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THE DEMAND FOR WINTER TOURISM IN AUSTRIA

A COMBINED ECONOMIC AND CLIMATIC APPROACH

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The Demand for Winter Tourism in Austria

Abstract

This paper develops a long-term econometric approach to model the demand for winter tourism in Austria. Thereby it combines both economic and meteorological determinants. The former is handled within a cointegration framework due to the non-stationary features of the economic time series used. Long-term tourism demand functions can be extracted, where tourism demand is determined by the real income and the purchasing power of travelers and the substitute price for winter tourism in competing destinations. This relationship is integrated into an error correction framework, which allows for a simultaneous treatment of economic and meteorological components. The analysis is conducted for German travelers, who constitute by far the largest share of winter tourists in Austria. The results are very promising, with tourism demand depending on both economic and meteorological factors significantly, on a regional basis (federal provinces) as well as for the country as a whole.
JEL: C32 · L83 · Q51
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1 Introduction

With 120 million overnight stays per year tourism plays a fundamental role in the Austrian economy. 40 billion Euros in direct and indirect value added, equal to 16.5% of the GDP, can be attributed to the tourism and recreational industry in the year 2005 (Laimer and Smeral, 2006). A majority of these activities is closely related not only to economic developments, but also to the meteorological conditions, as skiing in winter as well as hiking, swimming and other outdoor activities in summer are highly sensitive to the weather.
While on an international level economic and meteorological impacts on tourism demand are quite well understood by economists and respectively climate researchers, there is a lack of concepts to simultaneously examine these impacts. It seems to be evident that an integrated assessment of economic developments and impacts of climate variability is needed for a further understanding of the tourism industry's weather sensitivity.
A series of recent econometric studies have shown that tourists' income, tourism prices in a destination relative to those in the origin country, tourism prices in the competing destinations (i.e. substitute prices) and exchange rates are the most import economic determinants of tourism demand[1]. In these studies, various econometric methods, such as autoregressive distributed lag models (ADLM), error correction models (ECM), vector

[1]For an overview of the tourism demand modeling literature confer the extensive reviews of Li et al. (2005) and Song and Li (2008).

autoregressive (VAR) models, time varying parameter (TVP) models, or combinations of these techniques have been used to examine the causal relationships between tourism demand and influencing economic factors.
Examinations of the tourism industries' weather sensitivity are usually conducted within the field of climate impact research[2]. While the majority of studies focus on the relation between weather conditions and tourism, and respectively the impacts of climate change, there are also some recent attempts to include economic considerations in the models. Lise and Tol (2002) carry out a cross sectional analysis to estimate climatic and economic impacts on OECD tourists' choice of their holiday destinations. Agnew and Palutikof (2006) consider the before-mentioned economic determinants of tourism demand in a stepwise regression procedure to determine the impacts of variations in temperature, precipitation and sunshine hours on the demand for domestic and international tourism in the UK. Neither of these studies recognizes the recent advances in modeling economic impacts on tourism demand, although the employment of these econometric techniques seems to be crucial to avoid both the misinterpretation of economic relationships and technical pitfalls of traditional regression analysis based on ordinary least squares (OLS).
Consequently, this paper aims to provide an approach to integrate meteorological parameters into a profound econometric model. We first employ a cointegration framework to model the economic relationships, which is then embedded in a vector error correction model (VECM). Subsequently we will introduce a snow index (potential skiing days) to examine the impacts of short term climate variability on winter tourism in Austria. The paper scrutinizes the determinants of winter tourism demand of German citizens, who, with more than 40% of all the tourists, constitute by far the largest share of tourists in Austria.
The remainder of the paper is structured as follows: The next section deals with the construction of the variables used in the analysis. Section 3 investigates the variables with respect to their persistence over time. Section 4 shortly outlines the econometrics that is employed in the present analysis, and section 5 eventually presents the empirical results. The last section sums up the argument.

2 Variable Construction

Similar to Song and Witt (2000) and Song et al. (2003), the demand for winter tourism in Austria and its different provinces n_i is assumed to depend on own lagged values (through habit persistence, etc.), the level of income in the origin country y, which in this case is Germany, the purchasing power of German travelers p and the price differences in competing destinations pc. Furthermore, as a meteorological factor, the number of days with more than 30cm snow in skiing areas $snow_i$, is considered. Also, deterministic components

[2] Cf. also Scott et al. (2006) for a bibliography of relevant research papers.

d like constants and time trends are considered, if necessary,

$$n_i = f(n_i, y, p, pc, snow_i, d), \tag{1}$$

where i denotes the province, including all Austrian provinces but Vienna, Burgenland and Lower Austria, which are not regarded typical winter destinations, and Austria as a whole. n is the number of tourist nights per season.

Data range and frequency All data are (transformed into) biannual seasonal data, where the summer season ranges from May to October and the winter season from November to April. The data set ranges from winter 1973 (i.e. $11/72 - 04/73$) until winter 2003, and, hence, includes 30 observations for the summer season and 31 observations for the winter season.

Remark on the notation Vectors and matrices are denoted in boldface, while scalars are denoted in normal style. Furthermore, the same symbols might appear in different setups, if there is no danger of confusion; e.g. '$\mathbf{u_t}$' is used as a vector of residuals in different models.

2.1 Tourist Nights

The number of tourist nights is taken from the ISIS database (StatistikAustria, 2008) and is transformed into natural logarithms (logs), such that regression coefficients can be interpreted as elasticities. The time series are shown in figure 1. Since all of them exhibit a clear upward trend, the test for non(stationarity) later on will include the two hypotheses of trend-stationarity and a random walk with drift.

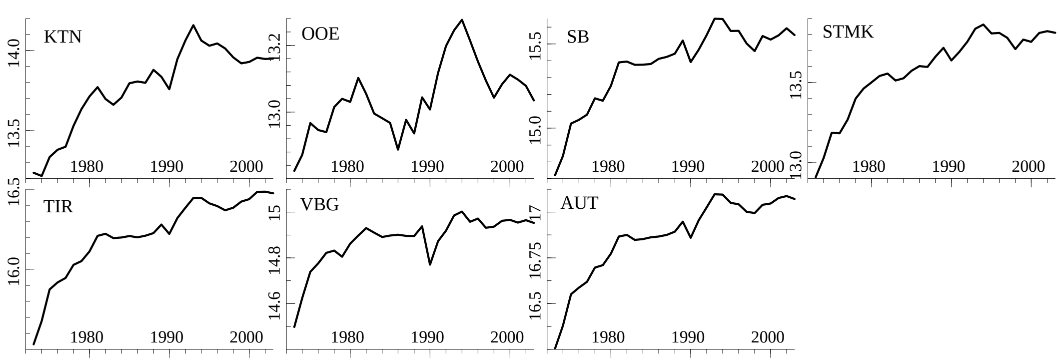

Figure 1: Tourist nights.

2.2 Real Activity

Real activity y is measured by quarterly GDP, obtained from the OECD database (OECD, 2008). The higher real income, the higher the demand for tourism is expected to be. To obtain a seasonal series for the summer, the second and the third quarter are added up, while the winter series is obtained by adding the fourth and the first quarter of two subsequent years. This procedure produces a slight mismatch between the time range of y (winter: October - March) and the time range of n (November - April), y_t^w lags one month behind n_t. However, due to the 'sticky' decision making process, which renders the time series component of the model valuable and necessary, this can be regarded to be an appropriate procedure. Like with n, logs are taken. In figure 2 both the winter and the summer series are shown.

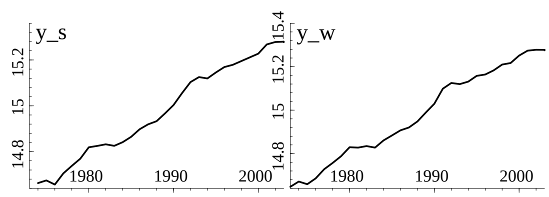

Figure 2: Real activity.

2.3 Purchasing Power

The purchasing power of travelers p is constructed in the same way as in Song et al. (2003, p. 438),

$$p = \ln \frac{CPI_{AUT}/EX_{AUT/US}}{CPI_{GER}/EX_{GER/US}}. \tag{2}$$

The monthly values, which are taken from the OECD database (OECD, 2008), are averaged such that seasonal values are obtained. One series for the summer (i.e. May - October) and one for the winter term (i.e. November - April) are created to introduce lags and, thus, account for the decision making process that precedes the journey. The higher p, the more expensive is a trip to Austria for German citizens. Therefore, the long-term elasticity with respect to p, i.e. the price elasticity, is expected to be negative. Figure 3 shows the winter and summer series for all the countries of origin.

2.4 Competing Destinations

Up to now two regressors that usually account for most of the variation of the demand for a good have been considered, namely income and price. As a third factor the price

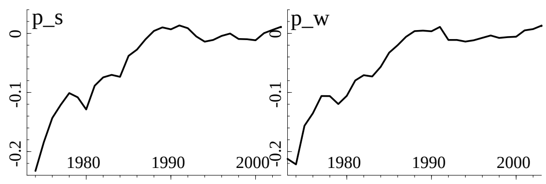

Figure 3: Purchasing Power.

for a substitute good will be included. Regarding the definition of a substitute good for winter tourism in Austria, we have taken price and exchange rate data of the three Alpine countries Switzerland, Italy and France, which we consider the major competing destinations for skiing holidays. The variable is constructed in a similar way as purchasing power in equation 2,

$$pc = \ln \frac{CPI_{AUT}/EX_{AUT/US}}{1/3 \cdot \sum CPI_c/EX_{c/US}} \tag{3}$$

where c denotes SWI, FRA and ITA. The higher pc, the more expensive is a vacation in Austria compared to an average of the three other destination countries and the less tourists are expected to arrive in Austria. Therefore, the long-term substitute-price elasticity is expected to be negative. The series pc is shown in figure 4.

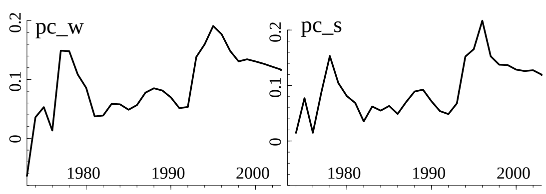

Figure 4: Substitute prices.

2.5 Potential skiing days

So far, only indicators for economic activities have been discussed. In addition, a meteorological variable will be considered to explain variations in the number of tourist nights. As the tourist industry in the majority of the Austrian provinces is extremely sensitive to snow cover, an index $snow_i$ is constructed to measure the deviance between the number of days with more than 30 centimeters of snow $snow_k$ and the long term meteorological average of the period 1971-2000 ($snow_{k,mean}$). For each Austrian province with a substantial skiing industry i several meteorological stations k (table 1) have been selected[3], whereby the index value for every province is simply the mean of the respective stations,

$$snow_i = \frac{1}{n_i} \sum_{k_i=1}^{n_i} \left(snow_{k_i} - snow_{k_i,mean} \right). \tag{4}$$

Additionally, in the aggregated whole-Austria series the stations are weighted according to the share of nights spent in each province, where the stations are located.
By reason that the majority of tourists travel to Austria for skiing activities, it is less attractive to travel to the ski resorts, if snow height is below a certain threshold. Although it seems to be difficult to choose the optimal threshold level, correlation analyses indicate that indices of different thresholds are highly correlated. Indeed, the selection of appropriate meteorological stations has much more impact on the consecutive results than the selection of the threshold level.
Another caveat one might have is that due to the possibility of artificial snow making the measurement of natural snow height does not have a real impact on the tourism industry anymore. In fact, our analysis focuses on the long term trend, and the large scale production of artificial snow has not started before the year 1990 in the majority of Austrian skiing areas. Thus, artificial snow making and its effects need to be considered especially for analysis of the weather sensitivity in the most recent years, which is beyond the scope of this paper.

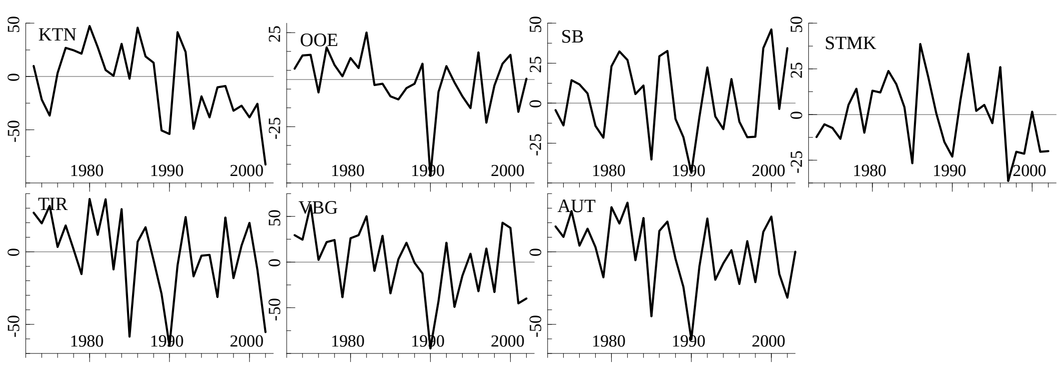

Figure 5: Potential skiing days.

[3]18 out of 71 meteorological stations, for which long term snow data can be provided, have been chosen, whereby the following selection criteria have been used: sea level as in winter tourism relevant areas (500 to 2250 meter), distance to main skiing areas, number of missing observations.

Table 1: Locations of meteorological stations (ZAMG, 2003).

Met. station	Province	Sea lev. (m)	Longitude (°O)	Latitude (°N)	#NA
Badgastein	SB	1100	13.07	47.05	1
Feuerkogel	OOE	1618	13.44	47.49	0
Galtür	TIR	1587	10.11	46.58	0
Holzgau	TIR, VBG	1100	10.21	47.15	0
Kanzelhöhe	KTN	1526	13.54	46.40	0
Kolbnitz	KTN	603	13.18	46.52	0
Krippenstein†	OOE, STMK	2050	13.42	47.31	2
Mondsee	OOE	491	13.22	47.51	0
Mooserboden	SB	2036	12.43	47.09	2
Patscherkofel	TIR	2247	11.27	47.12	2
Rauris	SB	945	13.00	47.13	0
Reisach	KTN	646	13.09	46.38	0
Schoppernau	VBG	835	10.01	47.18	0
Schröcken	VBG	1263	10.05	47.15	0
Seckau†	STMK	855	14.46	47.16	5
St. Jakob Def.	TIR	1400	12.21	46.55	1
Stolzalpe†	STMK	1305	14.12	47.07	2
Villacher Alpe	KTN	2140	13.40	46.36	0

† For higher lying areas of the Province of Styria snow data availability is quite unsatisfactory. Therefore we considered not only one station in the boarder region to Upper Austria (Krippenstein), but also two stations with some missing observations (Seckau and Stolzalpe).

3 Unit root tests

Two unit root tests are applied to determine the order of integration and, hence, avoid spurious regression problems, namely the Augmented Dickey Fuller (ADF) test, which tests the null of a unit root against the alternative of (trend)stationarity and the test of Kwiatkowski, Phillips, Schmidt and Shin (KPSS), which reverses the test hypotheses and, thus, provides additional insight[4].

In order to avoid nuisance parameters in the asymptotic distributions of the test statistics, the ADF test accounts for the residual auto-correlation in a parametric way in that it includes h lags of the differenced series, while KPSS estimates it in a non-parametrical way using a specific bandwidth length l. Due to the few observations at hand and hence the low test power, the results may vary with different choices of h and l, therefore the tests are conducted with various values for it, $h = 0, 1, 2$ and $l = 0, 1, 2$.

Table 2: Unit root tests, p-values.

	ADF			KPSS		
	$h = 0$	$h = 1$	$h = 2$	$l = 0$	$l = 1$	$l = 2$
n_{AUT}	0.03	0.06	0.50	< 0.01	< 0.01	< 0.05
y^w	0.83	0.53	0.58	< 0.01	< 0.01	< 0.05
y^s	0.85	0.54	0.52	< 0.01	< 0.01	< 0.05
p^w	0.38	0.01	0.66	< 0.01	< 0.01	< 0.01
p^s	0.03	0.32	0.63	< 0.01	< 0.01	< 0.01
pc^w	0.03	0.15	0.24	> 0.10	> 0.10	> 0.10
pc^s	0.12	0.22	0.08	< 0.10	> 0.10	> 0.10
$snow_{AUT}$	0.00	0.01	0.04	> 0.10	> 0.10	> 0.10

Dark gray cells show strong indices of non-stationarity (i.e. $p_{ADF} > 0.10$ or $p_{KPSS} < 0.05$).
Light gray cells show weak indices of non-stationarity (i.e. $0.10 > p_{ADF} > 0.05$ or $0.05 < p_{KPSS} < 0.10$).
White cells indicate stationarity.

Due to visual inspection of the series the unit root tests for all variables are conducted with a time trend, hence the null hypothesis of a random walk with drift is tested against the alternative of trend-stationarity (and vice versa for KPSS). However, the results are qualitatively similar if no time trend is included in the cases of p and pc, which could also be pure random walks (without a drift).

The overall result is that the tourist night series (the series under consideration is that for whole Austria, but qualitatively the results also hold for the provinces) and the economic

[4] For an extended discussion on unit root tests cf. an econometric textbook like e.g. Davidson (2006, p. 346 et seq.)

series (y, p and pc) show more or less clear signs of non-stationarity (at least, it cannot be ruled out), while the snow-index seems to be rather stationary. This paves the way for the model framework outlined in the next chapter, where the economic determinants of tourism demand will be modeled within a cointegration framework, while the meteorological determinant is added within the error correction representation. pc displays the weakest sign of non-stationarity, however, treating it within the cointegration framework if it was stationary is harmless and would only lead to a loss of efficiency, while wrongfully treating it as stationary would imply spurious regression and hence, inconsistent estimation results. Therefore it is also considered to be non-stationary.

4 The Model

4.1 Economic Determinants

The Vector Error Correction Model (VECM) that is applied in a first step (that is, to capture the underlying **economic** relationships) has the following general form[5],

$$\mathbf{\Delta x_t} = \mathbf{c} + \mathbf{\Pi x_{t-1}} + \sum_{i=1}^{p-1} \mathbf{\Lambda_i \Delta x_{t-i}} + \mathbf{u_t}, \tag{5}$$

where $\mathbf{x_t} = \begin{pmatrix} n_{i,t} & y_t^w & y_t^s & p_t^w & p_t^s & pc_t^w & pc_t^s \end{pmatrix}'$, $\mathbf{\Delta}$ is the difference operator, $\mathbf{c}$ is a vector of intercepts, $\mathbf{\Pi} = \boldsymbol{\alpha\beta}'$ is the cointegration space, $\boldsymbol{\alpha}$ is a vector of adjustment coefficients, $\boldsymbol{\beta}$ is the cointegration matrix and p is the number of lags that are included in the Vector Autoregressive (VAR) representation of the VECM,

$$\mathbf{x_t} = \mathbf{c} + \boldsymbol{\beta}_\mathbf{0} t + \sum_{i=1}^{p} \mathbf{\Psi_i x_{t-i}} + \mathbf{u_t}. \tag{6}$$

The Schwarz Bayesian Criterion always suggests a lag length of $p = 1$, which is expected, since yearly data are used. Therefore, the VECM in equation 5 can be simplified to

$$\mathbf{\Delta x_t} = \mathbf{c} + \mathbf{\Pi x_{t-1}} + \mathbf{u_t}, \tag{7}$$

A deterministic time trend is disregarded in the cointegration relations, since a gradual habit change or anything else that could be proxied by a time trend, is not considered (cf. Song and Witt, 2000, p. 115-116).
A favorable condition for a model to be useful in the sense that a long-term tourism demand function can be extracted from it is that the total number of cointegration relations, r,

[5] The econometric methodologies applied in the following analysis can be recapitulated from textbooks such as e.g. Lütkepohl and Krätzig (2007).

is accepted to be four, which is tested by means of the Johansen Trace Test (JTT) and the Maximum Eigenvalue Test (MET), and which is the case in the present analysis (cf. table 3). $r = 4$ seems to be sensible, since, apart from the tourism demand function, the summer and winter series of the regressors y, p and pc are pairwise cointegrated (which is evident from inspection of the series in figures 2, 3, 4). However, restrictions on $\boldsymbol{\beta}$ (which is a 7×4 matrix then) are imposed only such that it is just-identified (which provides exactly the three zero-restrictions on y_t^s, p_t^s and pc_t^s in the first column of $\boldsymbol{\beta}$ such that a tourism demand function can be identified in an econometrically satisfying way).

Table 3: Cointegration rank tests, p-values.

	$r = 3$		$r = 4$	
	JTT	MET	JTT	MET
AUT	0.00	0.00	0.11	0.25
KTN	0.00	0.01	0.16	0.47
OOE	0.01	0.03	0.19	0.11
SB	0.00	0.01	0.07	0.19
STMK	0.01	0.02	0.18	0.45
TIR	0.00	0.00	0.16	0.25
VBG	0.00	0.03	0.03	0.22

Dark gray cells display a p-value > 0.10.
Light gray cells display a p-value > 0.05.

The magnitude of the (negative) adjustment coefficient in the so-called loading matrix $\boldsymbol{\alpha}$ expresses the speed of adjustment of $n_{i,t}$ to the path given by the long-term tourism demand function, that is, how long it takes a short-term 'error' in $n_{i,t}$ to 'correct' back towards the long-term equilibrium given by the cointegrating relation.

4.2 Meteorological Determinants

After having modeled the economic relationships and especially their non-stationary, cointegrating features properly, it is possible to introduce the (stationary) **meteorological** factor *snow* as an independent regressor in the row of $n_{i,t}$ in equation 7,

$$\Delta n_{i,t} = c + \mathbf{\Pi^{(n)} x_{t-1}} + \sum_{k=0}^{l} \Omega_k snow_{i,t-k} + u_t, \tag{8}$$

where it turns out that only the contemporaneous values of the potential skiing days matters for tourism, while lagged values are insignificant. Therefore, this expression can be simplified to

$$\Delta n_{i,t} = c + \mathbf{\Pi^{(n)}} \cdot \mathbf{x_{t-1}} + \Omega \cdot snow_{i,t} + u_t. \tag{9}$$

5 Results

Long-Term German Tourism Demand - Economic and Meteorological Factors

$$n_{AUT,t} = \underset{0.24}{+1.36} \cdot y_t^w \underset{0.69}{-2.58} \cdot p_t^w \underset{0.56}{-2.85} \cdot pc_t^w + \epsilon_{n,t} \tag{10}$$

$$\begin{aligned} \Delta n_{AUT,t} = {} & \underset{0.63}{-0.21}^{\dagger} \underset{0.04}{-0.22} \cdot \epsilon_{n,t-1} \\ & \underset{0.49}{-1.02} \cdot \epsilon_{y,t-1} \underset{0.64}{-0.27}^{\dagger} \cdot \epsilon_{p,t-1} \underset{0.29}{-0.76} \cdot \epsilon_{pc,t-1} \\ & \underset{0.23 \cdot 10^{-3}}{+0.63 \cdot 10^{-3}} \cdot snow_{AUT,t} + u_t^* \end{aligned} \tag{11}$$

* Residual diagnostics (p-values): AR(4)[6]: 0.39, Heteroscedasticity[7]: 0.82, Normality[8]: 0.46

† Individually insignificant at the 10% significance level.

The coefficients in equation 10 and in the first row of table 4 are the values in the first row of $\boldsymbol{\beta}$ and represent the long-term income-, price- and substitute-price elasticities (since a constant elasticity demand function is assumed). All of them have the sign that is expected from economic theory (positive for income, negative for both price figures), have a sensible magnitude (winter tourism might be viewed as a 'luxury good' since the coefficient of y_t^w is greater than unity) and are significantly different from zero at low significance levels.
Equation 11 is the estimate of the error correction model 9 and displays rather astonishing results, since it reveals that both economic and meteorological factors play an important role as determinants for German winter tourism in Austria. Not only the cointegrating long-term economic relationship between tourism demand, income, prices and substitute prices loads significantly as error correction term, but also the variation in the number of skiing days helps explaining the variation in the first differences of tourist nights.
The adjustment coefficient of n_t (-0.22) is negative and significant, which indicates that some variation in Δn_t can indeed be explained by the fact that short-term fluctuations of n_t correct back to the tourism demand path given by economic determinants in the long run. The coefficient of $snow_t$ (Ω in equation 9) is significantly positive, meaning that the more skiing days, the higher the demand for winter tourism compared to the previous

[6]Lagrange multiplier F-test for autocorrelated residuals, the null hypothesis of no auto-correlation among the residuals is accepted.

[7]White F-test, unconditional homoscedasticity of the residuals is accepted.

[8]χ^2-Test of normality of the residuals in their third and fourth moments, the null that the residuals obey Gaussian kurtosis and skewness is accepted.

year (i.e. the higher the growth rate of tourism demand). The residuals of equation 11 are well behaved as far as non-auto-correlation, heteroscedasticity and normality in higher moments are concerned (cf. the residual diagnostics below equation 11)[9].

While the interpretation of the long-term elasticities in equation 10 is straight-forward (e.g. when real income of Germans increases by 1%, their demand for winter tourism in Austria increases on average by 1.36%), the nature and interpretation of the snow-coefficient Ω in equation 10 differs in two ways: First, it is not denoted in logs, but in days, second it refers to the dependent variable Δn_t instead of n_t, the former approximating the growth rate of tourist nights. One more skiing day induces an increase of Δn_t of about $\Omega = 0.63 \cdot 10^{-3}$ on average, that is 0.063%. Multiplied with a factor of ten, we obtain an increase of the seasonal growth rate of tourist nights by 0.63 percentage points, when there are 10 more skiing days per winter. This seems to be a rather plausible value given that the average annual growth rate of tourist nights is 2.73% and that the overall average of skiing days (i.e. cross-sectional and over time) amounts to 83.3 days per season.

On the other hand, the coefficients of the lagged residuals of the economic summer/winter cointegrating relationships in equation 11 are hard to interpret, since the cointegrating errors $\epsilon_{y,p,pc,t-1}$ basically mirror above-average changes between summer and winter values of the corresponding variables in the preceding year. However, a model reduction is not followed here, since the coefficients of the variables of primary interest, $\epsilon_{n,t-1}$ and $snow_t$, do not change with exclusion of insignificant figures of $\epsilon_{y,p,pc,t-1}$. Furthermore, (in-)significance of $\epsilon_{y,p,pc,t-1}$ varies region by region (cf. table 5), while $\epsilon_{n,t-1}$ is significantly different from zero for Austria as a whole as well as for each single province.

Table 4 reveals that there is not only one economic long-term tourism demand function for Austria as a whole, but also for each single province, except for Carinthia.

Although the cointegration residuals in figure 6 (where the first graph shows the residuals of equation 10) exhibit rather stationary patterns, they leave some space for interpretation about which events and/or other factors might have influenced German tourism demand in the long run. For example, it would be interesting to examine whether the sharp rise from 1978 to 1979 in all provinces has something to do with the introduction of the obligation to notify the authorities about the number of tourist nights.

Similar to the VAR with economic factors, the VECM that also incorporates meteorological factors, applies not only to Austria as a whole, but also to various provinces (table 5). However, the weather component loads only insignificantly in two cases, namely Styria and Vorarlberg.

[9] Also, all the other residuals of $\mathbf{\Delta x_t}$ are uncorrelated, homoscedastic and normally distributed, except for some minor non-Gaussian higher moments in the residuals of $\Delta pc_t^{w,s}$.

Table 4: Summary table long-term elasticities.

	Income El.	Price El.	Substitute Price El.
AUT	1.36 0.24	−2.58 0.69	−2.85 0.56
KTN	−351.19 93.96	1478.70 274.96	1030.00 224.21
OOE	1.57 0.35	−5.55 1.02	−3.52 0.84
SB	2.01 0.48	−5.03† 1.41	−5.90 1.15
STMK	1.02 0.27	−1.42† 0.80	−2.10 0.65
TIR	1.33 0.17	−1.99 0.51	−2.19 0.41
VBG	1.17 0.27	−3.53 0.80	−2.78 0.65

† Insignificant at the 10% significance level.

Gray cells contain values that have the sign that is expected from economic theory.

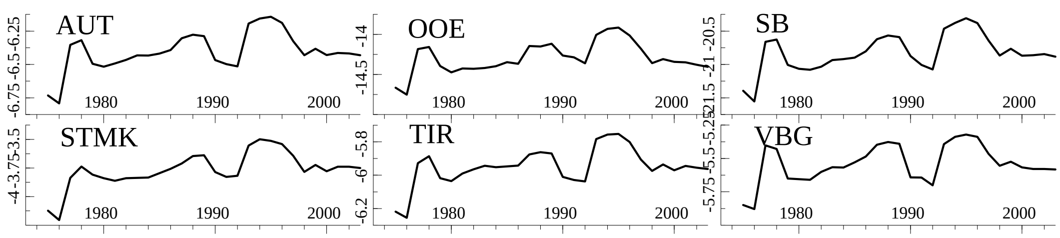

Figure 6: Residuals of cointegration relations (without KTN), $\epsilon_{n,t}$.

The figure shows the residuals of the long-term tourism demand functions with the elasticities tabulated in table 4, where those elasticities that do not have the expected sign or are individually not significantly different from zero are restricted to zero. However, there is no meaningful tourism demand function for Carinthia.

Table 5: Summary table error correction model.

	c	$\epsilon_{y,t-1}$	$\epsilon_{p,t-1}$	$\epsilon_{pc,t-1}$	$\epsilon_{n,t-1}$	$snow_t$
AUT	$-0.21^{\dagger}$	-1.02	$-0.27^{\dagger}$	-0.76	-0.22	$0.63 \cdot 10^{-3}$
	0.63	0.49	0.64	0.29	0.04	$0.23{\cdot}10^{-3}$
OOE	$0.17^{\dagger}$	$-1.49^{\ddagger}$	$0.15^{\dagger}$	$-0.88^{\ddagger}$	-0.11	$0.16 \cdot 10^{-2}$
	0.76	0.85	1.15	0.48	0.05	$0.05{\cdot}10^{-2}$
SB	$-0.81^{\dagger}$	$-1.17^{\dagger}$	$-0.25^{\dagger}$	-1.18	-0.17	$0.88 \cdot 10^{-3}$
	0.91	0.72	0.96	0.43	0.04	$0.35{\cdot}10^{-3}$
STMK	$0.82^{\dagger}$	-1.23	$0.37^{\dagger}$	-0.94	-0.27	$-0.04 \cdot 10^{-3}$ †
	0.58	0.57	0.76	0.32	0.04	$0.34{\cdot}10^{-3}$
TIR	$-0.29^{\dagger}$	$-0.84^{\ddagger}$	$-0.42^{\dagger}$	-0.66	-0.27	$0.41 \cdot 10^{-3}$
	0.57	0.47	0.62	0.27	0.04	$0.17{\cdot}10^{-3}$
VBG	$-0.25^{\dagger}$	$-0.50^{\dagger}$	$-0.16^{\dagger}$	$-0.55^{\dagger}$	-0.18	$0.31 \cdot 10^{-3}$ †
	1.30	0.62	0.77	0.35	0.07	$0.22{\cdot}10^{-3}$

† Insignificant at the 10% significance level.

‡ Insignificant at the 5% significance level.

Gray cells contain values that have the sign that is expected from economic theory.

6 Conclusion

The demand of German citizens for winter tourism in Austria depends on both economic and meteorological factors, but in different ways. The level of tourism demand is determined by the German income level, the relative price level between Austria and Germany and the relative price level between Austria and a mix of competing destination countries, hence economic factors. Fluctuations around this long-term path, on the other hand, can partly be explained by meteorological factors, in this case measured by snow cover.

To conclude the analysis, some flaws of the past and some challenges of future research should be pointed out. Firstly, as we have shown in this work, it is particularly important to deal appropriately with the non-stationarity features of economic and tourism data. In this regard the econometric perspective might be superior to conventional time series techniques like simple de-trending or regression analysis, as used by climatologists, e.g. in Agnew and Palutikof (2006).

Secondly, the analyses of meteorological impacts improve with a higher temporal resolution. Thus, examinations of the weather sensitivity of winter tourism require an approach to include not only the duration, but also the timing of the snow cover (e.g. winter openings, Christmas, Easter holiday etc). While at least a monthly scale, like in Agnew and Palutikof (2006) or preferably a daily scale, like in Hamilton et al. (2007) should be considered, this attempt is often limited by data availability. In the case of Austria tourist nights are not available on a monthly basis before 2000, which implies a trade off between longer seasonal data (35 years) and shorter monthly data (7 years).

Thirdly, weather impacts on tourism demand, and this is particularly true for the winter

season, are rather observable on a local and regional scale. The success of individual destinations rely on the meteorological conditions and their determining factors like altitude, weather currents etc., both in the destination itself, as well as in competing destinations and the origin regions of tourists[10]. Therefore further investigations need to tackle the discrepancy between weather sensitivity studies and economic studies, which are usually undertaken on a country or at most on a provincial scale.
As a last point it should be mentioned that future research should investigate the impact and significance of tourism demand factors beyond the log-linear assumption, which this paper's model is based on. In this perspective, the presumption that a decrease of skiing days might lead to a higher drop of the tourist nights' growth rate than a proportional rise increases the growth rate seems to be an interesting hypothesis, which, in our opinion, deserves attention.

[10]Indeed, the results of Hamilton et al. (2007) confirmed the so called 'backyard hypothesis', which says that not only mountain weather but also urban snow conditions significantly affect skier activities.

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