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TOURISM DEMAND IN AUSTRIAN SKI DESTINATIONS

A DYNAMIC PANEL DATA APPROACH

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Abstract

This paper employs panel data techniques to explain winter tourism demand to 185 ski destinations in Austria, based on the number of overnight stays from 1973-2006. By using income and relative purchasing power of the tourists together with snow coverage as determinants for tourism demand, both economic and climatologic aspects are combined in a single framework, based on an autoregressive distributed lag model. Analysis were conducted with the bias corrected two-way fixed effects model proposed by Bruno (2005) and the System-GMM estimator by Blundell and Bond (1998), using GDP as additional GMM style instrument, which have proven to be the most adequate within a pool of fixed effects and GMM estimators. Estimations results delivered a relative high robustness of Austrian winter tourism to external effects compared with sun-and sea tourism in Spain for instance. Short- and long-run income elasticities amount to 0.41-0.52 and 2.11-3.02, respectively. The study especially emphasizes the importance of climatologic variables in explaining winter tourism demand. Estimations for the whole time period point out that additional 10 days with a snow height of 1 cm will lead to an increase of overnight stays to an extent of about 0.7 to 1 percent, while for the last decade the estimate is substantially lower than in previous years. We suppose that this decline could be attributed to the major increase in snowmaking in recent years.

1 Introduction

This paper presents a dynamic model of winter tourism demand for Austrian ski destinations. As opposed to the major part of tourism demand literature, which uses purely time series data or cross section data, this paper will employ panel data techniques. Therefore, it is more closely related to Garín-Muñoz/Montero-Martín (2007) and Sequeira/Nunes (2008).

The analyzed panel data set contains the number of overnight stays of tourists from the 15 most important countries (including Austria) in 185 different skiing destinations in Austria in the winter season for the time period from 1973 to 2006. Data can be described as typical cross-section panel data, with a moderately large number of cross-section units (N=185), each observed for a small number of time periods (T=34). Analyses are made by the open-source statistical software package R (R Dev. Core Team, 2008) and the commercial STATA (StataCorp, 2007) software package.

2 Why use Panel Data?

An important motivation behind the utilization of panel data is the widening of the database (higher degree of freedom), which allows for more efficient and reliable estimations. Panel data are also more informative than time series data by capturing not only heteroskedasticity across time but also across regions. Therefore, they capture a higher variability of the data, which limits collinearity among the variables, a major problem in simple time series regression analysis. Furthermore, panel data allow for controlling two different forms of omitted variable biases, one caused by unobserved heterogeneity across regions, which is assumed to be constant over time and the other one caused by unobserved time effects. Not taking into account these unobserved effects leads to miss-specified models with inconsistent and biased estimates. Due to its high importance it will be briefly discussed.

- Individual-specific time constant effect (μ_i):

$$y_{i,t} = \alpha + x_{i,t}\,\beta + \underbrace{\mu_i\delta + \varepsilon_{i,t}}_{\text{not observed}} \quad i = 1\ldots N; t = 1\ldots T$$

As usual β and $x_{i,t}$ denote the vector of coefficients and the vector of regressors respectively. The impact of unobserved heterogeneity is captured by μ_i, which is constant over time for a given destination, but which can vary between destinations. Together with the idiosyncratic errors $\varepsilon_{i,t}$ it accounts for the total error term, which is not observed.

Due to ignorance of the unobserved heterogeneity term μ_i, assessing OLS of y on x would lead to inconsistent and biased estimates. With time series data unobserved heterogeneity across regions can be removed by differencing the data set, therefore eliminating μ_i, while accepting a loss of information and therefore less powerful estimations. However, the second potential omitted variable bias, concerning time varying effects, cannot be tackled by pure time series data anymore.

- Individual constant-time varying effect (λ_t):

$$y_{i,t} = \alpha + x_{i,t}\,\beta + \underbrace{\lambda_t\delta + \varepsilon_{i,t}}_{\text{not observed}} \quad i = 1\ldots N; t = 1\ldots T$$

where λ_t captures the impact of unobserved variables which affect all destinations alike in a given time period but which varies over time and can be interpreted as a common trend component.

Assessing simple OLS would again lead to inconsistent and biased estimates. Therefore, these unobserved time effects can be eliminated by using variables in deviation from their time average, which is the so called within estimator.

$$y_{i,t} - \bar{y}_t = (x_{i,t} - \bar{x}_t)\beta + (\varepsilon_{i,t} - \bar{\varepsilon}_t) \quad i = 1,\ldots N; t = 1,\ldots,T$$

where $\bar{y}_t = \sum_{i=1}^{N} \frac{y_{i,t}}{N}$; $\bar{x}_t = \sum_{i=1}^{N} \frac{x_{i,t}}{N}$; $\bar{\varepsilon}_t = \sum_{i=1}^{N} \frac{\varepsilon_{i,t}}{N}$;

To assess this transformation, panel data are essentially needed. As a consequence, only panel data makes it possible to control for both possible unobserved omitted variable biases simultaneously in a single framework.

3 Model specification and methods

3.1 TOURISM DEMAND FUNCTION

The number of overnight stays measures winter tourism demand, which is assumed to depend on relative purchasing power (PP) and income (GDP) of the tourists, on infrastructure, measured by the number of beds (BEDS) and on the climate variable snow (SNOW). To account for unobserved time effects, time dummies are included in the demand function.

$$NIGHTS_{i,t} = f(NIGHTS_{i,t-1}, SNOW_{i,t}, BEDS_{i,t}, GDP_{i,t}, PP_{i,t}, time\_dummies)$$

Thus, a typical neoclassical demand function follows, using prices and income variables. Because the main objective of this paper is to clarify the impact of weather (SNOW) on the number of overnight stays in Austria, these variables together with the infrastructure variable can be interpreted as control variables. As a further control variable, habit formation, which cannot be explained by other explanatory variables, will be captured by inclusion of lagged dependent variables.

3.2 MODEL SPECIFICATION

Model specification will follow a general-to-specific approach, beginning from a model with 2 lags for the explanatory variables as well as for the dependent variable. For annual data two lags for each variable are normally sufficient to capture the dynamics of tourism demand (Song and Witt, 2000, p28). Predictors will be selected according to their significance and model criterions corresponding to the log-likelihood (AIC, BIC). The dynamic tourism demand model has the functional form of a typical ADL-model and takes a double-logarithmic form, except for SNOW, which is not transformed by the natural logarithm. Therefore, coefficients - except for SNOW - can be interpreted as short run elasticities. Long run effects are assessed by dividing each of the coefficients with $(1-(\beta_1+\beta_2))$, where β_1 and β_2 are the coefficients of the dependent variable, at the lag of 1 and the lag of 2.

$$\ln(NIGHTS_{i,t}) = \alpha + \beta.\sum_{s=1}^{2}[\ln(NIGHTS_{i,t-s}) + SNOW_{i,t-s} + \ln(BEDS_{i,t-s}) + \ln(GDP_{i,t-s}) + \ln(PP_{i,t-s})]$$
$$+\mu_i + \lambda_t + \varepsilon_{i,t}$$

where λ_t and μ_i represent time and destination specific effects respectively. They account for a main advantage of panel data analysis over time series and cross-section analyses, because they allow simultaneously for heteroskedasticity across time and destinations. The idiosyncratic error term $\varepsilon_{i,t}$ captures the impact of unobserved variables, which varies between individuals and over time and is assumed to be i.i.d. for each destination. It is the orthogonality of these components, which allows the general error $v_{i,t}$ to be decomposed into cross-sectional specific, temporal, and individual error components.

$$v_{i,t} = \mu_i + \lambda_t + \varepsilon_{i,t}$$

By using lagged dependent variables, the tourism demand model becomes dynamic, allowing for endogenous taste changes in order to capture habit formation and/or tourism expectations (interdependent preferences). Past investigations emphasized that dynamic tourism demand models are preferable to static ones, because ignoring the impact of dynamic changes may lead to spurious regression and therefore to an overestimation of the effect of relevant variables (Baltagi, 2001).

3.3 DATA DESCRIPTION

Data has already been described in Toeglhofer and Prettenthaler (2009). Thus, only a brief summary of the data set together with the correlation matrix of the original and the differenced variables, as well as the variables in deviation from their time average (within-transformation) is given.

Table 1: Description of the panel data variables

Variable	Number of observations	Mean	Std. deviation	Minimum	Maximum
log(NIGHTS)	6290	11.30	1.46	5.03	14.51
SNOW	6290	128.17	31.31	13	182
log(BEDS)	6290	7.57	1.09	3.69	10.15
log(GDP)	6290	9.60	0.56	7.83	10.46
log(PP)	6290	0.014	0.198	-0.70	1.592

Table 2: Correlation matrix of the panel data variables

Variable	log(NIGHTS)	$\log(\text{NIGHTS})_{t-1}$	$\log(\text{NIGHTS})_{t-2}$	SNOW	log(BEDS)	log(GDP)	log(PP)
log(NIGHTS)	1.000						
$\log(\text{NIGHTS})_{t-1}$	0.994	1.000					
$\log(\text{NIGHTS})_{t-2}$	0.989	0.993	1.000				
SNOW	0.304	0.290	0.279	1.000			
log(BEDS)	0.951	0.948	0.945	0.281	1.000		
log(GDP)	0.097	0.113	0.132	-0.170	0.023	1.000	
log(PP)	-0.186	-0.179	-0.170	-0.122	-0.180	-0.004	1.000

Table 3: Correlation matrix of the panel data variables in differences

Variable	Δlog(NIGHTS)	$\Delta\log(\text{NIGHTS})_{t-1}$	$\Delta\log(\text{NIGHTS})_{t-2}$	ΔSNOW	Δlog(BEDS)	Δlog(GDP)	Δlog(PP)
Δlog(NIGHTS)	1.000						
$\Delta\log(\text{NIGHTS})_{t-1}$	-0.201	1.000					
$\Delta\log(\text{NIGHTS})_{t-2}$	0.016	-0.194	1.000				
ΔSNOW	0.082	-0.051	-0.064	1.000			
Δlog(BEDS)	0.126	0.060	0.063	-0.054	1.000		
Δlog(GDP)	0.094	0.111	0.146	0.003	0.094	1.000	
Δlog(PP)	0.010	0.019	0.007	-0.147	0.014	0.062	1.000

Table 4: Correlation matrix of the panel data variables in deviation from their time average

variable (within)	log(NIGHTS)	$log(NIGHTS)_{t-1}$	$log(NIGHTS)_{t-2}$	SNOW	log(BEDS)	log(GDP)	log(PP)
log(NIGHTS)	1.000						
$log(NIGHTS)_{t-1}$	0.871	1.000					
$log(NIGHTS)_{t-2}$	0.817	0.884	1.000				
SNOW	-0.112	-0.174	-0.201	1.000			
log(BEDS)	0.498	0.496	0.483	-0.052	1.000		
log(GDP)	0.388	0.430	0.476	-0.262	0.044	1.000	
log(PP)	0.045	0.071	0.097	-0.106	0.046	0.047	1.000

Although panel data are in general relative robust to multicollinearity, the high correlation between the levels of BEDS and the lagged values of NIGHTS may lead to problems in inferences. Objections are relieved by the substantial reduction in correlation when examining the differenced and the within transformed variables, which will be both assessed in our analysis. The importance of the infrastructure variable BEDS is therefore strengthened by its high correlation with the dependent variable NIGHTS, whereas it is little correlated with the other independent variables. What can be also seen is the high persistency of the dependent variable NIGHTS with a correlation coefficient of 0.99 with its lagged value.

3.4 ESTIMATORS

3.4.1 Pooled model (OLS)

Assuming that all coefficients including the intercept are constant for all destinations and over time t, data can be pooled. The pooled model represents the restricted model given by an equation with the same parameters over time and across regions. In the evaluation part of this paper (chapter 4), a pooled model will be estimated, which contains time dummies to account for time effects, however individual cross-section heteroskedasticity will not be considered. In general notation this means:

$$y_{i,t} = \alpha + x_{i,t}\,\beta + \lambda_t + \varepsilon_{i,t} \quad i = 1\ldots N; t = 1\ldots T$$

with $E(\varepsilon_{i,t}) = 0;\ E(u_i u_i') = \sigma_u^{\ 2} I_N$

This model is only estimated for comparison reasons, because unobserved individual effects are expected to be highly significant and therefore (b.o.) estimates of the pooled model will be inconsistent and biased.

3.4.2 Two-way fixed effects model (Within estimator)

The introduction of individual fixed effects is considered as highly important, because they are assumed to capture all remaining time-constant (fixed) determinants of tourism, which are not yet controlled for in this model. In other words, the heterogeneity between the destinations, which could be special features such as the natural landscape, is additionally considered as a factor in explaining tourism demand. The dynamic tourism demand model will be therefore treated as an error components model, containing unobserved fixed effects. For its specification see section 3.2.

The destination-specific effects and the regressors are assumed to be correlated, which makes OLS as well as random effects model estimation biased and inconsistent. Instead, the within estimator is assessed, which measures all observations in deviation of the individual time average. Therefore, it simply conducts a demeaning of the data, which eliminates the time-constant unobserved effect component before assessing OLS.

$$y_{i,t} - \bar{y}_t = (x_{i,t} - \bar{x}_t)\beta + (\varepsilon_{i,t} - \bar{\varepsilon}_t) \quad i = 1, \ldots N; t = 1, \ldots, T$$

$$\bar{y}_t = \sum_{i=1}^{N} \frac{y_{i,t}}{N}; \quad \bar{x}_t = \sum_{i=1}^{N} \frac{x_{i,t}}{N}; \quad \bar{\varepsilon}_t = \sum_{i=1}^{N} \frac{\varepsilon_{i,t}}{N};$$

Another way of obtaining identical fixed effects estimates would be to include a set of dummy variables identifying each cross-section unit, what is known as the LSDV (Least Squares Dummy Variables) estimator. This procedure reveals a disadvantage of estimating fixed effects models for cross-section panel data, because a large cross-section dimension also requires a large amount of dummy variables for model specification. "*Too many dummy variables may sap the model of sufficient number of degrees of freedom for adequately powerful statistical tests. Moreover, a model with many such variables may be plagued with multicollinearity, which increases the standard errors and thereby drains the model of statistical power to test parameters*." (Yaffee, 2003)

After obtaining the within estimator $\hat{\beta}_W$, one can estimate individual fixed effects with the assumption that they sum up to zero.

$$\hat{\mu}_i = \bar{y}_i - \bar{x}_i \hat{\beta}_W$$

Obtained estimates for the individual effects are unbiased, but inconsistent for small T. However, the within estimator for the coefficients is consistent and unbiased, if two main assumptions hold. Individual effects and error terms have to be uncorrelated and explanatory variables have to be strictly exogenous.

Strict exogeneity means, that variables are uncorrelated with current and past errors:

$$E(\varepsilon_{i,t} \mid x_i, \mu_i) = 0 \quad t = 1, \ldots T \quad \text{(strict exogeneity)}$$

However, the assumption of strict exogeneity rules out any feedback from current or past shocks to current values of the variable. Therefore, the introduction of lagged dependent variables injures the assumption of strict exogeneity of the regressors because the lagged dependent variable is – by definition - correlated with the lagged idiosyncratic error term. Therefore, it has to be dealt with a weaker form of exogeneity, that is sequential exogeneity.

$$E(\varepsilon_{i,t} \mid x_{i,t}, x_{i,t-1}, \ldots, x_{i,1}, \mu_i) = 0 \quad t = 1, \ldots T$$

Therefore, for the dependent lagged variable it holds that

$$E(\varepsilon_{i,t} \mid y_{i,t}, y_{i,t-1}, \ldots, y_{i,1}, \mu_i) = 0 \quad t = 1, \ldots T$$

Thus, initial conditions $y_{i,1}$ have to be predetermined, that means $y_{i,1}$ is assumed to be only uncorrelated with all subsequent (future) realizations of the disturbance term. In other words, an estimator is needed, which also holds consistency in case some explanatory variables are only weakly exogenous.

When using lagged dependent explanatory variables, strict exogeneity is lost and it can be shown that the within estimator is biased and inconsistent for $N \to \infty$ and fixed T (Nickell, 1981 and Hsiao, 2003, Section 4.2). In detail, "*standard results [...] indicate that, at least in large samples, the Within Groups estimator is biased downwards*" (Bond, 2002). Nickell also derived a formula for the bias, showing that the bias approaches zero as T approaches infinity. Unfortunately, this bias can be still substantial for a time dimension T of 30, according to Judson et al. (1997) and Judson/Owen (1999).

The bias of the within estimator will be especially severe when

- the value of the autoregressive coefficient is close to 1 or even exceeds 1
- the number of time periods, T, is low
- the ratio of variances, $\sigma^2{}_{\varepsilon} / \sigma^2{}_{y_{t-1}}$ is high or
- the within-transformed values of the lagged dependent variable and the exogenous variables are highly correlated

To eliminate this bias, one has to focus on estimators appropriate for using predetermined explanatory variables instead of strictly exogenous explanatory variables. The estimators taking into account the resulting bias can be grouped broadly into the class of direct bias corrected estimators and the class of instrumental estimators. Whereas first-difference IV regression or GMM estimator belong to the second group, the bias-corrected FE model by Bruno (2005) represents an estimator of the first group.

3.4.3 Bias-corrected fixed effects model (Bruno, 2005)

Bruno (2005) follows the same approach as Kiviet (1995), who suggested consistently estimating the extent of the Nickell bias by using a preliminary consistent estimator. This information allows for calculating a consistent corrected estimator based on additive bias correction, using for instance the procedure of Bruno, which is implemented in the STATA routine „xtlsdvc" (Bruno, 2005).

However, the use of a preliminary consistent estimator influences the finite-sample accuracy of the final estimates and can be also seen as a disadvantage of this procedure, according to Carree (2004).

In this paper, the SYSTEM-GMM by Blundell and Bond (1998) will be assessed for initialisation, using the standard settings for the SYSTEM-GMM in STATA[5] with an approximation of $O(N^{-1}T^{-2})$. The variance covariance matrix for the corrected estimators is obtained by a parametric bootstrap procedure, using 50 permutations.

3.4.4 First-difference IV regression (Anderson-Hsiao, 1982)

Anderson and Hsiao (1982) suggested obtaining consistent estimates in dynamic panel data models by first differencing the equation to remove individual effects and then assessing an instrumental variable

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[5] Bruno has already pronounced that future improvements of the code will enlarge the class of initial estimators, allowing also more flexibility in the definition of the instrument set for the IV and GMM estimators.

procedure for the lagged dependent variable, using as instruments the values of the dependent variable lagged two or more periods, either differenced or in levels.

This method will be described in a simple AR(1) model without time dummies and no explanatory variables, however with individual fixed effects.

$$y_{i,t} = \rho y_{i,t-1} + u_{i,t}, \text{ where } u_{i,t} = \mu_i + \varepsilon_{i,t}$$

Then first differencing delivers

$$\Delta y_{i,t} = \rho \Delta y_{i,t-1} + \Delta\varepsilon_{i,t} ,$$

which makes predetermined but not strictly exogenous variables as $y_{i,t-1}$ endogenous. Due to the dependence of $\Delta\varepsilon_{i,t}$ on $\varepsilon_{i,t}$, OLS on the differenced data set would deliver inconsistent estimates, "*with the direction of the inconsistency being downward and typically greater than that found for the Within Groups estimator*" (Bond, 2002). However, for the endogenous variable $\Delta y_{i,t-1}$, a two-stage least square procedure can be assessed, using instruments that are both correlated with $\Delta y_{i,t-1}$ and orthogonal to $\Delta\varepsilon_{i,t}$. Together with the general assumption of serially uncorrelated disturbances, levels (and differenced versions) of the dependent variable lagged for two periods or larger will be uncorrelated with $\Delta\varepsilon_{i,t}$ and can serve as instrumental variables.

At period 3:

$$\boldsymbol{y_{i,3} - y_{i,2} = \rho(y_{i,2} - y_{i,1}) + (\varepsilon_{i,3} - \varepsilon_{i,2})}$$

$y_{i,1}$ can be used as instrument.

At period 4, $y_{i,1}$ and $y_{i,2}$ can be used as instruments and so on. However "*since the model is overidentified with T>3, and the first differenced error term has a first moving average form of serial correlation, $\Delta\varepsilon_{i,t} \sim MA(1)$, 2SLS is not asymptotically efficient, even if the complete set of available instruments is used for each equation and the disturbances of the errors are homoskedastic*" (Bond, 2002).

3.4.5 Generalized method of moments estimator (GMM)

3.4.5.1. First Difference GMM (Arellano and Bond, 1991)

A similar approach, which delivers asymptotically efficient estimates, is the generalized method of moments (GMM) estimator. A common linear GMM estimator for short panels (low T) is the first-difference GMM proposed by Arellano and Bond (1991), a GMM that instruments the differenced variables that are not strictly exogenous with all their available lags in levels. As a consequence it makes use of all available moments on the differenced data.

The following moment conditions are explored:

$$E[y_{i,t-s}\Delta\varepsilon_{i,t}] = 0 \;\; and \;\; E[X_{i,t-s}\Delta\varepsilon_{i,t}] = 0 \quad \text{for } s \geq 2; t = 3, \ldots, T$$

Moment conditions are valid if past values of the lagged dependent variable and the exogenous explanatory variables are uncorrelated with future error term differences.

Linear GMM estimators have one-step and two-step variants. The one-step procedure of the first-difference GMM is preferred in general, because while the two-step procedure has only "*small efficiency gains […], even in the presence of considerable heteroskedasticity*", it delivers downward biased estimates of the standard errors. The two-step procedure will be estimated though in order to assess the standard GMM test of overidentifying restrictions (Sargan/Hansen-Test), testing the validity of the instrumental variables.

The first-difference GMM is as well not without weaknesses. Monte Carlo simulations showed that for dependent variables, which are close to a random walk, that means models with an autoregressive coefficient close to 1, first-differences will be close to innovations and are therefore poor instruments. In such a case first-difference GMM estimations are seriously upward biased (see Collado, 1997, Blundell and Bond, 1998, Kitazawa, 2001). Furthermore, "*the performance of the first difference GMM-estimators depends strongly upon the ratio of the variance of the fixed effects across individuals and the variance of the error term. In case the variance of fixed effects is much larger than that of the error term variance, the GMM-estimators perform poorly*" (Carree, 2002).

3.4.5.2. System-GMM (Blundell and Bond, 1998)

An augmented version of the first-difference GMM, the so-called System-GMM, outlined in Arellano and Bover (1995) and fully developed in Blundell and Bond (1998), will be also assessed in this paper to tackle the weak instrument problem. Efficiency improvements of the estimates are expected to be obtained by exploring additional moment conditions, taking the differences of the lagged dependent variable as additional instruments. Because this estimator builds a system of two equations - the original "level equation" as well as the transformed one, that is the "difference equation" - it is denoted as System-GMM.

In the following additional moments are explored:

$$E[\Delta y_{i,t-1}(\mu_i + \Delta\varepsilon_{i,t})] = 0 \;\; and \;\; E[\Delta X_{i,t-1}(\mu_i + \Delta\varepsilon_{i,t})] = 0 \text{ for } t = 3,\ldots,T$$

In detail, changes in the instrumenting variables have to be uncorrelated with fixed effects (Blundell and Bond, 1998). In other words, past values for the growth in the infrastructure variable BEDS, in SNOW, in income (GDP) and in relative purchasing power (PP) should be uncorrelated with current unobserved fixed effects, which is likely to hold. Concerning the initial conditions $y_{i,1}$ it should especially hold that the fixed effects are uncorrelated with the first difference of the first observation of the dependent variable.

First-difference GMM and System-GMM are closely related to each other. Differences between them can be explained as follows: "*where Arellano-Bond instruments differences […] with levels, Blundell-Bond instruments levels with differences. […] Instead of transforming [annot.: differencing] the regressors to eliminate the fixed effects, it [annot..: System-GMM] transforms the instruments using differences to make them exogenous to the fixed effects*." (Roodman, 2006). As Bond (2002) mentions, according to Monte Carlo simulations, "*extended estimator, denoted system GMM, has much smaller finite sample bias and much greater precision when estimating autoregressive parameters using persistent series*."

3.4.5.3. GMM performance and the validity of instruments

The performance of the GMM estimators depends (b.o.) on the validity of the instruments. Moment conditions of both GMM estimators are only asymptotically valid if instrumental variables are exogenous. The exogeneity assumption can be checked by autocorrelation tests for the idiosyncratic errors and by overidentifying restrictions tests.

- no autocorrelation in the idiosyncratic errors

Although they may have individual-specific patterns of heteroskedasticity and (temporal) serial correlation, the idiosyncratic errors $\varepsilon_{i,t}$ are not allowed to correlate between cross-section units, because this would indicate that "*lags of the dependent variable (and any other variables used as instruments that are not strictly exogenous), are in fact endogenous, thus bad instruments*" (Roodman, 2006).

The level of the residual term cannot be used to test for autocorrelation of the idiosyncratic error term. It is presumed to be autocorrelated because it contains fixed effects. Therefore, the Arellano-Bond autocorrelation test is applied to the residuals in differences. The test for first-order serial correlation in differenced residuals is expected to be significant (and it can be shown that it is likely to be negative), because two differenced series always have one level part in common. Of higher importance is the test for second-order correlation in residual differences, which checks for first-order serial correlation in residual levels. If second-order serial correlation in residual levels is assumed, a third-order correlation test in residual differences has to be assessed, and so on.

- Hansen/Sargan Test

The exogeneity of the instrumental variables, or in detail, whether the instruments, as a group, appear exogenous, can be evaluated by tests of over-identifying restrictions. The Sargan statistic will be reported, which is the minimized value of the one-step GMM criterion function. Because it is not robust to heteroskedasticity or autocorrelation, "xtabond2" by Roodman (2006) also reports the Hansen J-statistic, which is the minimized value of the two-step GMM criterion function. However, "*the J test has its own problem: it can be greatly weakened by instrument proliferation*" (Roodman, 2006), delivering a meaningless p-value of 1.000. Due to their oppositional weaknesses, final conclusions about the validity of the instruments are often difficult to make.

Using difference-in-Sargan statistics can assess whether subsets of instruments are valid. „*This is especially useful for testing the instruments for the levels equation based on lagged differences of the dependent variable, which are the most suspect in system GMM and the subject of the "initial conditions" in the title of Blundell and Bond (1998)"* (Roodman, 2006). However again, as Roodman explains, „*all of these tests [...] are weak when the instrument count is high*."

The correct choice of the instrumental variables is crucial for the performance of GMM estimators. As Blundell and Bond (2000) showed, GMM estimators suffer from finite sample bias when weak instruments are used. Although they also claim that the system GMM estimator not only improves the precision but also reduces the finite sample bias, relative to the Arellano and Bond (1991) estimator, the bias can be still severe. According to Bun and Kiviet (2002), this finite-sample bias increases with the number of used moment conditions. Because it is desirable from an asymptotic efficiency point of view to include as many moment conditions as possible, "*the statistical problem of the tradeoff between small sample bias and efficiency*" (Baltagi, 2001) arises. Hahn et al. (2003) therefore suggested that - in order to minimize bias - a strict subset of the full set of moment restrictions should be used in estimation, following the generous rule, which allows for the number of instruments to be below the number of cross-section units.

Besides this, the use of a large amount of instrumental variables can cause estimation problems in finite samples[6], which "*do not compromise the coefficient estimates but does dramatize the distance of [annot.: difference-] FEGMM from the asymptotic ideal*" (Bowsher, 2002, quoted from Roodman, 2006).

3.4.6 Summarizing and theoretical considerations

At first, a small summary of the models is given in Table 5.

Table 5: Summary of the panel data estimation procedures

Model	**Abbreviation**	**Transformation**	**Regressors**	**Consistency**
Pooled	Pooled	-	$y_{i,t-1}, x_i, 1, \lambda_t$	inconsistent/biased
Fixed effects	FE	Within	$y_{i,t-1}, x_i, 1, \mu_i$	inconsistent/biased
Two-way fixed effects	FE_tw	Within	$y_{i,t-1}, x_i, 1, \mu_i, \lambda_t$	inconsistent/biased
Bias corrected Two-way fixed effects	FE_tw_bc	Within	$y_{i,t-1}, x_i, 1, \mu_i, \lambda_t$	consistent/unbiased
First-difference IV	FD_IV	Δ	$\Delta y_{i,t-1}, \Delta x_i, 1, \lambda_t$	consistent/unbiased
First-difference GMM (onestep)	DIFF_GMM	Δ	$\Delta y_{i,t-1}, \Delta x_i, 1, \lambda_t$	consistent/unbiased
System GMM (onestep)	SYS_GMM	Δ	$\Delta y_{i,t-1}, \Delta x_i, y_{i,t-1}, 1, \lambda_t$	consistent/unbiased

Estimated models can be either distinguished according to the transformation method they use to remove unobserved effects or according to their consistency properties. Models with expected systematically inconsistent estimations should not be discriminated in advance. Earlier Monte Carlo studies (Arellano and Bond, 1991; Kiviet, 1995; Judson and Owen, 1999) demonstrated that the within estimator, although systematically inconsistent, has a relatively small variance compared to IV and GMM estimators. Consistency of the last three models bases on the validity of the instruments, which often has to be rejected. Furthermore, one has to keep in mind that the consistency properties of IV and GMM estimators only hold for large N, so they can be still severely biased (finite sample bias) and imprecise in panel data with a small number of cross-sectional units. In fact, „*Monte Carlo experiments highlight the LSDVC estimators as the preferred ones in comparison to the original LSDV and widely used IV and GMM consistent estimators when the number of individuals is small*" (Bruno, 2005).

[6] "*Since the number of elements in the estimated variance matrix of the moments is quadratic in the instrument count, it is quadratic in T. A finite sample may lack adequate information to estimate such a large matrix well. It is not uncommon for the matrix to become singular, forcing the use of a generalized inverse*" (Roodman, 2006). This is especially the case when there are more moment conditions than observations. As opposed to STATA, the function pgmm in the plm-package (Yves/Giovanni, 2008) for R is not able to calculate a generalized inverse and therefore delivers no estimation results.

3.5 AUTOCORRELATION AND HETEROSKEDASTICITY

In panel data analysis one has to deal with time series data problems like autocorrelation and with cross-section data problems like heteroskedasticity. Not taking into account these issues will lead to wrong inferences and therefore to incorrect standard errors. Autocorrelation can have twofold forms. There may be autocorrelation within panels/destinations (temporal autocorrelation) and autocorrelation across panels (contemporaneous autocorrelation), whereas the assumption of no contemporaneous autocorrelation is used for "*identification purposes rather than descriptive accuracy*". (De Hoyos/Sarafidis, 2006).

In static models either estimated or feasible generalized least squares (EGLS or FGLS) are used to correct for panel heteroskedasticity. For instance, Parks FGLS's uses a model that assumes an autoregressive error structure of the first order along with contemporaneous correlation among the cross-sections and this model is estimated by a two-state generalized least squares procedure. However, according to Monte Carlo studies of Beck and Katz (1995), Parks estimates have a higher variance than OLS estimators and lead to false t-statistics due to downward biased variance estimates. They prefer correcting the estimates of the standard errors by using panel corrected standard errors (PCSE), which use the assumption of a common variance structure within a cluster and the information that contemporaneous correlation across units follows a fixed pattern.

In the cross-section analysis, it was shown that an autoregression on lags of the residuals strongly indicated the presence of (temporal) autocorrelation and the need for dynamic analysis. As a consequence, analysis concentrates on dynamic panel data modelling, which means including lagged dependent variables into the regression, which fortunately eliminates temporal autocorrelation. So methods to remove the bias from temporal autocorrelation, for instance a Prais-Winston or a Cochrane-Orcutt transformation that amounts to first partial differencing as well as a fixed effect models with an additional AR(1) disturbance term, are not needed here.

Cross-section dependence and heteroskedasticity within and across panels will be generally reduced by following the advice of Roodman (2006), that it is "*almost always wise to include time dummies in order to remove universal time-related shocks from the errors*". Cross-section dependence in fixed-effects models will be tested by the parametric testing procedure proposed by Pesaran (2004), whereas the Breusch-Pagan Test (1980) cannot be used because it is not valid for cross-sectional panel data. Robust standard errors from nonparametric bootstrapping will be used in fixed effects models to obtain corrected t-statistics. For the first-difference IV model robust heteroskedasticity variances will be obtained by the Eicker/Huber/White/sandwich estimator, which allows residuals to be dependent within a cluster. In GMM models, heteroskedasticity will be tackled by using Arellano-Bond robust VCE in the one-step estimation, and the WC-robust estimator of Windmeijer in the two-step estimation, which are both consistent in the presence of any pattern of heteroskedasticity and autocorrelation within panels.

4 Evaluation

4.1 BEST MODEL SETUP AND GENERAL TESTS

Best model setup is detected by using the two-way fixed effects model. Time and individual effects are highly significant according to the Lagrange multiplier test by Honda (1985) and both reduce contemporaneous autocorrelation distinctly, although not eliminating it. The significance of unobserved time effects indicates that pure time series analysis, which is not able to control for common time effects, should suffer from omitted variable bias and therefore deliver less reliable estimates.

Two lags are chosen for the lagged dependent variable to assure the removal of temporal autocorrelation in our data. Using lags for other explanatory variables does not lead to significant model improvements. Although the first and the second lag of BEDS are significant, they do not seem to improve F-Statistics significantly and model evaluations show an increase of temporal autocorrelation in the data. The significant first lag of GDP seems to adopt the variance of the current value of GDP, which becomes insignificant with a counterintuitive negative sign. Differencing does not compensate the loss of information for any of the variables by significant higher F-Statistics. Differencing is therefore not used, although at least for differenced BEDS a small reduction in cross-section correlation can be detected. Therefore, best model specification follows finally:

$$\ln(NIGHTS_{it}) = \alpha + \beta.(\ln(NIGHTS_{it-1}) + \ln(NIGHTS_{it-2}) + \ln(SNOW_{it}) + \ln(BEDS_{it}) + \ln(GDP_{it}) + \ln(PP_{it})] + \mu_i + \lambda_t + \varepsilon_{it}$$

Individual fixed effects have to be interpreted with care, because the large number of cross-section units can arise the classical "incidental parameters problem", which may lead to inconsistent estimates. What can be said is that unobserved heterogeneity between cross-section units seems to be small (standard deviation=0.174), but highly significant with a large negative estimated mean of - 2.55. These results indicate that time series/cross section analysis not taking into account this negative level effect on the number of overnight stays must be seriously biased and inconsistent. However, due to the relatively small variation of these unobserved fixed effects across the destinations, this bias may be homogenously distributed, allowing comparisons of the coefficients on the relative level. These results hold for all destinations in a similar way, although the negative level effect seems to be especially distinctive for Carinthia, as can be seen in Figure 1. Not taking into account these negative unobserved individual effects may lead to an underestimation of predictor effects, which seems to be the case for GDP. Time effects from the two-way fixed effects model are plotted in Figure 2, which describes the common temporal evolution of overnight stays in Austrian ski destinations.

Figure 1: Unobserved destination-specific effects of the two-way fixed effects model

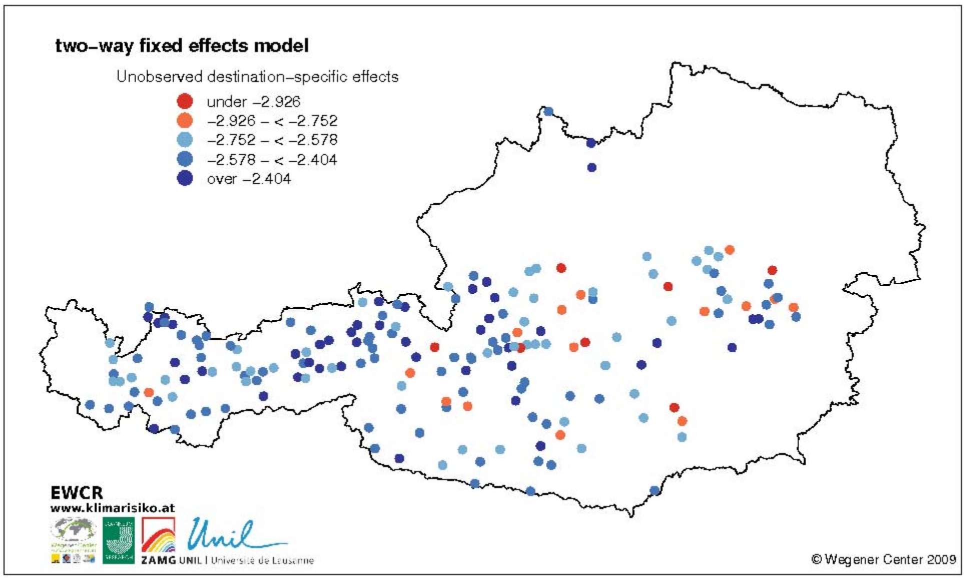
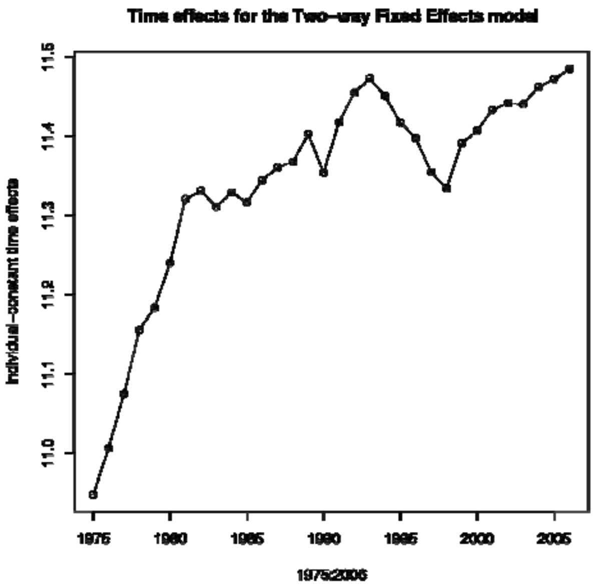


Figure 2: Unobserved common time effects of the two-way fixed effects model



The best model setup is used for the pooling test, which is a standard F-Test (Chow-Test), testing the hypothesis that the same coefficients apply to each cross-section unit, only allowing for differences in the intercept. The test rejects the absence of coefficient stability across destinations. This is not surprising considering the wide range of coefficients over all destinations, obtained from pure time series models for each destination. It therefore would suggest using a variable coefficient model with varying β_i coefficients, which is unsatisfactory because this can also be assessed using non-panel data analysis. Besides the weaknesses of this test[7] one can finally conclude, as Toro-Vizcarrondo and

[7] Toyoda demonstrated how wrong it is to apply the Chow test in case of heteroskedastic variances. (Baltagi, 2001). Furthermore after a

Wallace (1968, p. 560, quoted from Baltagi (2001)), that „*if one is willing to accept some bias in trade for a reduction in variance, then even if the restriction is not true one might still prefer the restricted estimator*". One still has to keep in mind that the estimated value of β for a specific independent variable has to be interpreted as an estimation of the average of the true coefficients β_i, which are assumed to vary across destinations.

To ensure the benefits of the fixed effects model over the random effects model, estimates of both methods using the best model setup are compared under the null hypothesis of no significant difference (Hausman, 1978). The null hypothesis is highly rejected (p-value<0.001), therefore individual effects and explanatory variables seem to be correlated, which makes the random effects model estimations inconsistent. Results of the Hausman test are not surprising, considering the very high correlation between individual effects and explanatory variables given by the two-way fixed effects model output (corr=0.924).

Monte Carlo study by Baltagi (1981), a high frequency of type I error occurred whenever the variance components due to the cross-section effects are not relatively small.

4.2 GENERAL MODEL ESTIMATION RESULTS WITH THE COMPLETE PANEL DATA SET

Table 6: General model estimation results with the complete panel data set.

Variable/Test	Pooled	FE	FE_tw	FE_tw bias_cor	FD_IV[1]	DIFF_GMM	SYS_GMM	SYS_GMM _valid	SYS_GMM _gdp
ln $NIGHTS_{t-1}$	.716*** (12.95)	.609*** (8.82)	.596*** (8.07)	.637*** (67.01)	.649 (0.77)	.475*** (6.48)	.627*** (11.03)	.602*** (4.68)	.634*** (11.52)
ln $NIGHTS_{t-2}$	.215*** (3.90)	.174*** (3.32)	.187*** (3.51)	.161*** (16.72)	-	.167*** (5.37)	.177*** (3.73)	.261*** (3.82)	.183*** (3.81)
$SNOW_t$ / 100	.067*** (8.69)	.076*** (6.20)	.070*** (3.71)	.071*** (4.44)	.062*** (3.26)	.071*** (3.68)	.096*** (4.33)	.116** (2.22)	.103*** (6.04)
ln $BEDS_t$	.086*** (8.51)	.113*** (4.17)	.132*** (4.33)	.119*** (10.34)	.150*** (3.27)	.202*** (4.58)	.198*** (6.26)	.149 (1.63)	.222*** (7.67)
ln GDP_t	.039 (0.98)	.013 (1.37)	.407*** (3.66)	.436*** (5.85)	.224 (0.37)	.985 (1.47)	.679 (1.52)	.322 (0.82)	.549*** (2.62)
ln PP_t	-.041** (-2.48)	-.035** (-2.21)	-.030* (-1.87)	-.028** (-2.36)	<.001 (0.01)	-.022 (0.725)	-.013 (-0.21)	-.028 (-0.50)	.006 (0.22)
Time dummy estimates are not displayed for space reasons									
R_squared within	-	0.776	0.785	-	-	-	-	-	-
corr(mu_i, Xb)	-	.954	.924	-	.965	-	-	-	-
rho[2]	-	.632	.592	-	.740	-	-	-	-
Pesaran AR(1) (p-value)	-	74.3 (<0.001)	2.8 (.005)	-	-	-	-	-	-
Wald chi2(37)	-	-	-	-	-	4331	21732	54046	141089
diff AR(2)	-	-	-	-	-	.215	.854	.223	.766
Sargan test	-	-	-	-	-	<0.001	<0.001	<0.001	<0.001
Hansen test	-	-	-	-	0.006	1.000	1.000	0.138	1.000
Diff_(GMM)	-	-	-	-	-	-	1.000	0.457	1.000
Diff_(IV)	-	-	-	-	-	-	1.000	0.521	1.000
No. of instruments	0	0	0	0	2	562	595	148	893
No. of groups	185	185	185	185	185	185	185	185	185
No. of observations	5920	5920	5920	5920	5365	5735	5920	5920	5920

p-value: <0.1 * ; <0.05 **; <0.01 ***
all regressions except FE include time dummies.
Numbers in parentheses beneath the estimates are t-statistics. t-statistics for
-Pooled and FD_IV base on the Eicker/Huber/White/sandwich variance estimator
-FE, FE_tw base on nonparametric bootstrapping with 100 permutations
-FE_tw_bias_cor base on parametric bootstrapping with 50 permutations
-GMM models base on Arellano-Bond robust VCE

[1] NIGHTS lagged at 3 and 4 is used as (internal) instrumental variable for the differenced dependent variable
[2] fraction of variance due to fixed effects mu_i

Table 7: Instrumental variables of the GMM estimators for the general model estimation.

Equation	Type	DIFF_GMM	SYS_GMM	SYS_GMM_valid	SYS_GMM_gdp
First difference equation	IV	Diff. (SNOW log_PP log_GDP log_BEDS) time_dummies	Diff. (SNOW log_PP log_GDP log_BEDS) time_dummies	-	Diff. (log_BEDS SNOW log_PP) time dummies
	GMM	Lag(2-.). log_NIGHTS	Lag(2-.). log_NIGHTS	Lag(4-7).log_NIGHTS	Lag(2-.).log_NIGHTS log_GDP
Level equation	IV	-	constant	constant log_GDP SNOW log_PP	log_GDP SNOW log_PP
	GMM	-	Diff.Lag.log_NIGHTS	Diff.(Lag(3).log_NIGHTS)	Diff.Lag.(log_NIGHTS log_GDP)

IV represents the standard instruments, which are normally assumed as strictly exogenous regressors. GMM represents the "GMM-style" instrument sets described in Holtz-Eakin, Newey, and Rosen (1988) and Arellano and Bond (1991). By default the function xtabond2 (Roodman, 2006) uses, for each time period, "*all available lags of the specified variables in levels dated t-1 or earlier as instruments for the transformed equation; and uses the contemporaneous first differences as instruments in the levels equation. These defaults are appropriate for predetermined variables that are not strictly exogenous*" (Bond, 2000) and are used for DIFF_GMM and SYS_GMM.

Coefficients are fulfilling the expectations concerning their signs. Additionally, for the lagged dependent variable, a value between 0 and 1 was strongly expected, which is the case for all models. Relative purchasing power does not seem to play a crucial role in our tourism demand model, probably due to the rather similar price developments in the largest origin country Germany. Though, the variable is kept in the model as a control variable.

4.2.1 Pooled and fixed effects models

The OLS coefficient of the lagged dependent variable is expected to suffer from an upward bias due to its ignorance of individual specific effects (Hsiao 1986), whereas the within estimator of the fixed effects model is expected to be downward biased (Nickell 1981, Judson et al. 1999). These biases are higher for more persistent series and seem to be present in our model estimations too. According to Blundell and Bond (1995), a plausible parameter estimate should therefore lie between the within and the OLS estimate.

Controlling for time effects in the fixed effects model results in a large increase in the coefficient for GDP, leaving all other coefficients practically unchanged. This is surprising, because controlling for time effects in the pooling model does not change coefficients substantially. Nevertheless, a more theoretically reasonable value for the GDP coefficient is obtained by including time effects. As we know that estimations of coefficients in dynamic panel data models using within estimators are systematically biased and inconsistent, the question arises, how large this bias is. Since the autoregressive coefficient is high but beneath 0.8, the length of the time scale of our data is at least moderate with originally 34 time points and the lagged dependent variable is not highly correlated with the exogenous variables, except for beds, this bias may not be substantial. Comparisons with systematically consistent and unbiased models will be of interest.

4.2.2 Bias corrected two-way fixed effects model and first difference IV model

As systematically consistent and unbiased estimator, the bias corrected estimator produces only minor changes to the two-way fixed effects model. The lagged dependent variable and the GDP are corrected upwards. The high correlation between BEDS and the lagged dependent variable of NIGHTS (see

Table 2) and the relatively high persistency of NIGHTS do not seem to implicate a substantial bias in the estimates of the fixed effects model.[8] Furthermore, both coefficients are highly significant, rejecting considerations about potential multicollinearity.

The first difference IV estimator should also deliver consistent estimates. However, estimated coefficients depend heavily on the number of lags taken for the 2SLS procedure of the dependent variables and are often unreliable. Using for instance lags of the dependent variable from 3-5 delivers a negative coefficient for GDP. As Roodman (2006) claims, "*2SLS is a good estimator under homoskedasticity. But after differencing, the [error] disturbances are far from i.i.d., far enough to greatly distort estimation*." To improve efficiency, one "*can take the Anderson-Hsiao approach further, using deeper lags of the dependent variable as additional instruments. To the extent this introduces more information, it should improve efficiency. But in standard 2SLS, the deeper the lags used, the smaller the sample, since observations for which lagged observations are unavailable are dropped*." In fact, increasing the number of instruments did not deliver satisfactory results either. Also repeating the analyses with a 2SLS procedure robust to heteroskedasticity was of little success.

4.2.3 GMM estimators

GMM estimations in general prove to be more robust to the chosen number of instrumental variables than the ones of the FD-IV model. Estimations of the SYS_GMM are similar to the ones of the bias corrected two-way fixed effects model, whereas the ones for the DIFF_GMM seem to be more far away. Differences between DIFF_GMM and SYS_GMM can be detected in the estimated value of the lagged dependent variable, where the former delivers the smallest ones and the latter the highest ones for all models by so far, excluding the pooling model. This downward bias in difference GMM estimates for the autoregressive coefficient is consistent with the finite sample bias found in Blundell and Bond (1998) for near persistent series, which could be even greater than the one for the within estimator, especially in the case of weak instruments. Indeed this seems to be the case here.

As opposed to the fixed effects model, where one is convinced about the internal validity of the model, GMM estimators involve a large set of moment conditions, which may not be valid. In fact, although the Arellano and Bond difference autocorrelation test of order two is rejected at a very high level for both GMM models, therefore strengthening the exogeneity assumption of the instruments, the Sargan test indicates for both models that instruments are weak, even though this test statistic is quite restrictive and has to be interpreted with care on account of its missing robustness to heteroskedasticity.[9] Especially estimations of the DIFF_GMM seem to suffer from biased estimations, resulting from the weak instrumental problem.

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[8] Leaving out BEDS in regression analysis of the bias corrected two-way fixed effects model would lead to a decrease in the snow and gdp coefficient (0.065 and 0.28 respectively) and to an increase in the sum of the lagged dependent variable (0.84). Results of the GMM_SYS_gdp without BEDS tend to the same direction. (snow=0.079, gdp=0.43, sum of lagged dependent var. = 0.98).

[9] The relevance of heteroskedasticity is confirmed by obtaining much higher t-statistics when using nonrobust standard errors, which would lead for instance to a highly significant coefficient for GDP for the DIFF-GMM model.

The insignificant coefficient for GDP in both models may result from the high robustness of the variance estimations by Arellano and Bond, which is likely to increase the standard errors, or it may simply indicate specification problems. Theoretically, the obtained insignificant coefficients could also result from a simple loss of power related to performing first differences instead of using the within transformation, because then one employs less information. However, this effect is not assumed to be distinctive due to our large data set. [10]

The problem of a large amount of instrumental variables, which are weakening the Hansen-Test and could lead to finite sample bias, is tackled in the SYS_GMM_valid model. This model aims at fulfilling the overidentifying restrictions test, needing less instrumental variables by leaving out the time dummies as standard instrumentals and using only lag 4 to 7 of the dependent variable as GMM-instrumentals. Estimations seem to fit well of what one is expecting. However, model specification for SYS_GMM_valid is quite arbitrary and the coefficients for BEDS and GDP are not significant, which is unreliable and hints at specification problems. Further attempts to find better instruments, for instance replacing the internal instruments (lagged values of NIGHTS) with the ones of BEDS as GMM-style instrumental variable have not proven to be satisfactory.

Theoretical considerations led to the construction of SYS_GMM_gdp. Until now GDP has been dealt as strictly exogenous in our tourism demand model, which does not have to be plausible. As a higher GDP is expected to increase the number of overnight stays, increasing tourism earnings lead to an increase of the Austrian GDP, which is relatively strongly weighted (9%) in the GDP variable. Although GMM estimators are in general assumed to be relatively robust to endogeneity problems, one could treat GDP not as standard but as GMM style instrumental variable. Assessing the SYS_GMM_valid estimator with all available moments leads to estimation results which are similar to the bias-corrected two-way fixed effects model, with reliable and significant coefficients for SNOW and GDP. Arellano and Bond difference autocorrelation of order two is also rejected at a very high level. The main weakness of this model is the use of a vast number of instrumental variables, which may enhance finite sample bias. It therefore breaks the rule that the number of groups should be larger than the number of instrumental variables. As a consequence, due to the weakening of the Hansen Test no clear statements can be given for the validity of the instruments. One has to accept that the overidentifying-restrictions test of Sargan is highly rejected, indicating weak instruments, which is though weakened by heteroskedasticity. However, because the value of the lagged dependent variable is only slightly above the one of the bias corrected FE model, finite sample bias seems to be small and therefore the gain in efficiency is preferred here.

Finally, the bias corrected two-way fixed effects model and the SYSTEM-GMM estimator using GDP as additional GMM style instrument have proven to be the most adequate models in this analysis and their results will be briefly discussed.

4.2.4 Interpretation and comparison with other studies

According to estimations of the last model SYS_GMM_gdp, short-term income elasticity amounts to 0.55, which would indicate the presence of inelastic demand to Austrian skiing destinations. However, in the long term elasticity increases to 3.01 and thus is strongly elastic as it is common for luxury goods. Estimations of the bias corrected FE model reveal a short-term income elasticity of 0.44 and a

[10] However a non-significant coefficient is obtained for GDP using the first difference IV model or the simple first difference model.

long-term income elasticity of 2.18. Snow estimation results deliver that additional 10 days with a snow height of more than 1 cm lead to an increase of overnight stays to an extent of about 0.7 to 1 percent. At an aggregate level for the winter season, 79-82 percent of total overnight stays in Austria can be attributed to habit persistence and/or word-of-mouth effects, indicating a very good reputation of the Austrian skiing destinations.

In Table 8, obtained income elasticity together with the coefficient of adjustment is compared with the ones estimated in previous tourism demand models, following the table design used by Muñoz in many of her tourism demand articles, except for the missing-out of the price elasticities. As opposed to other studies, they are not substantial in our study, probably due to the high amount of Austrian and German tourists in our data, having in common a similar price evolution and a fixed exchange rate regime.

Table 8: Comparison of estimated income elasticities in previous tourism demand literature

Study	**Data origin-destination**	**Income elasticity**		**Coefficient of adjustment**[1]
		Short-term	**Long-term**	
Song et al. (2000)	UK-Germany	2.30	2.26	-
Song et al. (2000)	UK-France	1.67	2.12	-
Garín-Muñoz (2007)	Germany - Spain	2.69	5.40	0.49
Garín-Muñoz & Montero-Martín (2007)	Rest of the world - Balearic Islands	0.92	2.02	0.46
Aslan et al. (2008)	Rest of the world - Turkey	0.04	0.06	0.72
Brida and Risso (2009)	Germany - South Tyrol	0.46	1.92	0.24
Present study	Rest of the world+Austria - Austria	0.44-0.55	2.18-3.01	0.18-0.21

[1] The coefficient of adjustment determines the relation between the short- and long-run elasticites and can be obtained by subtracting the total of the lagged dependent variables from 1.

It should be mentioned that i.a. as opposed to this study, these tourism demand models in general consider only foreign visitors and not visitors from the home country.

The adjustment coefficient in our study indicates that about 20 percent of the adjustment of tourism to changes in the variables takes place during the first two years, which is pretty low compared with estimations from previous tourism demand models.

Interestingly, they all use the difference GMM of Arellano and Bond (1991). This estimator may be appropriate in this case because the persistency of the dependent variable in these studies is quite small. Except for the latest one, Brida and Risso (2009), whose results concerning the income elasticity should be seriously biased, probably upward-biased according to our study. Nevertheless, their results correspond very close to ours. This may be due to similarities concerning the type of tourism and the origin-destination constellation.

4.3 ANALYZING THE TEMPORAL EVOLUTION OF TOURISM DEMAND DETERMINANTS

After finding two models, which seem to be appropriate for the whole panel data set, we are now interested in studying the time dimension in more detail. The time dimension with a length of 34 is therefore divided into 3 periods, consisting of 10, 11 and 11 time points respectively. (2 time periods are missing due to the lagged dependent variables). Separate models are estimated for each time period, using the bias corrected two-way fixed effects model and the SYSTEM-GMM with GDP as additional GMM-style instrumental variable. Results are listed in Table 9. Due to the moderately large cross-section dimension of 185, the GMM estimator should be theoretically preferable.

Table 9: Panel data estimation results for the separate time period models

	Bias corrected two-way FE[1]			SYSTEM_GMM_gdp[2]		
Variable/Test	**Period 1**	**Period 2**	**Period 3**	**Period 1**	**Period 2**	**Period 3**
ln NIGHTS$_{t-1}$	.654*** (24.7)	.589*** (20.10)	.728 (26.61)	.598*** (10.54)	.547*** (5.77)	.693*** (17.46)
ln NIGHTS$_{t-2}$	.084*** (3.48)	-.002 (-0.10)	-.029 (-1.24)	.209** (2.43)	.149** (2.22)	.124*** (3.52)
SNOW$_t$ / 100	.074* (1.75)	.102*** (3.73)	.056*** (2.67)	.142*** (4.97)	.115*** (3.40)	.069*** (3.01)
ln BEDS$_t$	.100** (2.24)	.256*** (5.83)	.245*** (7.06)	.229** (2.34)	.375** (2.27)	.224*** (3.56)
ln GDP$_t$	.856 (0.93)	-.021 (-0.11)	.522 (0.71)	1.370*** (3.31)	.080 (0.32)	.172 (1.19)
ln PP$_t$	-.051 (-2.87)	-.003 (-0.09)	-.273 (-1.28)	-.005 (-0.12)	-.049 (-1.17)	-.124 (-0.97)
Time dummy estimates are not displayed for space reasons						
R-squared within	0.62	0.34	0.50	-	-	-
F-Test **(k,n)**	202.23 (15,184)	36.93 (16,184)	69.60 (16,184)	-	-	-
corr(mu_i, Xb)	0.95	0.96	0.94	-	-	-
rho[3]	0.80	0.92	0.90	-	-	-
Pesaran AR(1) **(p-value)**	0.73 (0.47)	8.11 (<0.01)	1.78 (0.08)	-	-	-
wald chi2 (15)	-	-	-	20227	35629	89867
diff AR(2)	-	-	-	0.230	0.133	0.816
Sargan test	-	-	-	0.030	<0.001	<0.001
Hansen test	-	-	-	0.096	0.998	0.999
Diff_(GMM)	-	-	-	0.899	1.000	1.000
Diff_(IV)	-	-	-	0.358	1.000	1.000
No. of instruments	0	0	0	136	257	261
No. of observations	1850	2035	2035	1850	2035	2035
No. of groups	185	185	185	185	185	185
Obs. per group	10	11	11	10	11	11

p-value: <0.1 * ; <0.05 **; <0.01 ***
All regressions include time dummies.
Numbers in parentheses beneath the estimates are t -statistics. t-statistics for the
- Bias corrected two-way FE model base on parametric bootstrapping with 50 permutations
- GMM models base on Arellano-Bond robust VCE

[1] corr(mu_i, Xb), R_squared, F-Test, rho and AR(1) test are obtained from the standard two-way FE model
[2] using as GMM instruments NIGHTS and GDP lagged from 2 to 12 (period 1) or 2 to 13 (period 2)
[3] fraction of variance due to fixed effects mu_i

At first, the smaller time scale is expected to reduce finite sample bias of the GMM by allowing less lagged values of the dependent variable as instrumental variables. In fact, the model for the first period fulfils the advice of Hansen by using fewer instruments than observations. Hansen test statistics can therefore be assumed to be valid. They indicate that the exogeneity assumption of all instrumental variables cannot be rejected at least at a significance level of 5 percent. Even though the Sargan test statistic rejects validity of the instruments again, model specification seems to be acceptable.

Taking the means of the estimated coefficients for all periods and comparing it with the ones obtained for the whole panel data set, one detects very similar values for the GMM estimations, whereas the values for the two-way FE model seem to correspond less. Especially the autoregressive coefficient in the two-way FE model seems to be – despite of bias correction – downward-biased. This is probably a direct result of the smaller time period.

Results for the GDP coefficient seem to be less reliable and vary to a large extent, which may be reducible to large unobserved heterogeneity. Although the GMM estimator is robust to large heteroskedasticity, inference can be inaccurate, especially when using fewer instruments (Hayakawa, 2006).

Results for relative purchasing power are mostly not significant, though one can assume that the influence of this variable becomes more important with time, probably due the increasing amount of Eastern European tourists.

The main interest lies in the substantial decline of the SNOW coefficient, which can be seen in both models, though more pronounced in the GMM estimations. This result has proven to be robust when using the other SYSTEM-GMM specifications explained before, which deliver similar results for SNOW. Remembering that unobserved fixed effects in the simple two-way fixed effects model seem to vary little, one may be interested in studying cross-section analyses and compare the results obtained in the last estimation.

A variable coefficient model is calculated with the two-way fixed effects model setup. Using the function “pvcm” from the package “plm” in R (Croissant/Millo, 2008), a different model is estimated for each time period. Figure 3 shows the evolution of the coefficients from 1975 to 2005. Mean values for each time period for each coefficient are given in Table 10.

Figure 3: Plot of the temporal evolution of the coefficients from the cross-section analysis

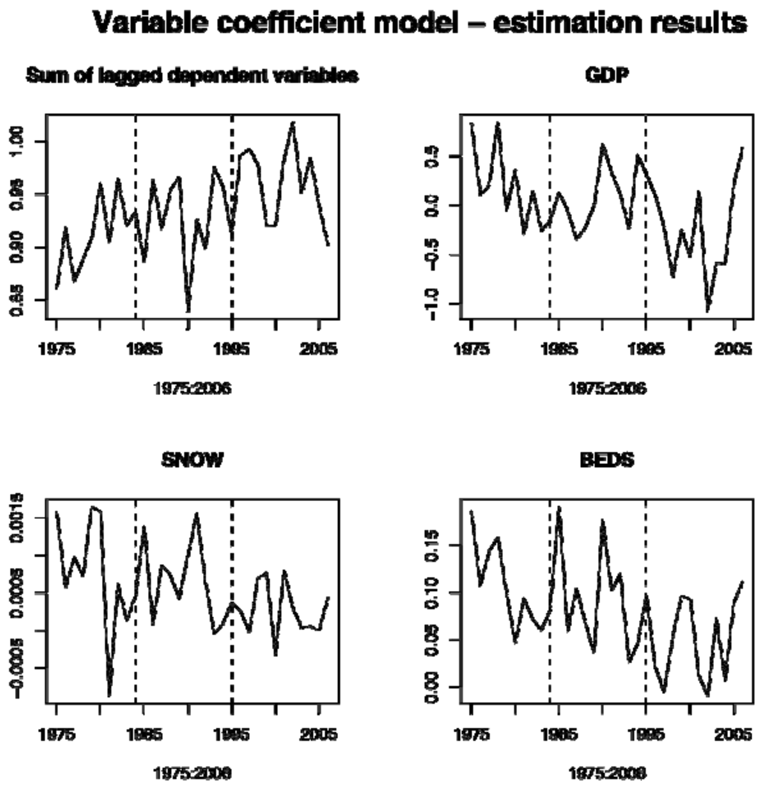

Table 10: Coefficient means for the three periods from the cross-section analysis

Variable	Period 1	Period 2	Period 3
$NIGHTS_{t-1}$+$NIGHTS_{t-2}$	0.913	0.927	0.962
SNOW	0.074	0.065	0.027
BEDS	0.105	0.094	0.049
GDP	0.177	0.108	-0.263

The results of the cross-section analysis should be only used for comparing the trending behaviour of the variables with our estimations in Table 10, because the levels of all the coefficients are highly biased. For instance, the lagged dependent variables are - as expected - highly upward biased, due to the ignorance of individual effects.

The trending behaviour of the lagged values of NIGHTS and BEDS cannot be verified in our panel data models. However, the strong inverse temporal evolution between these variables is also present in panel data estimations, especially in GMM models. This is probably due to a weak form of multicollinearity, resulting from the high correlation between these variables.

The most important result is that the downward trend for the SNOW coefficient seems to be also present in the simple cross-section analysis, strengthening the suspicion from the results of the panel data estimations. We suppose that this observed decline could be attributed to the major increase in snowmaking in recent years, making skiing areas more independent from natural snow cover, as measured by SNOW.

4.4 ANALYZING THE CROSS-SECTION DIMENSION – TYROL, SALZBURG AND CARINTHIA

After investigating the time dimension of the panel data set, we are now interested in studying the cross-section dimension in more detail. Therefore separate models are estimated for three important skiing federal states in Austria, which are Tyrol, Salzburg and Carinthia. Results are only presented for the bias corrected two-way fixed effects model developed by Bruno (2005), using the initialisation of the Blundell and Bond (1998) estimator.[11] The GMM estimator is not appropriate for panel data with a small number of cross-section units, especially in combination with a large amount of instruments, which would enhance small sample bias.

Table 11: Panel data estimation results from 3 different federal states in Austria.

	Bias corrected two-way fixed effects model[1]		
Variable/Test	**Tyrol**	**Salzburg**	**Carinthia**
ln $NIGHTS_{t-1}$	.755*** (45.45)	.721*** (28.29)	.495*** (9.27)
ln $NIGHTS_{t-2}$	.090*** (7.79)	.112*** (5.97)	.224*** (4.45)
$SNOW_t$ / 100	.093*** (5.28)	.012 (0.43)	.059 (0.61)
ln $BEDS_t$	.103*** (6.81)	.112*** (6.60)	.074 (1.02)
ln GDP_t	.984*** (4.67)	.023 (0.07)	1.668** (2.47)
ln PP_t	-.007 (-0.28)	.011 (0.31)	-.047 (-0.35)
Time dummy estimates are not displayed for space reasons			
R_squared (within)	0.91	0.91	0.70
F-Test (k,n)	556 (37,67)	2367 (31,31)	7 (13,13)
corr(mu_i, Xb)	0.83	0.93	0.70
rho[2]	0.53	0.71	0.60
Pesaran AR(1) (p-value)	-2.07 (0.04)	-2.65 (0.01)	6.62 (<0.01)
No. of observations	2176	1024	448
No. of groups	68	32	14

p-value: <0.1 * ; <0.05 **; <0.01 ***
All regressions include time dummies.
Numbers in parentheses beneath the estimates are t–statistics, which are obtained by parametric bootstrapping with 50 permutations.

[1] corr(mu_i, Xb), R_squared, F-Test, rho and AR(1) test are obtained from the standard two-way FE model.
[2] Fraction of variance due to fixed effects mu_i

[11] Estimation results do not depend substantially on the preliminary consistent estimator for the initialisation process. Similar results are obtained with Arellano and Bond (1991) and Anderson-Hsiao (1982). Also t-statistics obtained from a parametric bootstrap procedure are barley sensible to the number of permutations between 50 and 200.

Estimated income elasticities again vary to a large extent and their reliability may be questioned. For the most important skiing federal state in Austria, Tyrol, estimations are more robust concerning the statistical inferences in both models and better comparable. While the coefficient for SNOW and BEDS are similar to the results for whole Austria, (short term) income elasticity is larger with 0.98. Estimated income elasticity for Carinthia is even 1.67, whereas the SNOW coefficient is ranging beneath the estimate for Tyrol. The fixed effects model for Salzburg does not seem to work very well with its suspiciously low income elasticity. A careful statement can be made concerning the SNOW coefficient, which seems to be lower than that for Tyrol and Carinthia. A main difference between the three federal states can be detected in the sum of the lagged dependent variables, which is substantially lower for Carinthia, indicating a less extent of habit persistence. When considering the rate of adjustment, for Tyrol and Salzburg it amounts to 0.15 and 0.17, whereas in Carinthia the adjustment rate is substantially higher with 0.28.

5 Conclusion and future work

A dynamic ADL panel data model was estimated to explain the determinants of winter tourism demand for Austrian ski destinations in the period from 1973 to 2006. While most empirical models measure demand by referring only to visitors arriving from the rest of the world, this study also includes local tourist overnight stays. Within a pool of several fixed effects and GMM estimators, the bias-corrected two-way fixed effects estimator proposed by Bruno (2005) and the System-GMM estimator by Blundell and Bond (1998) have proven to be the most adequate.

Income elasticities obtained in this study suggest that economic conditions are an important factor in determining winter tourism demand in Austria and may be representative for winter tourism destinations in general. Estimated values for the short- and long-run income elasticities amount to 0.41-0.52 and 2.11-3.02, respectively. As opposed to other studies, relative purchasing power of the tourists is not substantial in our estimation results, probably due to the high amount of German tourists in our data, having in common a similar price evolution and a fixed exchange rate regime.

The study indicates that about 20% of the adjustment of tourism to changes in the variables takes place during the first two years, which is pretty low compared with estimations from previous tourism demand models and may represent a relative high robustness of Austrian winter tourism to external effects compared with sun-and sea tourism in Spain for instance. It may also indicate high habit persistence and/or word-of-mouth effects, due to the good reputation of Austrian winter tourism destinations.

Using a variable for snow cover revealed the importance of integrating climatologic variables in winter tourism demand models. For the whole time period estimations indicate that additional 10 days with a snow height of 1 cm will lead to an increase of overnight stays to an extent of about 0.7 to 1 percent, while for the last decade the estimate is substantially lower than in previous years. We suppose that this decline could be attributed to the major increase in snowmaking in recent years.

Future work will aim at improving the estimation results by employing panel data cointegration techniques, using recently developed non-stationary panel methodologies that assume cross-section dependence (Constantini, 2009). Instead of eliminating or reducing nonstationarity in the data by transformations like differencing, cointegrating panel data models in general incorporate nonstationary data in form of building cointegrating relationships among the variables. As a consequence especially long-run elasticity estimates obtained by these models may be favourable.

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