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METHODS FOR ESTIMATING THE IMPACTS OF SHORT-TERM CLIMATE VARIABILITY ON ECONOMIC ACTIVITIES

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Table of Contents

List of Figures

List of Tables

Abstract

In recent years there has been a soaring interest in understanding the sensitivity of economic activities towards short-term climate variability. Climate impact researchers as well as practitioners from the weather risk management industry made efforts in quantifying the weather exposure of economic activities. We review the relevant literature and compare the effectiveness of the different approaches from a statistical perspective, using also own empirical data for winter tourism in Austria. We find that in the majority of studies considered there is a lack of rigorous statistical checking, which clearly limits the usefulness of the empirical results. In fact, it needs to be supposed that trend-stationarity is not given for many of the economic variables in the models based on static regression analysis. It is also worthy discussing, whether autocorrelation in the residuals may distort the results of those models. For the tourism dataset it is shown that an autoregressive distributed lag (ADL) model fits the data better than several static model specifications.

1 Methods for estimating the impacts of short-term climate variability on economic activities

In recent years there has been a soaring interest in understanding the sensitivity of economic activities towards short-term climate variability. Climate impact researchers as well as practitioners from the weather risk management industry made efforts in quantifying the weather exposure of economic activities like tourism, agriculture, retail and energy. Understanding the relationship between the weather conditions and the economy is seen as a first step for quantifying long term climate change impacts on the economy and consequently finding adequate adaptation strategies as well as for applying short term financial strategies to hedge weather risks. Therefore, the aim of this paper is twofold. Firstly, the relevant literature is reviewed for methods to quantify the weather sensitivity of economic activities. Secondly the effectiveness of the different approaches is compared from a statistical and econometric perspective, using also an own empirical dataset to emphasize our ideas (chapter 2).

1.1 REVIEW OF THE RELEVANT LITERATURE

1.1.1 Modeling the impact of climate variability on economic activities

In the climate change literature research efforts to determine the impacts of climate variability on economic activities can be broadly classified into supply and demand analysis. Studies on the supply side typically examine the vulnerability towards climate change in asking how climate change alters climate indices, which are related to economic activities. For the tourism industry in the Alps this could be changes in the natural snow reliability (e.g. Elsasser and Bürki 2002, Abegg et al. 2007) or the conditions for snowmaking (e.g. Scott et al. 2003, Steiger and Mayer 2007, Scott et al. 2008). Similarly, for the energy industry it is asked how heating and cooling degree days will change due to climate change (e.g. Christenson et al. 2006).

In contrast, demand analyses focus on the question, how the demand in specific sectors is influenced by climate variability. In these studies usually a statistical relationship between economic data and weather data is estimated. How well these relationships are examined for certain sectors is determined primarily by two constraints, namely by the obviousness of the weather impact and data availability.

While for some sectors human response to weather is instantaneous and the relationship is clear (e.g. the energy sector), for other activities it is more difficult. As Subak et al. (2000) state, this is particularly the case for tertiary activities, which are often not included in assessments of the potential impacts of climate change. In fact, as these activities are very important to developed economies, even small perturbations in output due to weather variability may have significant impacts.

For some sectors especially data availability is considered to be a constraint to comprehensive demand analysis. For example, tourism analyses prevailingly examine the supply side, as extensive data about tourism activities is more difficult to obtain than the considered weather data. Therefore, demand side studies use tourist data either on the case study level (e.g. Hamilton, Brown and Keim, 2007, or Shih, Nicholls and Holecek, 2009), or on the national scale (e.g. Lise and Tol, 2002, or Agnew and Palutikof, 2006). While for the former studies it is difficult to extrapolate from a few case study regions to the tourism industry of a country, the latter are not able to differentiate between the regions of a country, which seems to be important, as weather impacts may vary substantially within a country.

For analysing the impact of climate variability on the demand of economic activities quantitatively, three approaches are commonly used: The analogue approach, time series regressions and cross-sectional micro data studies.

The analogue approach quantifies how economic activities change in years with deviating meteorological conditions and take these years as analogue to possible future states of the climate. This approach is applied for the ski industry in Dawson, Scott and McBoyle (2007) and in a more qualitative way in Koenig and Abegg (1997). Furthermore the approach is discussed in Giles and Perry (1998) and Subak et al. (2000). The advantages of the analogue approach are that it uses observed data and not only abstracted model outputs as supply side analyses do, and that it captures the impacts when the full range of current supply- and demand- side adaptation occur (Dawson, Scott and McBoyle, 2007).

Indeed, one drawback with the analogue approach is that it does not consider the time series characteristics of the economic data and the occurrence of climatically normal years and climate change analogue years is quite arbitrary. Therefore, trends in the underlying economic series could be misinterpreted and contributed to weather impacts. Moreover, the approach claims that weather impacts are determinable even when only a short period of (suitable) observations is available. However, as the underlying dynamic of the economic time series is not observable, it is questionable whether the results really reveal the difference between climatically normal years and climate change analogue years or rather are influenced by economic processes.

The second and more widely used approach to determine weather dependencies of economic activities are time series regressions and related simple panel data methods. Time series regressions are run for data with different time horizons, time intervals (daily, monthly, annual) and spatial scales (international, national, regional, local). Models with a higher temporal resolution are generally easier to be used for specific case study data, as most time series on a national level are available rather on a monthly or annual scale. Analyses of daily and monthly data need to consider a range of additional time series features (seasonality, public holidays etc.). These features are further discussed in several case studies examining the weather sensitivity of visitors in ski areas, like in Hamilton, Brown and Keim (2007), Prettenthaler and Amrusch (2009) and Shih, Nicholls and Holecek (2009).

On the national level time series regressions of the weather sensitivity have mainly been done on an annual or monthly basis. Subak et al. (2000) identify weather dependencies for several economic sectors in the UK, such as energy, manufacturing, retailing, tourism and health. Agnew and Palutikof (2006) look more closely on the impacts of short-term climate variability in the UK on the demand for international and domestic tourism. Bigano et al. (2005) apply a similar approach to Italy but expand it to a fixed panel estimation for Italian regions. On the international level Lise and Tol (2002) use OLS time series regressions and pooled cross section methods to examine the impacts of climate on the destination choice of OECD tourists. A further discussion of the methods used in the mentioned time series studies will be given in section 1.2.

The third approach to mention are studies which rely on cross-sectional micro data, but do not focus on time effects to find weather impacts on international tourism. Examples for this approach can be found in Lise, Spaninks and Tol (2000) and Bigano et al. (2006), where regression analysis is used to determine the optimum temperature for tourists, and in Hamilton (2003), where pooled travel cost models are taken for examining the impacts of climate on the destination choice of German tourists.

1.1.2 Modeling the impacts on tourism demand

Worldwide tourism demand has increased rapidly in recent decades, and so have research efforts in modeling and forecasting tourism demand. Li, Song and Witt (2005) count 420 studies, which have been published in the period 1960 to 2002. Although none of the studies in their review – except one Danish investigation – explicitly deal with the impacts of weather conditions, the methodological considerations in these studies are generally very beneficial for the estimation of weather sensitivities. Therefore, we will fall back several times on approaches from the tourism demand literature within this paper.

In general, mostly quantitative approaches are applied in the tourism demand literature, whereby both non-causal time series models (ARIMA etc.) and econometric methods for identifying causal relationships between tourism demand and economic variables are used. The variety of applied econometric methods is high. Among the causal models the most common are ADL-models (Autoregressive Distributed Lag), ECM (Error Correction Models), VAR (Vector Autoregressive models), TVP (Time Varying Parameter models) or combinations of these approaches. Some of the elder studies solely rely on static regression models. In some recent studies also Panel Data approaches are considered. Moreover, system-of equations approaches like the AIDS model (Almost Ideal Demand System) are applied, which have a much stronger underlying in economic theory (Song and Li, 2008).

1.1.3 Approaches to determine the weather dependency of companies

A quick note should also be given on the weather risk markets and the approaches to determine the weather dependency of companies, who wish to hedge their weather risks by financial instruments such as weather derivatives, weather insurances, etc. Although dozens of studies have been published discussing the appropriate valuation and pricing of weather derivatives (see e.g. Alaton, Djehiche and Stillberger, 2002, Cao and Wei, 2004, Benth and Benth, 2007, or Svec and Stevenson, 2007), to the knowledge of the authors none of these studies covers the often mentioned ‘first step’, namely the ‘identification of weather dependencies’, more closely. Comprehensive books covering this topic like Dischel (2004) and Jewson, Brix and Ziehmann (2005) solely give blank numbers (company A faced weather related losses in year B in the amount of X million dollar), without mentioning how they have derived these numbers. Some academic publications examining the application of weather derivatives in the agricultural sector (see e.g. Berg et al. 2004) use static regression analysis to determine the weather sensitivity, while others do not even deal with the topic. All in all, it seems that in most sectors (the energy sector might be an exemption) simple comparisons to previous years and static regression analyses dominate, with no explicit public available guidelines on how ones weather dependency could be estimated more precisely.

The reasons for the particular poor coverage of this methodological issue seem to be plentiful. Firstly, suppliers of weather derivatives might think that companies themselves know best how dependent they are. Secondly, estimating the weather sensitivity requires sensitive business data and the results might also be confidential, therefore data, methods and results are rarely published. Thirdly, in many cases complex price-quantity interactions as well as time-delayed effects make the estimation challenging. Fourthly, the application of appropriate statistical tools might be disillusioning, as it can be shown very often that the seemingly high relationship, usually measured in R-squared, is caused by the few observations at hand, spurious correlation etc.

This methodological gap can be seen as one major obstacle for the development of weather risk markets. Companies do not have any recommendations how to appropriately and easily estimate their weather dependency and this avert increasing awareness. Indeed, the weather risk markets have developed by far the most in the energy sector, where the relationship between weather and demand is clear and well known, and profound statistical methods are already used for demand forecasting, including the effects of weather anomalies. All in all, the subsequent methodological considerations might be also helpful for stakeholders in the weather risk management industry, even though they are not specifically targeted.

1.2 MODEL SPECIFICATIONS

In this section the model specifications, which are used in the listed studies in section 1.1.1 to determine weather dependencies of economic activities by means of time series regression, are discussed. While the model considerations are held very general in this section, they will be explained in more detail using empirical data in chapter 2. A broader discussion of the applied modeling approaches follows in section 1.3.

The following model specifications are adapted to our research question from Song, Witt and Li (2009), who do not explicitly include weather variables into their considerations. For the sake of convenience, let us assume that we analyze the influence of a single weather variable x_t (e.g. snow) on an economic variable y_t (e.g. tourist nights). Moreover to keep things simple we assume the data is given on an annual basis.

1.2.1 Static Model

Our considerations start with a static regression model, which can be written as:

$$y_t = ß_0 + ß_1 x_t + \varepsilon_t \ .$$

Although this model is still used for analysing weather sensitivities, one should be cautious interpreting the results of these studies, especially if trending parameters are obviously included and standard statistical diagnostic checking is not applied. One recent example for this approach in the Austrian context is Fleischhacker and Formayer (2007), where the impact of diverse climate parameters on tourism demand is misleadingly depicted using R-squared for a small sample size, ignoring the finding that a relationship between two or more trending variables might be caused by spurious regression.

In general the error terms in static tourism demand models have been found to be highly autocorrelated, and this indicates that the demand relationships are likely to be spurious and that the normal t and F statistics are invalid. Indeed, static models are not seen as appropriate approach by researchers in tourism demand modeling, except when applying them in the Engle and Granger (1987) two-stage cointegration analysis (Song, Witt and Li 2009, p. 48).

1.2.2 Static Model including time trends

In many static models either time trends (linear, quadratic etc.) are included or trends are removed from the series and the adjusted time series are then used in the model. The estimated coefficients remain the same with both procedures, as it is shown in Wooldridge (2006, p. 369). The inclusion of a linear time trend can be denoted as:

$$y_t = ß_0 + ß_1 x_t + ß_2 trend_t + \varepsilon_t \ .$$

This approach is chosen by Subak et al. (2000) for determining the temperature dependency of energy consumption, as well as in Lise and Tol (2002) for estimating the optimal temperature of OECD tourists. A static model is also applied in a recent study by Shih, Nicholis and Holecek (2009) to evaluate the impact of weather conditions on downhill ski lift ticket sales in two skiing areas on a daily basis, whereby the annual linear trend is included in the model.

However, while removing time trends is sufficient when solely working with meteorological data, the results might still be unsatisfactory when working with economic data. This can be explained by the fact that many economic time series still remain non-stationary after the elimination of time trends. Thus, if applying static models including time trends spurious correlation might still be a problem. While the econometric literature has extensively discussed methods to detect non-stationarity and deal with it appropriately, this issue is left out in the examination of weather sensitivities. Thus, this issue will be particularly discussed in chapter 2.2, using empirical data for Austria.

1.2.3 Growth Rate Model

In a growth rate model the differences are taken for each of the variables, which is formally written as:

$$\Delta y_t = ß_0 + ß_1 \Delta x_t + \varepsilon_t \ .$$

First-differencing is used by Prettenthaler and Amrusch (2009) to evaluate the snow and temperature sensitivity of two skiing communities and their cableway companies.

First-differencing is seen as one possible approach to correct for non-stationarity and might therefore be preferred to the undifferenced, static model. Although the growth rate model overcomes the problem of spurious regression results, when economic variables are included the long-run properties of the model are lost due to data differencing (Song, Witt and Li, 2009, p. 49).

1.2.4 Finite Distributed Lag Model

Finite distributed lag models are used when it is believed that the weather in previous periods influences the current level of the economic activities. If only one lag of the weather variable is used, this can be denoted formally as:

$$y_t = ß_0 + ß_1 x_t + ß_2 x_{t-1} + \varepsilon_t \ .$$

This model is applied by Subak et al. (2000) for evaluating the weather dependency of the manufacturing sector. Both same-month variables and up to eleven months lagged predictor variables are used, whereby the variable selection is done by a stepwise regression analysis.

Finite distributed lag models are beneficial to find relationships between past weather and present day activities. Nevertheless they may still produce spurious results, as long as one does not deal explicitly with non-stationarity and autocorrelation issues, for example through first-differencing (as done in Subak et al. 2000) or the inclusion of lagged dependant variables.

1.2.5 Partial Adjustment Model

The inclusion of lagged dependant variables is seen as a key strategy in tourism research model building. From a theoretical perspective the inclusion of an autoregressive term is done to consider tourist expectations and habit persistence (Witt, 1980). Behavior patterns are expected to be stable, as people, who have been on holiday to a particular destination and liked it, tend to return to that destination. Uncertainty is reduced and knowledge about the destination spreads by mouth to mouth recommendation, which may well play a more important role in destination selection than commercial advertising does (Song, Witt and Li, 2009, p. 6).

If only lags of the dependent variable y_t are included, the model is called partial adjustment model. Formally, the inclusion of an autoregressive term for one time period *(t-1)* can be written as:

$$y_t = ß_0 + ß_1 x_t + ß_2 y_{t-1} + \varepsilon_t \,.$$

1.2.6 Autoregressive Distributed Lag Model

The inclusion of both dependent and independent lag parameters is called autoregressive distributed lag model (ADLM). The ADLM is a dynamic regression model that incorporates both the autocorrelation between successive observations of y_t and the correlation of y_t with the explanatory variable x_t and its lags. It therefore extends both the static regression model, which does not include autoregressive terms and the general ARMA model, which does not include explanatory variables like x_t. It is said that in the ADLM the effect of the explanatory variable x_t on the dependent variable y_t is distributed over time (Heij et al., 2004, p. 640).

If the lags of y_t and x_t for one single time period are used, the ADLM is denoted as:

$$y_t = ß_0 + ß_1 x_t + ß_2 x_{t-1} + ß_3 y_{t-1} + \varepsilon_t \,.$$

The ADLM is deployed frequently in the tourism research literature (Song, Witt and Li, 2009 count 21 peer reviewed studies), and has also been used in recent studies to determine the weather sensitivity of tourism demand, for example in Agnew and Palutikof (2006) and Bigano et al. (2005).

1.2.7 Error Correction Model

Error correction models (ECM) appeared in the tourism demand literature in the mid-90s, but had already been applied in many other areas of economics in the the mid-80s. The application of ECMs does not only avoid the problem of spurious regression, but also the problems associated with the simple growth rate model. Notably, the inclusion of an error correction term ensures that no information on the levels of the variables is left out (Song, Witt and Li, 2009, p. 51).

In a simple form the ECM can be written as:

$$\Delta y_t = ß_0 + ß_1 \Delta x_t + \left(ß_2 - 1 \right)\left(y - Kx \right)_{t-1} + \varepsilon_t$$

A more detailed discussion on the application of Error Correction Models for estimating weather sensitivities is given in Schiman, Toeglhofer and Prettenthaler (2009).

1.2.8 Further Models

An ARMAX time series model is chosen by Hamilton, Brown and Keim (2007), whereby the applied ARMAX approach is in principal similar to an ADLM, except that it includes a moving average term. Furthermore, panel data approaches are chosen in some studies (e.g. Bigano et al., 2005). A discussion of panel data methods is done in Eigner, Toeglhofer and Prettenthaler (2009).

1.3 MODELING APPROACHES

Beside the detailed specification of the models a fundamental discussion about which modeling approach should be chosen is needed. In 1995, Witt and Witt (1995, p. 470) reviewed the efforts in tourism demand research and concluded:

"However, it is clear that virtually no attention has been paid to improving model building techniques. In particular, the considerable advances in econometric methodology during recent years have largely been ignored. It is essential for future econometric studies of tourism demand to take on board these developments, in particular in the areas of diagnostic checking, error correction models and co-integration. The lack of diagnostic checking in the econometric studies considered clearly limits the usefulness of the empirical results."

This conclusion is to a large extent still valid for the weather sensitivity studies considered. While some of the studies do not use rigorous statistical checking at all in order to determine the statistical acceptability of the models, some efforts are made in others. However, these efforts are mostly limited to a qualitative discussion of the residuals, while diagnostic tests, such as those for structural instability, functional form, autocorrelation and heteroscedasticity are not carried out, or at least not are reported explicitly in the relevant examinations.

Thus, we will take into account several tests within the worked example given in Chapter 2. The Breusch-Godfrey Test, also known as Lagrange Multiplier Test, is used testing for autocorrelation. This test is preferred to the more common Durbin-Watson-statistic, because the Durbin-Watson-statistic is biased when a lagged dependent variable is included. Among the multiple tests available for testing for heteroscedasticity, we will use the Breusch-Pagan Test. Moreover, the Jarque-Bera-Test is used testing for normality and the Ramsey RESET Test is taken for testing misspecifications. These tests are discussed in more detail in Song, Witt and Li (2009, p. 53).

In a more general way, two broad approaches towards modeling can be distinguished. The first and more traditional approach to tourism demand modeling is called specific-to-general modeling. It starts with a simple model that is consistent with demand theory. Then the model is estimated and tested for statistical significance. Thereby the model is expected to have a high R^2, and the estimated coefficients are expected to be both statistical significant and "correctly" signed. In addition, the residuals from the estimated model should be properly behaved, namely normally distributed with zero mean and constant variance (Song, Witt and Li, 2009, p. 46).

The specific-to-general modeling approach is criticized for its excessive data mining. Often researchers only publish their final models, which are acceptable on both theoretical and statistical grounds, while the intermediate modeling process is not reported. With this approach, the same data set is fitted to a range of potential models and the same statistics are calculated repeatedly, until a model that fits the a priori beliefs of the researcher is discovered (Song, Witt and Li, 2009, p. 47).

Therefore, the general-to-specific modeling approach is seen to be better suitable for tourism demand modeling. This approach was initiated by Sargan (1964), and further developed by Davidson and Saba (1978) and other researchers. In contrast to the specific-to-general modeling approach it starts with a general model which contains as many variables as suggested by economic theory. In this framework, if a dependent variable y_t is determined by k explanatory variables the data generating process can be written as an autoregressive distributed lag model (ADLM) of the general form for p time lags:

$$y_t = ß_0 + \sum_{j=1}^{k} \sum_{i=0}^{p} ß_{ji} x_{jt-i} + \sum_{i=1}^{p} \phi_i y_{t-i} + \varepsilon_t$$

Second, the t, F, and Wald (or Likelihood Ratio or Langrange Multiplier as appropriate) statistics are used to test various restrictions in order to achieve a simple but statistically significant specification. Third, the normal diagnostic tests are carried out to examine whether the final model is statistically acceptable or not. Fourth, the final model can be used for policy evaluation or forecasting (Song, Witt and Li, 2009, p. 60).

Alternatively to the restrictions tests in the general-to-specific modeling approach also formal selection criteria can be used, like Akaike's Information Criterion (AIC) and especially for small sample sizes its corrected version (AICc), the Bayesian information criterion (BIC) or Mallows' C (Cp). Information criteria basically attempt to select the best model from the candidate models available. For a more detailed discussion of selection criteria see Burnham and Anderson (2002) and Burnham and Anderson (2004).

In some of the weather sensitivity studies stepwise regression analysis is used for determining the final models (e.g. Agnew and Palutikof, 2006, and Subak et al., 2000). Stepwise regression analysis can be performed using different selection criteria. While the considered selection criteria is often not even mentioned in the studies, this could be crucial, as some selection criteria like BIC are generally to be seen as more conservative than others (AIC), which means that they select fewer predictor variables. Furthermore the direction of the selection procedure is decisive, as the predictor variables can vary significantly when using forward or backward procedures. The choice of the selection criteria and the direction of stepwise procedures are especially determining when near-equivalent models are judged, which is usually the case when there are many predictors and they are strongly correlated.

Moreover, Burnham and Anderson (2002, p. 282) are skeptical of classical stepwise model selection for several reasons. In general there is no theoretical background for stepwise selection, as regards any optimality criterion. A major failing is that no model inferential weights are computed and provided. Moreover, the user is misled about how much model selection uncertainty exists, because only a small number of all possible models are fit and often, one single model is chosen. Therefore stepwise selection cannot lead to model-averaged-inference, nor reliable inference about the importance of predictors, nor unconditional measures of uncertainty. Rather, one pretends that the selected model was the one and only a priory model considered.

From the considerations done by Burnham and Anderson guidelines can be derived. Firstly, based on theory the predictors should be reduced in number and refined. For selection procedures taking weather parameters this could mean that rather than including several highly correlated parameters (neighboring stations, different threshold definitions) only one parameter might be included. Different variations of similar parameters can still be compared ex-post, using encompassing tests. Secondly, instead of using stepwise procedures, all possible regression models can be calculated, which is manageable with up-to-date statistical software (2^n -1 models need to be estimated). The best model can be determined using appropriate selection criteria like AIC_c or BIC, whereby it is particularly important to consider selection uncertainties. Ideally, also full multimodel inference is done.

2 A Worked Example

The snow sensitivity of German tourist nights in Austria in the winter season is taken as an example for the application of the different model specifications. Since our focus is on the modeling process, we rather consider four independent variables derived from theoretical considerations, instead of focusing on the pre-modeling selection process of meteorological and economic variables. The latter will be focused in Toeglhofer and Prettenthaler (2009).

2.1 THE DATA

We use the same dataset as it is described in a more detailed way in Schiman, Toeglhofer and Prettenthaler (2009). The pivotal question is, whether the number of tourist nights spent by German citizens in Austria in the winter seasons 1973 to 2002 does depend on the snow cover. Intuitively, and from the considerations in the climate change literature it seems to be evident that the overall tourist nights are positively affected by snow cover. Furthermore, the tourism forecasting and demand literature suggests that a bundle of economic variables influences the level of tourist nights. Three indices are commonly used to include income and price variables (see Song and Li, 2008). While the gross domestic product of the origin country is used representing the income of the tourists, the price level in the destination country is considered in relative terms both to the price level in the origin country and the price level in competing destinations. The corresponding time series are illustrated in Figure 1.

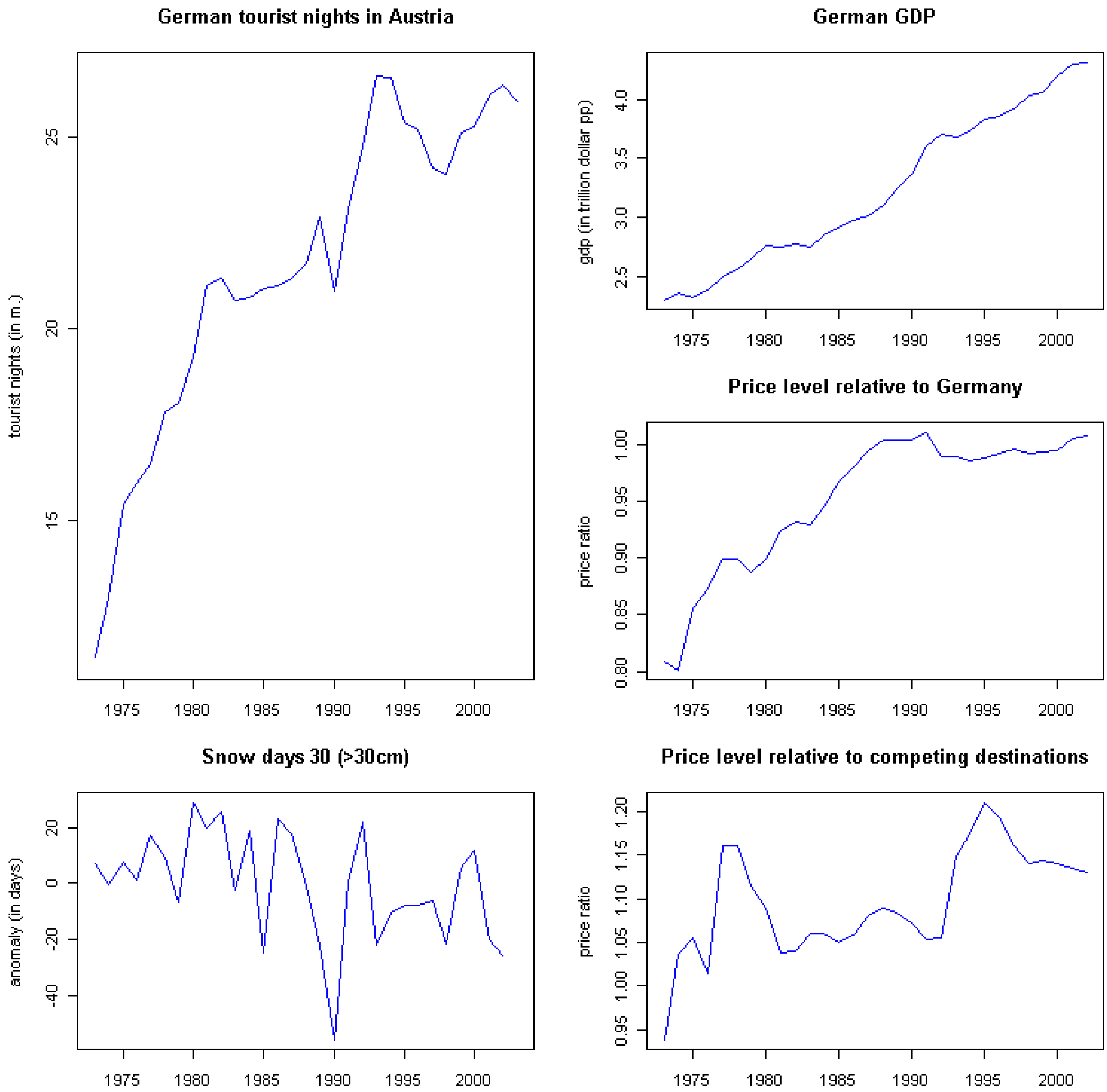

Figure 1: Time series of tourist nights, GDP, price levels and snow days 1973-2002

The German tourist nights in Austria as well as the German GDP and the Price level ratio exhibit a clear upward trend, while the snow days used for this example show a slightly declining trend, as it can be seen in Figure 1. Before we will analyze which of the model specifications should be chosen, it is important to better understand the basic characteristics of the underlying meteorological and economic data and their consequences for the modeling process.

2.2 COMPARING METEOROLOGICAL AND ECONOMIC DATA

In general, economic time series like the gross domestic product or the number of tourist nights have special characteristics, which require that they must be dealt differently than meteorological variables in regression models. Firstly, economic time series are likely to be non-stationary processes, even after deterministic trends have been removed. This means that the joint distributions are not constant across different epochs of the time series process. Secondly, economic time series are typically highly persistent, meaning that there is a relation between what happens this period and what happened the period before and so on. Outcomes in the distant future are highly correlated with current outcomes and consequently we have to deal with the dependence between the observations.

A closer understanding of these characteristics is particularly important, as spurious regression may arise in case of regressing a non-stationary time series on one or more non-stationary time series. While processes with deterministic trends that are weakly dependent can be used directly in regression analysis (provided time trends are included in the model), extreme caution is necessary when dealing with highly persistent time series. Using highly persistent time series of the type displayed by a unit root process in a regression equation can lead to very misleading results, in case that the assumptions of the central limit theorem are violated. (Wooldridge 2006, p. 404).

In principle two different procedures can be distinguished for transforming non-stationary processes. Some time series might become stationary processes, once a time trend has been removed. This is referred to as a trend-stationary process, whereby it is usually implicit that the detrended series is weakly dependent. When data is strongly dependent (highly persistent) it is preferable to first-difference the time series data. Unit root processes are said to be integrated of order one, or I(1), which means that the first difference of the process is weakly dependent and in most cases stationary (Wooldridge 2006, p. 397).

2.2.1 Testing for stationarity

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 hypotheses 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.

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 1 illustrates the results of the unit root test, testing both for level and trend stationarity of the economic and meteorological variables. More meteorological parameters than the described snow day index are indicated to emphasize the generality of the results also for seasonal temperature and precipitation indices. For the sake of clarity results are only shown for h=1 and l=1. Indeed, the results are similar when varying h and l between 0 and 2.

Table 1: Testing level and trend stationarity of the economic and meteorological variables (h = 1, l = 1)

	KPSS test level stationarity		**KPSS test trend stationarity**		**ADF test trend stationarity**	
economic variables	test statistics	p-value	test statistics	p-value	test statistics	p-value
tourist nights (log)	1.33	0.01	0.26	0.01	-3.58	0.05
tourist nights	1.40	0.01	0.22	0.01	-2.97	0.20
gdp (log)	1.57	0.01	0.10	>0.1	-2.63	0.33
price ratio (log)	1.27	0.01	0.35	0.01	-3.53	0.06
price ratio$_{competing}$ (log)	0.75	0.01	0.08	>0.1	-2.69	0.31
meteorological variables	test statistics	p-value	test statistics	p-value	test statistics	p-value
snow days	0.53	0.03	0.06	>0.1	-4.36	0.01
mean temperature (winter)	0.51	0.04	0.10	>0.1	-3.73	0.04
mean temperature (summer)	0.96	0.01	0.04	>0.1	-3.57	0.05
precipitiation (summer)	0.25	>0.1	0.07	>0.1	-4.76	0.01

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.

Firstly, the results for the KPSS test on level stationarity in Table 1 clearly show that both the examined economic and meteorological variables include trends (which can also easily be depicted in Figure 1) and consequently level stationarity is not given. The only stationary parameter is the precipitation sum in the summer months, which has remained constant for the last thirty years, while the summer and winter temperatures have risen and the number of snow days has decreased substantially within this period.

Secondly, when testing for trend stationarity it is evident that only for meteorological variables a removal of deterministic trends is sufficient, while for the examined economic variables it is suggested that detrending is not appropriate. However, all but one economic variables become stationary when they are differenced (integrated of order one). In one particular case (price ratio) the KPSS test suggests that a second differentiation (integrated of order two) is needed.

All in all, these results are consistent with the results of Url and Wehinger (1990, p. 131), who examined 13 important Austrian macro-economic time series. They conclude that for using these time series in model building an integration of order one should be preferred to de-trending.

2.2.2 Autocorrelation functions

Another illustration should clarify the difference between de-trending and differencing as strategies for dealing with non-stationarity. For non-stationary time series the sample autocorrelation function (ACF) fails to die out rapidly as the lags increase. This is due to the tendency for non-stationary series to drift slowly, either up and down, with apparent trends (Cryer and Chan, 2008, p. 125). Figure 2 depicts the sample ACFs and Partial autocorrelation functions (PACF) for German tourist nights in Austria for the original series as well as the detrended and first-differenced series, and in comparison for the de-trended snow days.

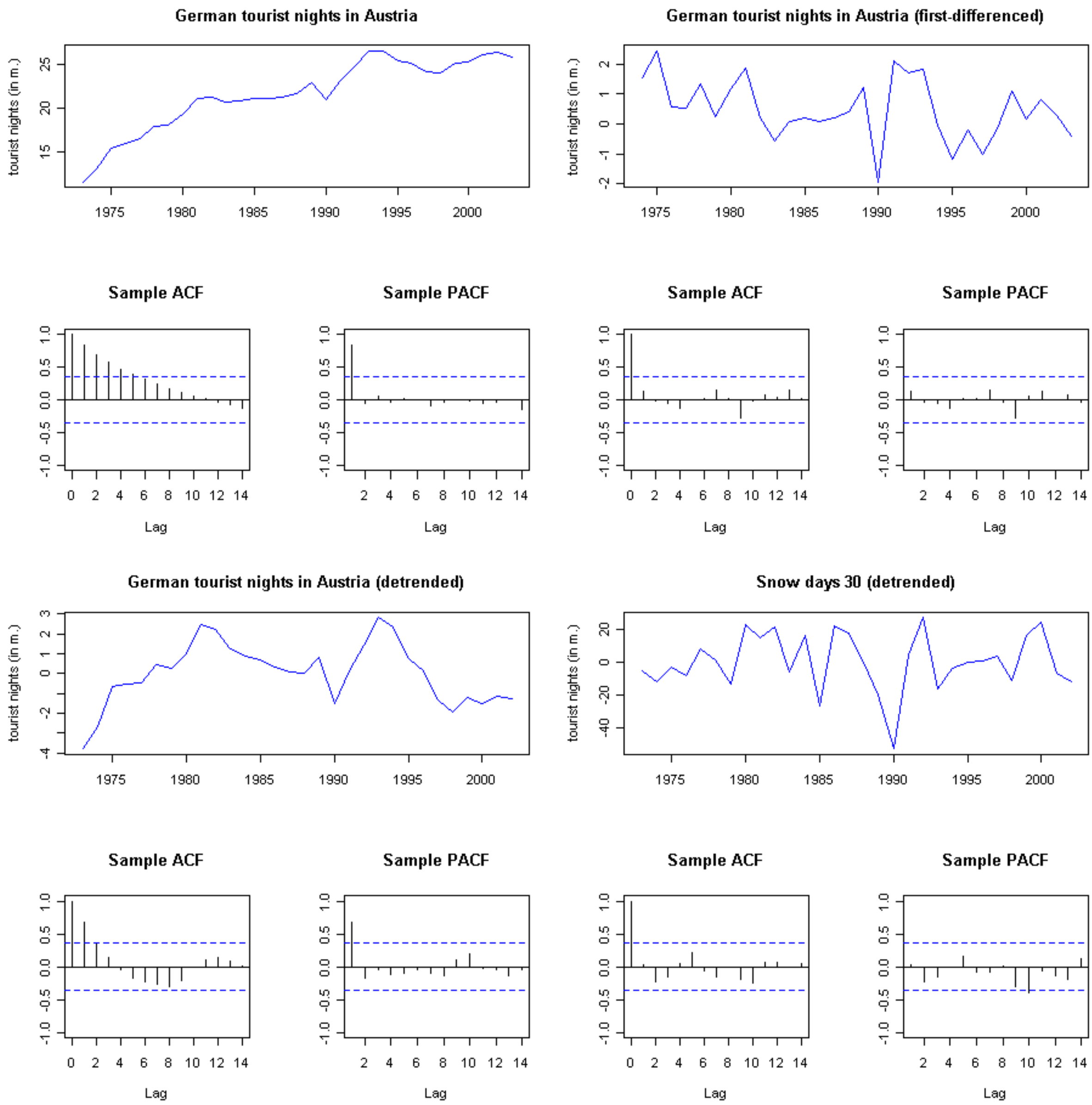

Figure 2: Sample autocorrelation functions for tourist nights and snow days

The autocorrelation functions in Figure 2 reveal the basic difference between first-differencing and de-trending tourist nights. As expected from theory, the autocorrelation is quite strong for the original time series with a strong upward trend. While the de-trended time series still shows autocorrelation (which can be anticipated due to the clear peaks in the early-80s and early-90s), the first-differenced series is not affected by autocorrelation any more (although there is still a trend observable due to the decline in growth rates). In contrast, for the snow day index no autocorrelation is visible (ignoring the outlier for lag 10 in the PACF).

2.3 ESTIMATED GENERAL MODEL

From the considerations in chapter 2.2 it is supposed that we have to deal with the non-stationarity feature of the economic data. We use several different strategies in doing so. Firstly, an error correction model is used, which is described in more detail in Schiman, Toeglhofer and Prettenthaler (2009). Secondly, we apply the frequently used modeling approach in tourism research, namely specifying an ADL model. Thirdly, we estimate a growth rate model. For the sake of comparability we also show static regression models with and without the inclusion of time lags.

We start with a general ADL model with one lag for both of the dependent and the explanatory variables. Lags are denoted adding *1*, the GDP is denoted as *y*, the snow days are denoted as *snow*, tourist nights are denoted as *nights* and price levels are written as *pp* and *ppc* respectively for the competing destinations. All, but the meteorological parameters *snow* and *snow1* are transformed into logs when used for this analysis, which is not explicitly shown in the model output. Using OLS we calculate:

	Estimate	Std. Error	t value	Pr(>|t|)	Sign.
(Intercept)	3.778475	2.443414	1.55	0.13850	
nights1	0.536098	0.128990	4.16	0.00054	***
snow	0.000833	0.000395	2.11	0.04854	*
snow1	0.000160	0.000485	0.33	0.74469	
y	-0.460932	0.583839	-0.79	0.43957	
y1	0.729868	0.555696	1.31	0.20468	
pp	0.612215	0.529820	1.16	0.26220	
pp1	-0.157215	0.583284	-0.27	0.79042	
ppc	-0.104583	0.219411	-0.48	0.63905	
ppc1	0.027842	0.203613	0.14	0.89267	

```
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.037 on 19 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared: 0.973,      Adjusted R-squared: 0.96
F-statistic:   75 on 9 and 19 DF, p-value: 6.16e-13
```

Diagnositic tests		p-value
Breusch-Godfrey Test for autocorrelation	0.87	0.35
Jarque-Bera-Test for normality	1.1	0.58
Breusch-Pagan Test for heteroscedasticity	7.6	0.58
Ramsey RESET Test for misspecification	1.3	0.31

The diagnostic statistics reveal that the general model passes all tests, which means that it is statistical acceptable. Though they are very high, the multiple R-squared and the adjusted R-squared, are not recommended to be interpreted when a lagged dependent variable is included.

The general form of the model reveals two significant variables. The lagged dependent variable *nights1* is showing a high influence on the tourist nights, as it is expected from theoretical considerations. The other significant variable is the snow day index. The prefix of the coefficients is positive, which is expected by the hypothesis that more snow leads to more tourist nights. The very low snow estimates are explained by the different levels of the logarithmized tourist nights and the snow variable. The given coefficient would mean that 10 days less with fewer than 30 cm snow cover lead to a decrease in tourist nights by 0.8 percent.

All the included economic variables derived from economic theory and the corresponding lag variables are not showing any significance. However, this is also affected by multicolllinearity, which is frequently present when lags of the economic explanatory variables are considered. The correlation coefficient between *y* and *y1* is 0.996, and respectively 0.97 between *pp* and *pp1*. This problem is avoided with either using partial adjustment models or some testing down procedure, which will likely remove one of the related variables (although, as mentioned before, it is more than uncertain which of the highly correlated variables will be removed).

2.4 TESTS OF RESTRICTIONS ON REGRESSION PARAMETERS

2.4.1 Testing for the static model

Let us now compare the general ADL model to some more restricted models, starting with a static model.

	Estimate	Std. Error	t value	Pr(>|t|)	Sign.
(Intercept)	1.25e+01	1.97e+00	6.37	1.1e-06	***
snow	1.19e-03	6.77e-04	1.75	0.092	.
y	3.31e-01	1.23e-01	2.70	0.012	*
pp	2.00e+00	3.41e-01	5.87	4.0e-06	***
ppc	5.38e-01	2.72e-01	1.98	0.059	.

```
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.064 on 25 degrees of freedom
Multiple R-squared: 0.922,      Adjusted R-squared: 0.909
F-statistic: 73.7 on 4 and 25 DF,  p-value: 1.82e-13
```

Diagnositic tests		p-value	Sign.
Breusch-Godfrey Test for autocorrelation	8.3	0.004	**
Jarque-Bera-Test for normality	0.68	0.71	
Breusch-Pagan Test for heteroscedasticity	3.7	0.45	
Ramsey RESET Test for misspecification	9	0.001	***

The static regression model gives 'impressive' regression results, if spurious regression is not considered. Indeed, if the focus is solely on the p-values, all of the coefficients are significant. However, the spurious regression problem is clearly indicated in the residuals and also formally in the tests for autocorrelation and misspecification. Therefore, the static model can not be accepted.

2.4.2 Testing for the static model including time trends

Using the commonly applied strategy, we add a time trend to the model. We also add a logarithmic trend variable, since the slope of the logarithm of tourist nights is decreasing steadily (as the growth rates of tourist nights have declined steadily within the examined period). In contrast, the slope of the logarithmized GDP (y) is quite stationary, because the GDP growth was fairly constant, suggesting also the inclusion of a linear time trend.

	Estimate	Std. Error	t value	Pr(>|t|)	Sign.
(Intercept)	9.1330	5.1770	1.764	0.091	.
snow	0.0005	0.0004	1.095	0.285	
y	0.4803	0.3534	1.359	0.187	
pp	-0.3780	0.5034	-0.751	0.460	
ppc	0.0086	0.2084	0.042	0.967	
trend	-0.0120	0.0087	-1.371	0.184	

```
trend_log    0.2871   0.0518      5.539 1.24e-05 ***

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.04368 on 23 degrees of freedom
Multiple R-squared: 0.9667,     Adjusted R-squared: 0.958
F-statistic: 111.2 on 6 and 23 DF,  p-value: 8.158e-16
```

Diagnositic tests		p-value	Sign.
Breusch-Godfrey Test for autocorrelation	2.9	0.086	.
Jarque-Bera-Test for normality	1.6	0.457	
Breusch-Pagan Test for heteroscedasticity	7.5	0.281	
Ramsey RESET Test for misspecification	0.826	0.452	

The static model changes enormously, when time trends are included. None of the explanatory variables is significant any more, unlike the logarithmic time trend. The autocorrelation tests indicate that the inclusion of the time trends is not able to remove the autoregressive characteristics of the economic variables. The Breusch-Godfrey Test for autocorrelation is somewhat on the brink of being significant, and also the Durbin-Watson (DW)-Test indicates some form of autocorrelation (DW 1.4). In the case of the static model the DW-Test may be applied, since no autoregressive terms are included in the model.

2.4.3 Testing for the growth rate model

The growth rate model corrects for non-stationarity and might therefore be preferred to the undifferenced, static model. However, the long-run properties of the model are lost due to data differencing.

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.025596	0.018318	1.40	0.18
snow	0.000497	0.000426	1.17	0.26
y	-0.268145	0.609711	-0.44	0.66
pp	1.063096	0.636925	1.67	0.11
ppc	0.237953	0.244124	0.97	0.34

```
Residual standard error: 0.052 on 24 degrees of freedom
Multiple R-squared: 0.209,      Adjusted R-squared: 0.0766
F-statistic: 1.58 on 4 and 24 DF,  p-value: 0.212
```

Diagnositic tests		p-value
Breusch-Godfrey Test for autocorrelation	1.4	0.23
Jarque-Bera-Test for normality	1.3	0.52
Breusch-Pagan Test for heteroscedasticity	5.1	0.28
Ramsey RESET Test for misspecification	1.7	0.2

For our dataset the growth rate model fits the data badly. All variables are statistically insignificant and the prefixes of all economic variables have the 'wrong', unexpected sign. For this empirical data the growth rate model can not be accepted. However, it can not be concluded from this specific case that the growth rate model is generally inappropriate for similar empirical analyses.

2.4.4 Testing for the finite distributed lag model

Alternatively to using first differencing, we may apply a finite distributed lag model. This model is very similar to the general ADL model, except that we restrict for the lagged explanatory variables.

	Estimate	Std. Error	t value	Pr(>|t|)	Sign.
(Intercept)	2.685607	1.769002	1.52	0.1426	
nights1	0.620580	0.100138	6.20	2.5e-06	***
snow	0.000818	0.000390	2.10	0.0473	*
y	0.242786	0.082500	2.94	0.0073	**
pp	0.213814	0.313625	0.68	0.5022	
ppc	-0.111426	0.185360	-0.60	0.5536	

```
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.0366 on 23 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared: 0.967,      Adjusted R-squared: 0.96
F-statistic:  135 on 5 and 23 DF,  p-value: 3.04e-16
```

Diagnositic tests		p-value
Breusch-Godfrey Test for autocorrelation	0.312	0.576
Jarque-Bera-Test for normality	1.8	0.406
Breusch-Pagan Test for heteroscedasticity	3.55	0.615
Ramsey RESET Test for misspecification	0.039	0.962

It can be observed that the finite distributed lag model yields very similar results as the general model. The estimates for the snow coefficients are 0.000818 and 0.000833 respectively. However, as the GDP variable *y* and its lag *y1* are not both included like in the ADLM, the GDP turns out to be significant, also showing the expected sign. Also note that the estimate for y (0.24) almost equals the difference between *y* and *y1* in the ADLM (0.26), which can be expected from the high correlation between *y* and *y1*.

2.5 TESTING DOWN PROCEDURES

In this section we apply several selection criteria for the model reduction process. We start with the general model and compare the resulting models chosen by AIC, AIC_c, BIC, Mallows' C and the adjusted R-squared.

The results indicate that the choice of the selection criteria influences the number of selected variables. While the models chosen by the AIC and the adjusted R-squared include five explanatory variables (plus the intercept), the models selected by AIC_c, BIC and Mallows' C take into account only three explanatory variables (plus the intercept).

The difference between the BIC and the AIC is expectable, because the BIC generally punishes additional variables more than the AIC (except when the number of observations is extremely low). In our case of n=30 and k=10 the AIC_c is nearly identical to BIC, since the penalty per parameter is 3.4 for BIC and 3.16 for AIC_c (in contrast to 2 for AIC). Indeed, the selection given by AIC_c or BIC should be preferred for our research question because of the small sample size. Burnham and Anderson (2004) suggests that AIC_c should be used instead of AIC to correct for a second-order bias, unless n/k > about 40 for the model with the largest value of k, which is clearly not the case for our sample.

The model suggested by AIC and the adjusted R-squared is:

	Estimate	Std. Error	t value	Pr(>|t|)	Sign.
(Intercept)	4.534427	1.422146	3.19	0.0041	**
nights1	0.521046	0.096785	5.38	1.8e-05	***
snow	0.000857	0.000358	2.39	0.0253	*
y	-0.622631	0.398986	-1.56	0.1323	
y1	0.863699	0.399460	2.16	0.0412	*
pp	0.540356	0.296141	1.82	0.0811	.

```
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.0337 on 23 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared: 0.972,      Adjusted R-squared: 0.966
F-statistic:  160 on 5 and 23 DF,  p-value: <2e-16
```

Diagnositic tests		p-value
Breusch-Godfrey Test for autocorrelation	0.56	0.455
Jarque-Bera-Test for normality	0.98	0.613
Breusch-Pagan Test for heteroscedasticity	6.25	0.283
Ramsey RESET Test for misspecification	1.28	0.298

Three things are worth of mentioning regarding this reduced model. Firstly, when comparing the model with the general model the R-squared is extremely similar (0.972 versus 0.973), although we include four explanatory variables less (five instead of nine). This shows us that deciding solely by R-squared can likely lead to overfitting, as R-squared will always increase with additional variables. Secondly, despite the high correlation between the within the GDP variable (*y*) and its lag (*y1*), both variables are included. The overall GDP estimate is positive, which confirms the assumptions of the economic theory that more GDP generally leads to more tourist demand.

Thirdly, the pricel level (*pp*) is included and is revealed to have a significant impact. However, the estimate is positive and therefore counterintuitive to the economic theory, which suggests that higher prices lead to less demand. Interestingly the error correction models applied in Schiman, Toeglhofer and Prettenthaler (2009) show negative signs for the same data. This difference once again show the importance to take into account economic considerations, when including economic data to study the weather sensitivity of tourism demand, rather than solely putting as many variables as possible in the model and let the statistical program to do the job.

In comparison to the AIC and the adjusted R-squared, the BIC, AIC_c and Mallows’ C all reveal the following model:

	Estimate	Std. Error	t value	Pr(>|t|)	Sign.
(Intercept)	2.096022	0.569937	3.68	0.0011	**
nights1	0.650956	0.067816	9.60	7.3e-10	***
snow	0.000808	0.000370	2.18	0.0387	*
y1	0.255148	0.074299	3.43	0.0021	**

```
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.035 on 25 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared: 0.967,      Adjusted R-squared: 0.963
```

```
F-statistic:  245 on 3 and 25 DF,  p-value: <2e-16

Diagnositic tests                                     p-value
Breusch-Godfrey Test for autocorrelation      0.11  0.74
Jarque-Bera-Test for normality                1.86  0.393
Breusch-Pagan Test for heteroscedasticity     3.19  0.363
Ramsey RESET Test for misspecification        1.35  0.279
```

This reduced model only includes highly significant variables, leaving out the price variable and also the GDP variable, while the GDP lag variable is still in the model. The GDP lag estimate roughly equals again the difference of both variables in the before mentioned model.

Focusing again on the model selection process, Figure 3 illustrates the ranking of models as it is suggested by BIC. On the left hand side for each number of predictors only the best model is shown, while on the right hand side the five best models are depicted. It can be seen that the BIC ranks the model chosen by the AIC only fourth, but nearly on the same level as the model with 3 and 5 variables (incl. intercept). The intercept and the lagged dependent variable are highly suggested to be included, followed by the lagged income and snow variable.

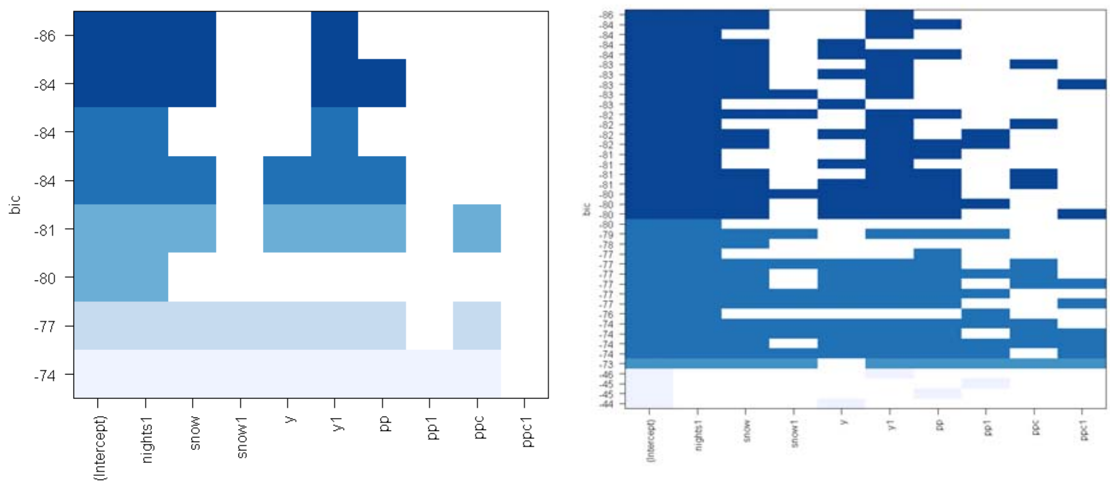

Figure 3: Ranking of models by BIC, showing for each number of predictors the best models (left) and accordingly the five best models (right)

Notably, the snow days are identified to be among the most important variables. In fact, the intuition that the snow conditions are essential for tourism demand in Austria in the winter season is confirmed by this result. The snow coefficient (0.000808) is very similar to the other dynamic models (ADLM: 0.000833, Finite Distributed Lag Model: 0.000818, AIC selection: 0.000857). Again, the very low estimates in all of these models are due to the log-linear model configuration. Thus, when interpreting them the inter-annual variations of snow cover affect tourist demand by hundreds of thousands of tourist nights on the national level. This snow dependency will be discussed in more detail in Toeglhofer and Prettenthaler (2009).

3 CONCLUSIONS

In this paper we focus on methods for estimating the impacts of short-term climate variability on economic activities. We find that with the exemption of some recent studies static regression analysis is chosen to determine weather sensitivities in most of the literature. However, as we demonstrate on empirical tourism data, this approach might be misleading, even when time trends are included in the model. In fact, it needs to be supposed that trend-stationarity is not given for many of the included economic parameters. In general the error terms in static demand models have been found to be highly autocorrelated, and this indicates that the demand relationships are likely to be spurious and that the normal t and F statistics are invalid.

Alternatively, either growth rate models or some dynamic models like autoregressive distributed lag (ADL) models or error correction models (ECM) could be applied. For our tourism dataset the growth rate model fits the data badly. All variables are statistically insignificant and the prefixes of all economic variables have the ‘wrong’, unexpected sign. In contrast, the ADL model fits the data very well and is statistically acceptable (we do not explicitly apply an ECM in this paper). The ADL has also been used in recent studies to determine the weather sensitivity of tourism demand, for example in Agnew and Palutikof (2006) and Bigano et al. (2005).

Several recommendations are worth to be mentioned concerning the modeling approaches. Firstly, the general-to-specific modeling approach seems to be preferable over the specific-to-general modeling approach, which is often criticized for its excessive data mining. Instead of taking into account as many variables as possible, the predictors should be reduced in number and refined based on theoretical considerations. Then, instead of using stepwise procedures, all possible regression models can be calculated, which is manageable with up-to-date statistical software in most cases. Also, the choice of the selection criteria is important and should be reported, as different numbers of predictor variables are chosen by different criterions. Since sample sizes are usually relatively small, the BIC or AIC_c should be preferred to AIC or the adjusted R-squared to correct for a second-order bias.

Furthermore, diagnostic tests, such as those for autocorrelation, structural instability, functional form, and heteroscedasticity should be carried out to examine whether the final model is statistically acceptable or not. Indeed, in the majority of considered studies there is a lack of rigorous statistical checking, which clearly limits the usefulness of the empirical results. Efforts are mostly limited to a qualitative discussion of the residuals, while normal diagnostic tests are not carried out, or at least are not reported explicitly in the relevant examinations.

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