Sources: IMF and OECD, own calculation and illustration

Concerning the relative magnitude (ratio of average growth rates in absolute terms between 2013Q4 and 2017Q4) of the development of the country-specific LNXRSA trajectories with respect to LNGDPRSA, projected growth of the global economy results in over-proportional real tourism export growth for all but three EU-15 countries (AT, ES, and IT). Even though real tourism export growth for AT, ES, and IT is still conditionally expected to be positive, the projected increase is not that pronounced. IE, although adhering to the expectations from theory concerning correlation directions, stands out as the only country from the sample for which projected global real GDP increases do not materialize in increases in real tourism exports.

To summarize, predicted global real GDP growth seems likely to materialize in real tourism export increases at the EU-15 country level, and therefore benefit the politically and macroeconomically distressed EU-15 as a whole. This increase, however, is not necessarily substantial in each and every EU-15 member country, which raises questions about the ability of the EU-15 to defend its market share in the global travel market given the continuing growth and increasing (geographic) diversification of global travel (WTTC, 2016). The conditional forecast increases in real tourism exports are supported by conditional forecast decreases in relative destination price. Thus, most likely, not only expected tourist income increases alone but also becoming more price competitive is a crucial economic factor for ensuring sufficient export earnings from international tourists in the long run (WEF, 2015).

7. Conclusion

Employing panel data ranging from 1994Q1 to 2013Q3 for a cross-section of 45 countries from IMF and OECD databases, a GVAR model was estimated and used for forecasting real tourism exports and relative tourism export prices of the EU-15, conditional on expert real GDP growth forecasts for the global economy provided by the OECD for the years 2013-2017, thereby embedding tourism demand for the EU-15 in a comprehensive global tourism demand model. The direction of the projected future trajectories of these two variables were analyzed.

In line with standard microeconomic theory, growing global tourist income together with decreasing relative destination price ensures, in general, growing tourism demand at the country level for the EU-15. *Per se*, this is good news for the politically and macroeconomically distressed continent. However, the conditional forecast increases in tourism demand are under-proportional for some EU-15 member countries despite growing tourist income supported by decreasing relative destination price.

Since the EU-15 countries are among the least price-competitive destinations, not only expected tourist income increases alone but also becoming considerably more price competitive is a crucial economic factor for ensuring sufficient export earnings from international tourists in the long run. This improvement has to be achieved by the EU-15 countries in order to counter the rising competition for market shares from other destinations around the world.

The policy implication of this finding is that in order to remain competitive as a destination, tourism planners and developers in the EU-15 should not rely purely on the projected increases of global tourist income as this may only under-proportionally manifest in increasing tourism demand. They are rather encouraged to take up supply-side measures – not limited to relative destination price terms – to make their tourism products and services more attractive and competitive. Furthermore, tourism planners and developers in the Western Mediterranean (and in other Central and Western European destinations as well) should not misinterpret the surges in tourist arrivals in 2016 as a carte blanche to refrain from taking up supply-side measures to overcome their price-related disadvantages. These increases are mainly caused by the migration crisis in the Eastern Mediterranean and thus may only be temporal. Since the migration crisis lies beyond the forecast origin of the study sample, the present results are more likely to be representative of the structural development of the variables under “normal economic activity.”

Apart from missing data for other potentially important explanatory variables of tourism demand, one limitation of the present study is that the conditional forecasts calculated and discussed are purely *ex ante*. As such, the discussion has been limited to the direction of the projected future trajectories of the variables, while ignoring the absolute magnitude of the projected changes. Thus, future research could analyze the *ex post* forecast accuracy of tourism demand of the presented GVAR model in a forecast competition with other univariate and multivariate time series and even panel forecast models. In addition, the investigation of the transmission mechanisms of local, regional, or global shocks to the variables in terms of impulse responses (e.g. in an adapted framework: “How do EU-15 real tourism exports and relative tourism export prices react to a negative GDP shock in the UK due to the Brexit?”) could be of interest.

Notes

1. Austria (AT), Belgium (BE), Denmark (DK), Finland (FI), France (FR), Germany (DE), Greece (GR), Ireland (IE), Italy (IT), Luxembourg (LU), the Netherlands (NL), Portugal (PT), Spain (ES), Sweden (SE), and the UK (GB; as of 2016) are the member countries of the EU-15.
2. Data were only available for Belgium and Luxemburg combined.

3. As noted in Section 1, modeling the dependence of all countries on a common global development, global real GDP, and investigating the impact of expert OECD real GDP growth forecasts on real tourism exports and relative tourism export prices precludes the use of different real GDPs specifically aggregated for the individual source markets of each country.
4. While abandoning the statics and exogeneity assumptions makes a (G)VAR model a quite flexible and powerful forecast model, it precludes the interpretation of its estimated coefficients as price and income elasticities (even if the data are given in natural logarithms; Neusser, 2009).

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