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From Climate Variability to Weather Risk:

The Impact of Snow Conditions on Tourism Demand in Austrian Ski Areas

Doctoral Thesis

to be awarded the degree of
Doctor of Social and Economic Sciences (Dr. rer.soc.oec.)
at the University of Graz, Austria

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Graz, January 2011

Author's Declaration

Unless otherwise indicated in the text or references, or acknowledged above, this thesis is entirely the product of my own scholarly work. Any inaccuracies of fact or faults in reasoning are my own and accordingly I take full responsibility. This thesis has not been submitted either in whole or part, for a degree at this or any other university or institution. This is to certify that the printed version is equivalent to the submitted electronic one.

Date: Signature:

Acknowledgements

I have had the fortune to work on my Ph.D. thesis under the supervision of my advisers Roland Mestel and Stefan Schleicher. Special thanks also to Franz Prettenthaler, who supported me and my work wherever possible. The sharing of their knowledge during the course of research for this thesis has been invaluable.

Over the years I have been lucky to work with many tremendous people at the Wegener Center for Climate and Global Change (WEGC) and the Centre for Economic and Innovation Research (POLICIES) at Joanneum Research. I am indebted for valuable contributions and fruitful discussions to Judith Köberl, Petra Amrusch, Nadja Vetters, Markus Zahrnhofer, Nikola Rogler, Stefan Schiman, Franz Eigner, Birgit Bednar-Friedl, Andreas Gobiet and many others. My thanks goes in particular to Michael Pock for providing this LaTeX template as well as to Florian Ladstädter, Lisa Kapper, Barbara Pirscher and Matthias Themessl for sharing their experience with LaTeX and *R* respectively. Thanks to all office colleagues for contributing to the excellent and unique working atmosphere and to the WEGC and EconClim team under the lead of Gottfried Kirchengast and Karl Steininger, who provided me an excellent surrounding and infrastructure for my work.

I am grateful to Wolfgang Schöner and Roland Potzmann (ZAMG), Jürgen Weiß (Statistik Austria), Alex Stomper (MIT, IHS) and Franz Hartl (Österreichische Hotel- und Tourismusbank) for providing data and support as well as Maria Unterberger for proofreading. I benefit from extensive and very helpful comments received during several scientific conferences and summer schools as well as a research visit at the University of Lausanne (UNIL) under the supervision of Hansjoerg Albrecher. Furthermore, I acknowledge financial support from the Jubiläumsfonds of the ÖNB (Central Bank of the Republic of Austria) for the research project EWCR1 (Economics of Weather and Climate Risks 1) as well as from a research grant from the URBI faculty of the University of Graz.

Most of all, I would like to thank my family and friends, who have been of great support while writing this thesis and throughout my entire life.

Abstract

In this thesis a methodological framework for assessing non-catastrophic weather risk is presented and applied on the winter tourism industry in Austria by examining the impacts of snow conditions on tourism demand in 185 ski areas in the period 1972/1973 to 2006/2007. A three-step approach is proposed: (1) modelling the distribution of several weather indices, e. g. days with snow depth >1 cm, (2) estimating the dependency of overnight stays on snow conditions by means of an Autoregressive Distributed Lag (ADL) model, (3) measuring Value at Risk(weather), in short VaR(weather), corresponding to the maximum loss from adverse weather conditions which is not exceeded with a given probability level over a given period of time. Results emphasize the importance of considering both the probability of an event and its potential impact for estimating weather risks. Trend analyses provide evidence that the probability of seasons with adverse natural snow conditions substantially increases. At the same time, analyses show a predominantly positive dependence of overnight stays on snow conditions, but also suggest that impacts have decreased in recent years, probably owing to the major increase in snowmaking. Overall, estimates of the 95%-VaR(weather), corresponding to a 1 in 20 year event, range from a 1.7 % to 50.5 % loss in overnight stays in ski areas (median ski area: 7.2 %). This is equivalent to a loss in sales of up to 19 million Euro (median ski area: 500 000 Euro) and yields an aggregate 95%-VaR for the accommodation industry of 157 million Euro. Potential sources of biases in these estimates are e. g. uncertainties in the meteorological data and changes in the level of adaptation. Finally, a linking of weather risk estimates to financial ratios for hotels reveals that hotels in lower lying and smaller areas do not only face higher weather risk, but also tend to be less profitable and exhibit higher debt ratios.

Zusammenfassung

Die vorliegende Arbeit präsentiert einen Ansatz zur Schätzung von Wetterrisiken sowie dessen Anwendung am Beispiel des österreichischen Wintertourismussektors. Dabei werden für 185 Schigebiete und die Saisonen 1972/73 bis 2006/07 die Auswirkungen der Schneebedingungen auf die Nächtigungsnachfrage geschätzt. Die Modellierung erfolgt anhand von 3 Schritten: (1) wird die Verteilung mehrerer Wetterindices (z. B. Tage mit Schneehöhe >1 cm) modelliert (2) wird die Abhängigkeit der Nächtigungen von den Schneebedingungen mithilfe von ADL ('autoregressive distributed lag')-Modellen geschätzt, und (3) wird das resultierende Risiko mithilfe des Value at Risk(Wetter) bzw. VaR(Wetter) dargestellt, welcher den maximalen wetterbedingten Verlust wiedergibt, der mit einer bestimmter Wahrscheinlichkeit in einer bestimmten Periode nicht überschritten wird. Die Resultate unterstreichen die Wichtigkeit, im Zuge der Analyse von Wetterrisiken sowohl die Wahrscheinlichkeit des Auftretens eines Ereignisses als auch dessen mögliche Schadenshöhe zu betrachten. Trendanalysen weisen auf eine erhöhte Wahrscheinlichkeit von Wintern mit ungünstigen Schneebedingungen hin. Gleichzeitig zeigt sich für die meisten Gebiete eine positive Abhängigkeit der Nächtigungen von den Schneebedingungen, jedoch deuten Analysen auf eine Abnahme der negativen Auswirkungen von schneearmen Wintern hin. Insgesamt beträgt der 95%-VaR(Wetter) je nach Schigebiet zwischen 1.7 % und 50.5 % (Median: 7.2 %), mit einem entsprechenden Umsatzverlust für die Beherbergungsunternehmen von bis zu 19 Millionen Euro (Median: 500 000 Euro) und einem aggregierten 95%-VaR(Wetter) von 157 Millionen Euro. Mögliche Schätzfehler sind u. a. durch Unsicherheiten in den meteorologischen Daten und durch Änderungen des Adaptionsniveaus bedingt. Des Weiteren zeigt sich, dass Betriebe in tiefer gelegenen und kleineren Schigebiete verstärkt verwundbar sind, da sie neben einem höheren Wetterrisiko meist auch eine geringere Rentabilität und höhere Verschuldung aufweisen.

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Notation

N	Number of cross-sectional observations (usually ski areas).
T	Number of time points (usually winter seasons).
$VaR(weather)_{1-\alpha}$	Maximum loss from weather impacts which is not exceeded with a given probability level α over a given period of time.
$VaR_{1-\alpha}$	Value at Risk given for a probability of α over a given period of time.
WI	Any kind of distribution of the standardized ($\mu = 0$, $\sigma = 1$) weather index WI (see also WI_{normal}, WI_{nonpar}, WI_{hist} and WI_{trend}).
WI_t	Standardized ($\mu = 0$, $\sigma = 1$) weather index for the respective ski area in the winter season t.
WI_{hist}	Historical (Empirical) distribution of WI.
WI_{nonpar}	Non-parametric distribution estimated for the respective ski area in the winter season t.
WI_{normal}	Normal distribution fitted to the standardized ($\mu = 0$, $\sigma = 1$) weather index WI for the respective ski area in the winter season t.
WI_{t-1}	Standardized ($\mu = 0$, $\sigma = 1$) weather index for the respective ski area in the previous winter season t.
WI_{trend}	Weather index WI distribution including linear time trends.
Δ	Change.
α	Quantile.
β	The estimated regression slope coefficients; β_1 generally refers to the coefficient for WI_t.
β_1	The estimated regression slope coefficient for WI_t.
η	Disturbance term.
γ_1	Skewness, equals 0 for a normal distribution.
γ_2	Excess kurtosis, equals 0 for a normal distribution.
$\mathcal{G}$	Any discrete distribution.
$\mathcal{N}$	Normal distribution.

μ	Arithmetic mean.
ω_j	Weights given to the snow conditions in ski area j for calculating the non-parametric distribution.
ρ	Pearson product-moment correlation coefficient.
σ	Standard deviation.
σ/μ	Coefficient of variation.
ε	Unobserved effects.
$beds_t$	Tourist beds over time.
$cVaR(weather)_{1-\alpha}$	Weather-related Conditional Value at Risk given for a probability of α over a given period of time.
$cVaR_{1-\alpha}$	Conditional Value at Risk given for a probability of α over a given period of time.
gdp_t	Income index over time.
$lnWI_t$	Logarithmized and then standardized ($\mu = 0$, $\sigma = 1$) weather index for the respective ski area in the winter season t.
$nights_t$	Overnight stays in the winter season t.
$nights_{t-1}$	Overnight stays in the previous winter season $t-1$.
$nights_{t-2}$	Overnight stays in the second-last winter season $t-2$.
pp_t	Relative price index over time.
$snow_t$	Non-standardized weather index for the respective ski area in the winter season t.
tc_t	Transport capacity (TC) over time.
x_t	Weather index at time point t.
y_t	Economic or business indicator at time point t.

Acronyms

S_{mean}	Mean snow depth.
$Sday_1$	Days with snow depth >1cm.
$Sday_{30}$	Days with snow depth >30cm.
$Sday_{AVG}$	Weighted average snow conditions ($Sday_1(alt_{50})$ weighted by μ_{nights}).
$Sday_{cities}$	Average urban snow condition; *cities* might also be replaced by one of the respective cities (Vienna, Graz, Linz, Salzburg, Innsbruck).
T_{mean}	Mean air temperature.
alt_0	Lowest altitudes of ski areas.
alt_{100}	Highest altitudes of ski areas.
alt_{50}	Mean altitudes of ski areas.
ADL	Autoregressive Distributed Lag model.
AR	AutoRegressive model.
ARMAX	AutoRegressive Moving Average model plus eXogenous input.
CC	Cable cars and chair lifts.
cCFaR	conditional Cash Flow at Risk (Expected Shortfall).
CDF	Cumulative Distribution Function.
CFaR	Cash Flow at Risk.
CPI	Consumer Price Index.
cVaR	conditional Value at Risk (Expected Shortfall).
cVaR(weather)	Weather-related conditional Value at Risk.
DL	Drag lifts.
ECM	Error Correction Model.
GDP	Gross Domestic Product.
ME	Moving Estimates process.

OLS	Ordinary Least Squares.
TC	Transport capacity (in Pm/h).
VaR	Value at Risk.
VaR(weather)	Weather-related Value at Risk.

Glossary

Basis risk Basis risk is defined as the risk that the payoffs of a given hedging instrument do not correspond to shortfalls in the underlying exposure. For weather contracts it might typically comprise geographic, product or local basis risks.

Best estimate A best estimate attempts to define one specific point within a range of reasonable estimates. A reasonable estimate is defined simply as an estimate based on reasonable assumptions and methods (Blum and Otto 1998). However, in this thesis the term *best estimate* does not refer to statistical efficiency, where it is applied to unbiased estimates which have a minimum variance.

Catastrophic risks Catastrophic risks relate to losses caused by weather events such as floods, drought, storms and hail. They have a small chance of occurring but might cause huge monetary losses.

Climate Climate is usually defined as the "average weather", or more rigorously, as the statistical description of the weather in terms of the mean and variability of relevant quantities over periods of several decades (typically three decades as defined by WMO). These quantities are most often surface variables such as temperature, precipitation, and wind, but in a wider sense the "climate" is the description of the state of the climate system (IPCC 2005).

Climate change Climate change as referred to in the observational record of climate occurs because of internal changes within the climate system or in the interaction between its components, or because of changes in external forcing either for natural reasons or because of human activities. It is generally not possible clearly to make attribution between these causes. Projections of future climate change reported by IPCC generally consider only the influence on climate of anthropogenic increases in greenhouse gases and other human-related factors (IPCC 2005).

Climate variability Climate variability refers to variations in the mean state and other statistics (such as standard deviations, the occurrence of extremes, etc.) of the climate on all spatial and temporal scales beyond that of individual weather events. Variability may be due to natural internal processes within the climate system (internal variability), or to variations in natural or anthropogenic external forcing (external variability). (IPCC 2005).

Extreme weather events Signifies individual weather events that are unusual in their occurrence (minimally, the event must lie in the upper or lower tenth percentile of the distribution) or have destructive potential, such as hurricanes and tornadoes (NAP 2008).

Non-catastrophic risks Non-catastrophic risks describe the financial exposure that a business may endure after weather events such as heat, cold, snow, rain and/or wind. They occur quite commonly and cause generally comparatively small losses.

Transport capacity The transport capacity (TC), measured in *person altitude meters per hour* (Pm/h), refers to the maximum number of persons, which can be transported within one hour, multiplied by the altitude difference of the transport facility. Note, that while the transport capacity is helpful for comparing the size of ski areas, it does not indicate the actual capacity utilization of the ski areas.

Weather Condition of the atmosphere at a particular place and time measured in terms of wind, temperature, humidity, atmospheric pressure, cloudiness, and precipitation. In most places, weather can change from hour to hour, from day to day, and from season to season (NAP 2008).

Weather risk The risk that unfavourable weather conditions lead to economic damage, e.g. adverse financial results for companies. It comprises both the probability that unfavourable weather conditions occur and the resulting economic impacts.

1 Introduction

Sometimes it can be confusing to follow reports on climate and winter tourism in Austria. On December 13th 2006, the public broadcasting company featured on its online news service the headline: 'OECD-study: Climate change threatens ski tourism (ORF 2006)'. This headline referred to the finding of Abegg et al. (2007) that with a 2 °C increase in temperature, snow reliability will not be given any more in half of Austrian ski areas[1]. Six months later and after a winter season with extremely poor snow conditions the release of tourism data showed record sales for this season and only a marginal decrease in overnight stays[2]. Consequently, the ministry for tourism affairs (BMWFJ 2007) announced with relief that even a relatively snowless winter season could not substantially affect the industry any more.

So what causes these seemingly contradicting perceptions on the impact of weather and climate on the winter tourism industry? As it will be shown in this thesis, they result from several factors (different time horizons, consideration of snow making etc.). Most importantly, they seem to occur because the focus is on interpreting either the change in the climate, or the change in the respective economic demand indicator. However, in order to truly understand the impact of weather and climate variability on tourism, the relationship between the two needs to be examined. This thesis is fully dedicated to this issue. In order to do so, three priorities have been set, leaving out a range of other potentially interesting research issues:

Priority 1: Climate ⇒ Tourism In general, both economic and climatic issues are of particular relevance in the context of tourism. In both cases, it is a two way relationship, as will in the following briefly be explained on a series of examples. While it needs to emphasized that it would be worth studying all of these relationships (Tourism ⇒ Economy, Economy ⇒ Tourism, Tourism ⇒ Climate, Climate ⇒ Tourism) in more detail, this thesis focuses on the latter one.

Tourism ⇒ Economy: Winter tourism has — in contrast to summer tourism — grown over the past decades and so has its importance for the Austrian economy. Laimer, Ostertag and Smeral (2009) estimate that in 2008 altogether 21.6 billion € in direct and indirect value added (7.7 % of the GDP) resulted from tourism activity. Supposedly more than a third of this can be attributed to activities in one of the 345 municipalities

[1] see Subsection 2.2.2
[2] see Subsection 3.3.3

with major ski areas in the winter season[3]. For example, within the financial year 2009, the 254 Austrian cable car enterprises altogether invested 550 million €, whereof 163 million € (30 %) were spent on new and upgraded snowmaking infrastructure. The remaining 387 million € were invested into the improvement of comfort and security, the (re)construction of transport facilities, the construction of slopes, etc. (Austrian Cable Cars 2009).

Economy ⇒ Tourism: On the other hand, tourism is heavily influenced by economic developments in the origin countries of guests and Austria as well[4]. Take, for example, the impacts of the latest world financial and economic crisis on tourism. While some short-term effects could been observed in recent years, less for overnight stays, but more visibly for turnovers, additional effects are expected in the longer term: Owing to the crisis, necessary investments are delayed or not carried out, which might deteriorate service quality. Tight consumer budgets are first spent on necessary consumer goods and governments need to reduce the huge debt burden accumulated by cutting public spending and increasing taxes, which in turn affects consumers expenditure (Smeral 2009*a*, p 37).

Tourism ⇒ Climate: Beside manifold other environmental and social problems related to tourism, winter tourism does significantly contribute to climate change. While its total contribution is hard to estimate due to its cross-sectoral nature and the accounting of international travel flows, there can be generally little doubt that current business models in the industry are highly carbon intensive. Problem areas range from travel, where increased efforts to attract travellers from emerging but long-haul markets automatically lead to higher emissions, to accommodation, where many hotel's swimming pools are still heated by using tens of thousands of litres of oil per year, to skiing, where energy is used for preparing ski runs, snowmaking and and the uphill transport of skiers[5]. However, there do indeed appear to be blue skies on the horizon, including initiatives to lower the carbon footprint of the Austrian tourism industry[6], or to name one specific example, the case of a British internet platform which offers rail inclusive ski packages to Austrian ski areas to facilitate high speed train travel[7].

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[3]see Subsection 3.3.3

[4]see Subsection 3.3.4

[5]For example, considering a bandwidth of 5 000 to 27 000 kWh/ha/a of electricity use for snowmaking (Teich et al. 2007, p 94), the same amount of electricity is needed for a hectare of ski slope as for 1-5 average Austrian households. With currently more than 13 000 hectare of ski runs being equipped with snowmaking equipment, this approximately equals 0.4 % to 2.0 % of annual household electricity consumption. These figures are for illustrative purposes only and call for more systematic examinations of the tourism industry's share in energy use and greenhouse gas emissions.

[6]For example, consider activities which are conducted within the framework of the Austrian climate protection initiative klima:aktiv (http://www.klimaaktiv.at/article/archive/11906/).

[7]For example, http://www.snowcarbon.co.uk offers return tickets from London to St. Anton and with changes in Paris and Zuerich for 220 € and the journey takes 12:35 h only. Coming from the other direction but travelling the same distance, a train journey from Sofia to Nassfeld/Hermagor with changes in Belgrade and Villach would cost marginally less, but take 22:46 h.

CLIMATE ⇒ TOURISM: As early as in the 1960s, researchers have begun to study the influence of weather on recreation activities like skiing on the local scale (Scott, Wall and McBoyle 2005). In recent decades, research efforts on the relationship between winter tourism and climate have been increasingly intensified, fuelled by emerging concerns over the impacts of global warming on the industry as well as several winters with adverse snow conditions in the European Alps in the early 1990s. This thesis builds on these research efforts, which are discussed in more detail in Chapter 2, but distinguishes itself from the vast majority of studies for the skiing industry for two reasons: Firstly, it looks into the statistical relationship between weather conditions and tourism demand, and secondly, the main emphasis is on measuring short-term weather risks rather than on the impacts of long-term climate change. This leads to the second priority.

Priority 2: Weather Risk > Climate Change This second priority on weather risks goes in line with the observation that while a lot of attention has been on the impacts of climate variability and change on snow conditions in ski areas, including snow making as a technical adaptation strategy in recent years, little attention has been paid to quantifying past demand changes due to weather variability. In other words, while main attention has been on studying the past and likely future length of the ski season, less is known on how much is currently at risk from a period of adverse weather conditions, in particular for individual stakeholders in the industry, but also on an aggregate level. So far, consequences for the industry can only be deduced from media reports, interviews with stakeholders or changes in demand indicators, but a systematic examination of weather risk has not yet been provided. However, this would be absolutely necessary in order to plan and adopt strategies to deal with these risks.

Examining weather risks raises a series of questions, which are introduced using a historic and wide-known example for the retail trade. Basically, the weather sensitivity of an enterprise or an industry can be examined by a correlation or regression approach. For example, such an approach can be applied to relate the sales of winter coats in department stores in New York to the average monthly temperature in September and October, as Linden (1962) already did half a century ago and many more did after him for various other examinations[8].

However, there might be substantial methodological problems with such an approach, most notably a phenomenon widely known as spurious correlation or regression problem,

[8] This example has been cited in Maunder and Ausubel (1985) and illustrates that the interaction between revenues and weather has been of interest since more than 50 years. However, it is probably not the earliest work that should be considered. To name another example for how long climate impacts have been studied, Maunder and Ausubel (1985) indicate results from an early climate impact assessment conducted by the US department of transportation (CIAP 1975). This study gives estimates of economic impacts of a hypothetical global climatic change and finds overwhelmingly negative impacts, namely for 14 out of 18 subcategories examined. Interestingly, these results are projected for a −1 °C change in global temperature.

and it needs to be dealt with them accordingly[9]. Furthermore, indicating the economic impact of a one unit change in the respective weather index, which tends to be the final step of an analysis, is only one side of the coin. The other side is the probability of occurrence, or in other words for the beforementioned example, the likelihood that the temperature in September and October is above a certain level. Even if a 1 °C change in temperature would have the same impact for a department store in New York, Vienna and Tokyo, temperature variability might be different in these cities and so are the risks from adverse weather conditions faced by the department stores. Therefore, two questions have to be investigated simultaneously when examining weather risk, namely[10]:

- *How likely do adverse weather conditions occur?*
- *What is at risk from the occurrence of adverse weather conditions?*

In this context, a series of other questions needs to be addressed. Related to the likelihood that adverse weather conditions occur, it might be asked whether there is any evidence that it differs from previous experience, e. g. due to an observed increase in temperature caused by global warming. Related to the impacts of adverse weather conditions, the relative importance of the examined economic indicator also needs to be considered. For example, a department store's resilience towards weather risk depends on whether it is solely specialised on winter coats or offers a wider range of products. In addition, the economic and financial impacts of weather need to be studied in the context of other risk factors. For example, it can be asked how likely adverse results may cause financial distress or eventually even lead to bankruptcy.

This thesis takes into account these questions on weather risks in the context of winter tourism, which can be seen in the research objectives defined below and in more detail in Subsection 3.1.4. Above all, the interest is on identifying weather risks by means of statistical methods and to report them using a single risk measure. This leads to the third priority.

Priority 3: Risk Identification and Measurement > Risk Mitigation This third priority refers to the aim of this thesis to provide and discuss a probabilistic risk measure which allows comparability between weather risks faced by different stakeholders, regions or originating from different exposures. Due to the nature of weather risks in the tourism industry, the risk measure provided intends to capture non-catastrophic risks. However, it is similar to interpret to those commonly given for catastrophic events, even if the method for calculating it might differentiate[11]. For example, an event with a probability of occurrence of 5 % can be reported as a *1 in 20 year event*. Referring to the financial literature and under several assumptions discussed in Subsection 3.1.3, the monetary

[9] see Section 2.6
[10] see Section 3.1
[11] see Subsection 3.1.1

loss from such an event can also be denoted as Value at Risk from adverse weather conditions or $\text{VaR(weather)}_{0.95}$. Of course, the quality of the weather risk estimate for a certain period provided by such an approach fundamentally depends on how well the statistical assumptions behind such a risk measure are fulfilled[12].

From a risk management point of view, this thesis primarily focuses on identifying and measuring weather risks, which are considered to be the first two steps in a continuous risk management cycle. However, these first two steps provide an important precondition for further steps, namely for finding appropriate risk mitigation strategies (step 3), and for reviewing and monitoring these strategies (step 4). Correspondingly, results from the risk assessment for the winter tourism industry conducted in this thesis are supposed to provide valuable insights for designing weather risk mitigation strategies, for example hedging weather risks by the heavily discussed financial instrument of weather derivatives[13].

Objectives Altogether, based on these three priorities, the following objectives have been set in this thesis. The *primary objective* is to develop a methodological framework for assessing non-catastrophic weather risk and apply it on the winter tourism industry in Austria. Key steps for achieving this objective are an econometric modelling of the relationship between snow indices and demand indicators as well as a modelling of the distribution of the respective indices. In order to meet the challenge that stakeholders in the industry are typically organized on a sub-regional scale and that weather exposure can differ from valley to valley or municipality to municipality, modelling is conducted at the local scale. *Secondary objectives* include

- analysing changes of weather risk over time, which either occur because of changes in the probability of adverse weather conditions, or because of changes in the sensitivity of demand indicators to weather conditions;
- examining the interrelationship of weather risk and other risk factors in the tourism industry, e. g. by comparing weather risk indicators to key financial indicators in the accommodation industry;
- assessing the economic implications both at the local scale and for the entire industry.

Structure The remainder of this thesis is organized as follows. In Chapter 2 I review the literature on the climate-tourism interaction and compare different approaches which have been used to quantify the relationship between weather and economic or business indicators. In Chapter 3 follows an introduction into the methodological framework for

[12]see Subsection 4.3.1
[13]see Chapter 6

assessing weather risks and a description of the data which is necessary to apply this framework to the winter tourism industry in Austria. In Chapter 4 I give full detail on the modelling approach to apply the presented methodological framework on the empirical data. Chapter 5 presents results for individual ski areas as well as on the aggregate level (provinces, altitude and size categories), analyses time varying effects, gives *best estimates* of current weather risk and relates these to other risk factors in the accommodation industry. In Chapter 6 I outline the impacts of a relatively snowless and warm winter on winter tourism in general as well as other industries and discuss different strategies for mitigating weather risks in winter tourism. Finally, Chapter 7 summarizes and concludes this thesis.

2 Literature Review

In this chapter I will review the literature on the climate-tourism relationship and compare different quantification approaches. This requires the coverage of studies from a broad range of disciplines and methodological backgrounds. I start with a short remark on the terminology used (Section 2.1). After briefly presenting the findings from tourism climatology on how climate interacts with tourism activities and especially climate change affects winter tourism (Section 2.2), I will then focus on how the relationship between climate and tourism demand has been quantified in the literature. While the research topic *climate and tourism* in general is dominated by geographers, the latter issue has also been covered by researchers with an astonishing variety of backgrounds, including statisticians, mathematicians, sociologists and economists. Since modelling the impacts of weather variability on tourism demand is pivotal in this work, I will not only consider the methodological approaches used in the climate-oriented literature (Section 2.3), but also review economic studies dealing with tourism and energy demand modelling (Section 2.4) and discuss experiences from the weather risk industry (Section 2.5). I will conclude the chapter summarizing the model specifications presented in the literature (Section 2.6).

2.1 A Note on Terminology

Before reviewing the impacts of climate/weather on tourism, a short remark on the terminology used in this thesis is necessary. Please note that definitions of *emphasized* key terms can also be found in the glossary at the beginning of this document.

To begin with, a differentiation between *weather* and *climate* is quite straightforward from a climatological point of view:

> The difference between weather and climate is a measure of time. Weather is what conditions of the atmosphere are over a short period of time, and climate is how the atmosphere "behaves" over relatively long periods of time. Weather can change from minute-to-minute, hour-to-hour, day-to-day, and season-to-season. Climate, however, is the average of weather over time and space. An easy way to remember the difference is that climate is what you expect, like a very hot summer, and weather is what you get, like a hot day with thunderstorms (NASA 2005).

Based on this definition, this thesis generally focuses on the impacts of *weather* on tourism, as the primary objective is to estimate the impacts of seasonal variations in snow conditions rather than the impacts of long-term changes in climate conditions. However, if appropriate, I will also refer to the more general term *climate*. For example, the term *short-term climate variability* is used more commonly in the literature than the term *weather variability*, and while *climate variability* usually denotes variation over longer time scales, it is sometimes used synonymously for *short-term climate variability* as well, if the meaning is clear from the context. Therefore, I will also speak about *weather and (short-term) climate variability* interchangeably, while I consistently refer to *climate change*, when discussing long-term changes in climate conditions.

A bundle of terms is used to describe risks resulting from exposure to weather and climate conditions: *Weather risk* (810 000 google hits[1]), weather related risk (168 000), climate risk (510 000), climatic risk (35 000), climate related risk (108 000), climate change risk (4 060 000) and climate change related risk (65 000). Thereby the distinction between weather risk and climate risk is quite heterogeneous. Especially the term climate/climatic risk is used both as a synonym of weather risks and climate change risks[2]. The latter interpretation of climate risks sometimes also includes risks which go beyond direct physical risks from climate change, such as regulatory risks, supply chain risks, product and technology risks, litigation risks and reputational risks[3]. Moreover, an understanding of the term climate/climatic/weather risk might rather focus on the probability that unfavourable weather/climate conditions occur, or on the resulting economic impacts (damage, adverse financial results). I will discuss both aspects of risk in more detail in Subsection 3.1.1.

Another differentiation is necessary between *catastrophic risks* and *non-catastrophic risks*. *Catastrophic risks* relate to losses caused by weather events such as floods, drought, storms and hail. They are unlikely to occur but might cause huge monetary losses. The term *non-catastrophic risks* describes the financial exposure that a business may endure after weather events such as heat, cold, snow, rain and/or wind. They occur quite commonly, generally cause comparatively small losses, and only for so-called weather-sensitive companies (Clemmons and Radulski 2002). However, it must be emphasized that non-catastrophic risks might be also considered to be *extreme weather events*, e. g. in form of an unusually snow-poor winter season.

Furthermore, in conformity with other authors (Bigano et al. 2005; Dawson, Scott and McBoyle 2009; Shih, Nicholls and Holecek 2009) I will classify studies in *supply side studies* and *demand side studies*. Thereby *supply side studies* for one or several study areas deal with the 'physical conditions that make tourism possible in these areas for a certain activity, that is the supply of tourism services for a specific market segment'

[1] Google search conducted on 12/01/2011. It is important to note that this is only a rough estimation.

[2] This leads me to avoid the term climate or climatic risk. Instead I use, dependent on the context, either *weather risk* or climate change risk.

[3] For a more detailed discussion of the different risk categories see Lash and Wellington (2007).

(Bigano et al. 2005). In contrast, *demand side studies* focus on the question how the demand in a specific market segment is influenced by climate variability. In these studies, statistical models are usually estimated to explain variations in some kind of tourism data, with climate indices being used as the only or one of several explanatory variables. While I turn attention on *supply side studies* in Section 2.2, I will then focus on *demand side studies* in Section 2.3 to Section 2.6.

2.2 Supply Side Studies

2.2.1 Climate and Tourism

Both economic and other factors, like cultural and natural environmental factors, influence where tourism is located. Climate is one of the natural environmental factors (amongst geology, hydrology, soil, topography, natural vegetation) and is a basic resource for various activities, like winter sports, water sports, sun and beach tourism and health tourism. For these activities, climate is often the main resource upon which a whole series of activities designed to satisfy tourism demand depends. Especially skiing activities depend directly on climatic resources, as without snow or low temperatures for the artificial production of snow, the development of ski areas would not have been possible. Elsewhere, however, climate merely complements other basic resources, because it does not directly generate tourism, but rather facilitates its development if weather conditions are favorable for certain outdoor tourist or recreational activities, e. g. hiking, climbing or golf. (Gomez-Martin 2005)

For the skiing industry it is important to note that, while snow conditions are an important prerequisite for facilities to remain open, other climate elements also determine the number of visitors to ski areas. Wind chill and related cold stress might discomfort skiers, and on stormy days facilities might be partly or completely closed. Fog is also unfavorable, as it decreases visibility. Furthermore, as Balazik (2001) stresses, rainfall is judged to be a significant deterrent and snowfall can also inhibit visibility and, depending on how much is falling, even block roadways. In contrast, while sunshine is not necessary to support a ski day, even moderate levels increase satisfaction amongst skiers. All in all, it can be said that climate as it influences tourism is a set of interrelated elements.

In order to deal with the multifaceted nature and the complex ways in which weather variables are intertwined, a series of researchers in the fields of tourism climatology and human biometeorology have developed indices which integrate the various facets of climate and weather. One recent example, where one single index is constructed to deal holistically with all the essential facets of tourism climate, is the Climate Index for Tourism (CIT) by de Freitas, Scott and McBoyle (2008). A similar approach, which combines the thermal conditions with physical elements (rain, wind) and aesthetic factors (clouds, sunshine, visibility), is used by Matzarakis, Koch and Rudel (2007) for examining the climatic potential for summer tourism in Austria.

However, as it can be seen in the following sections, empirical studies investigating the impacts of climate variability on tourism are mostly limited to one or several climate elements, without constructing more complex indices. The reasons for this are probably either the believe of researchers that they capture the most important climate elements anyway, or simply data availability. Supposedly, in many cases data needed for index construction can not be sufficiently provided for all the climate elements, the specific research area location and the considered time period and frequency. In addition it needs to be stressed that even if all the data for index construction were available, an interpretation for single elements (e. g. a 1 °C increase in temperature results in a certain revenue change) might be more intuitive than for 'abstract' indices (e. g. a 1 point change in the index results in a certain revenue change).[4]

2.2.2 Climate Change Impacts on Natural Snow Conditions

In the 1980s a series of researchers started to examine climate change impacts on ski areas, mainly for the United States, Canada and the European Alps, but also for countries like Japan or Australia (see Table 2.1). The principal concern of these studies was to understand the impacts of temperature rise on ski season length and the snow reliability of areas. In the majority of studies a temperature rise of 2-3 °C was assumed, which goes in line with the projections of earlier IPCC reports for the year 2050 (Breiling, Charamza and Skage 1997).

These studies apply some measure of ski season length and then report either its relative climate-induced decline, or the number of ski areas which fall below a certain threshold of operation days and are therefore not snow-reliable any more. For defining snow reliability, the so-called 100 days-rule became popular and was heavily applied. This rule, which was first suggested by Witmer (1986), states that to operate a ski area with profit, snow depth sufficient for skiing (>30cm) should last at least 100 days per season. König and Abegg (1997) concluded that under current climate conditions this rule is matched by most of Swiss ski areas above 1200 m and that this "line of snow-reliability" would rise to a minimum altitude of 1500 m by a warming of 2 °C.

The basic message from this first generation of studies (see Table 2.1[5]) is clear cut and has been widely heard by the public: The ski industry is extremely vulnerable to climate change, the ski season length will decline, the number of snow reliable areas will drop sharply, and particularly lower lying areas will be forced to withdraw from the market. For example, Elsasser and Bürki (2002) conclude for Switzerland that

> Climate change will lead to a new pattern of favoured and disadvantaged

[4] I will cover the choice of appropriate climate elements and indices for my own research question in more detail in Section 3.2.

[5] Note that for the sake of brevity this table only includes a number of internationally well recognised studies, while leaving out a range of other similar examinations, e. g. Kromp-Kolb and Formayer (2001) or Breiling, Charamza and Feilmayer (2008).

Table 2.1: First-generation studies of climate change impacts on ski areas in order of their appearance

Author (Year)	Region	Findings
Harrison et al. (1986)	US - Great Lakes region	Ski season length: −30 % to −40 % (north of Lake Superior) −40 % to −100 % (central Ontario)
Lamothe and Périard Consultants (1988)	Canada - Southern Québec	Skiable days: −50 % to −70 %
Galloway (1988)	Australia - 3 areas	Ski season length: −54 % to −81 %
Lipski and McBoyle (1991)	US - Michigan	Ski season length: −30 % to −100 %
McBoyle and Wall (1992)	Canada - Québec - Lower Laurentian Mountains	Ski season length: −40 % to −89 %
Breiling, Charamza and Skage (1997)	Austria - 48 winter sport districts	Major low elevation areas are at risk; Winter tourism revenue would decline by 10 %
König and Abegg (1997); Elsasser and Bürki (2002)	Switzerland - 230 ski areas	Number of snow reliable areas would drop from 85 % to 63 %(+2 °C) and 44 % (+4 °C)
Breiling and Charamza (1999)	Austria - 48 winter sport districts	Snow depth: −21 % to −53 % (+2 °C)
Fukuskima et al. (2003)	Japan - 61 ski areas	Skier visitation: −30 % to −50 % (+2 to +3 °C)
Abegg et al. (2007)	Austria, France, Germany, Italy, Switzerland -666 ski areas	Number of snow reliable areas would decrease from currently 609 to 500 (+1 °C), 404 (+2 °C), 202 (+4 °C)

> ski tourism regions. If all other influencing factors remain the same, ski tourism will concentrate in the high-altitude areas that are snow-reliable in the future too. "[...] "Ski areas at lower altitudes will withdraw from the market sooner or later because of the lack of snow. The only areas with good prospects will be those with transport facilities that provide access to altitudes higher than 2000 m. The regions at higher altitudes may experience greater demand, prompting a further expansion in quantitative terms.

Similarly, Breiling and Charamza (1999) summarize the economic impacts of a warming for Austrian ski tourism, if factors other than climate remain stable:

> Low altitude ski areas in the neighborhood of cities will disappear first; access to suitable areas will become more difficult and expensive; the number of 1-day visitors will sharply decline." [...] "If warming at high altitudes turns out to be stronger than at low altitudes, the impact of warming might be worse than what we have anticipated in this paper, and even high-altitude areas will have trouble". [...] "However, we cannot say what level of warming is necessary to ruin areas economically. An adaptation with artificial snow making seems - at least partly - possible, but it might not be economically feasible.

Another study by Abegg et al. (2007) applies the 100-days rule for comparing the snow-reliability of ski areas between provinces in Austria, France, Germany, Italy and Switzerland. In this study the natural snow-reliability line is broadly adapted to the variations in the alpine climate regimes. For regions with a more continental climate (Salzburg, Lower and Upper Austria, Styria and Bavaria) the current altitude of the line is defined to be 1050 m, for regions with a Mediterranean influence (Italian provinces, Provence-Alpes-Côte d'Azur and Ticin) it is defined to be 1500 m while for regions with a more Atlantic-maritime climate (Rhône-Alpes, other Swiss and Austrian provinces) it is defined to be 1200 m. The results of this study are presented in Figure 2.1.

In general, there have been more and more concerns about the methodologies used in the first generation of climate change impact studies in recent years. Firstly, local climate conditions are not incorporated in those studies which solely rely on some general altitude criteria for determining snow reliability. Secondly, an important limitation of all of these mentioned studies is the inadequate consideration of snowmaking, which became an integral component of the ski industry and reduces the vulnerability to climate variability (Scott et al. 2006). Thirdly, studies are largely incomparable due to the wide variety of approaches employed and inconsistent methodologies and do not allow to understand the differential vulnerability between local, regional, national, or international ski area marketplaces (Dawson and Scott 2009). I will deal with each of these limitations in more detail in the following subsections.

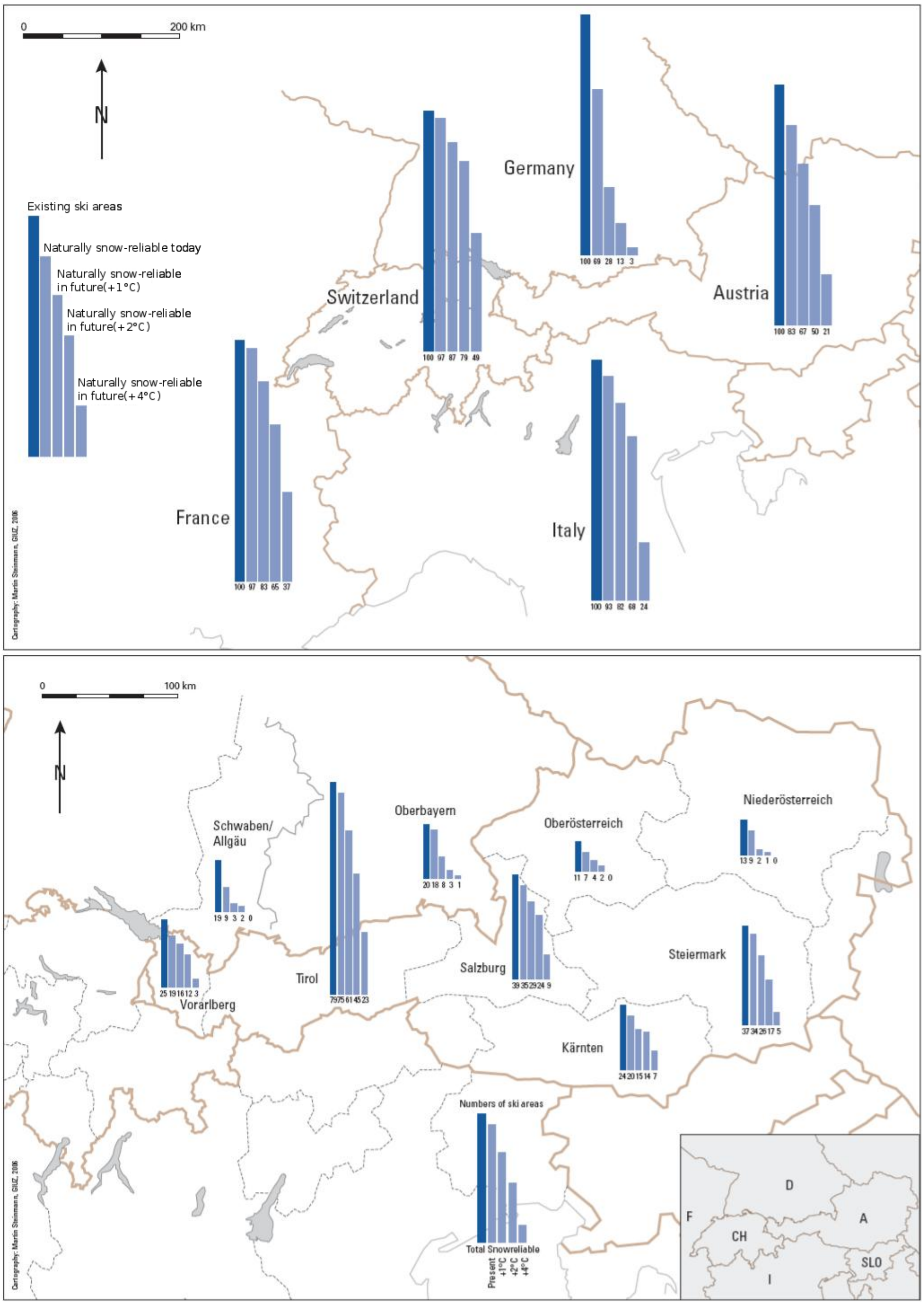

Figure 2.1: Number of naturally snow-reliable ski areas under present and future climate conditions (+1 °C, +2 °C, +4 °C) for Alpine countries (upper plot) and Austrian and German provinces (lower plot); Source: Abegg et al. (2007)

2.2.3 Recent Studies of Local Climate Conditions in Austria

From an Austrian perspective, it has become evident from recent studies that the methodologies used in Breiling and Charamza (1999) and Abegg et al. (2007) underlay too many simplifying assumptions and should be replaced by more detailed examinations of local climate conditions. Although Abegg et al. (2007) admit that they present 'broad patterns and do not account for site specific characteristics' (p. 32), they mention on the next page (p.33) the names of particularly affected areas (Schladming, Kitzbuehel), which caused a stir in the respective municipalities right after the publication of this study.

Proebstl et al. (2008), to name one example, analyse the local climate conditions in the area of Schladming in more detail, which has been identified to be particularly vulnerable before. They find for this area that the narrowness of the valley provides a climate which allows snowmaking at the valley station (750 m) more frequently than above 1000 m and conclude that temperature conditions will allow snowmaking under current technology at least until 2030 (see also Subsection 2.2.4). This example particularly illustrates that it is necessary to understand local conditions before jumping to conclusions from broad patterns.

More generally, the specification of the current altitude of the natural snow-reliability line by Abegg et al. (2007) poorly fits local climate conditions in Austria, as recent climatological examinations of the snow line in Prettenthaler et al. (2009) show. In this study the snow line is derived from the equivalent potential temperature and calculated for the Pre-Christmas season (1.Nov-24.Dec), the main winter months (Dec to Feb) and Easter (Mar to Apr) and is given for the altitudes where on average 50 % and respectively 90 % of the precipitation are snow fall. Figure 2.2 presents the key results from this examination on the example of the 90 % index. It can be summarized that

- there exists a significant north-south differential in all parts of the season, and due to the more continental conditions in eastern Austria, a west-east differential can be observed north of the Alpine main chain;

- the differentials might be more pronounced than assumed in Abegg et al. (2007), especially in the pre-Christmas season (90 %: north 1200 m, west 1500 m, south 1800 m), but also in the main winter months (90 %: north 1100 m, west 1300 m, south 1500 m) and to a less extent around Easter time (90 %: north 1250 m, other 1350 m);

- results vary within provinces (especially those which are divided by the Alpine main chain), which further emphasize the need for considerations on a more local level.

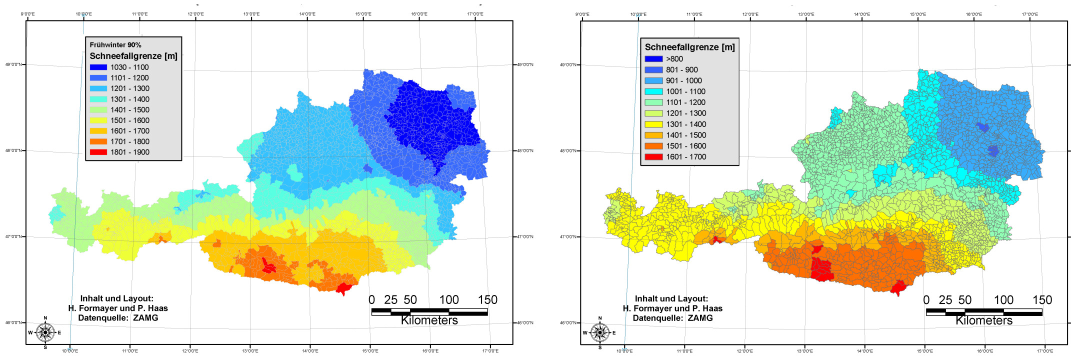

Figure 2.2: Altitudes where at minimum 90 % of the precipitation falls as snow, Left: Pre-Christmas-Season, Right: Winter months, Source: Prettenthaler et al. (2009)

2.2.4 Climate Change Impacts on Snowmaking Conditions

The fundamental weakness of the first generation of studies, namely that they do not incorporate snowmaking, brought up a second generation of studies. These studies use detailed simulation models for assessing the number of skiable days under current and improved snowmaking techonology as well as the impacts of higher temperatures on snowmaking requirements. Table 2.2 shows the main results from these studies.

In general, the message from this second generation of studies is less dramatic compared to impact studies which do not incorporate snowmaking in their assessments. For example, Scott et al. (2006) reassess six locations in eastern North America where previous impact studies had been completed. They find that ski season losses due to climate change expected in the 2050s will not be as severe as projected in earlier studies. According to their study, in the 2020s ski areas will even under the high impact climate change scenario face a very minor risk. Despite this attenuation, the authors of this reassessment are still in accordance with earlier studies that climate change will create winners and losers and in combination with other business factors, such as access to capital, demand trends, energy prices and water supply, it will likely result in a further contraction and consolidation in the ski industry.

Similar works for Austria show that not only the changes in natural snow conditions, but also changes in snow making conditions and their economic implications should be investigated in more detail. Steiger and Mayer (2008) show for Tyrol that even at lower altitudes, snow making might climatically still be possible under a 2 °C warming scenario, but the intensified application will lead to significantly higher operation costs. In this sense Steiger (2009) emphasizes the shift from a climatological towards a more economic research question:

> [...] the snow volumes produced will be rising continuously. Taken into account that energy costs are likely to increase in the next decades, it can

Table 2.2: Second-generation of studies of climate change impacts on ski areas in order of their appearance

Author (Year)	Region	Findings
Scott, McBoyle and Mills (2003)	Canada - Southern Ontario	Number of skiable days in the 2050s: −40 % to −100 % (without snowmaking), −7 % to −32 % (current snowmaking capabilities), −1 % to −21 % (improved snowmaking capabilities)
Hennessy et al. (2003)	Australia - New South Wales and Victoria	Average number of hours suitable for snow-making in 2020s: −2 % to −7 % (low impact scenario) −17 % to −54 % (high impact scenario)
Scott et al. (2006)	Canada, US - Québec, Ontario, Michigan, Vermont	Ski season length in the 2050s: −4 % to −14 % (low impact scenario) −35 % to −62 % (high impact scenario) Snow making requirements in the 2050s: +18 % to +62 % (low impact scenario) +21 % to +161 % (high impact scenario)
Teich et al. (2007)	Switzerland - Graubuenden and Glarus	Ski season length in the 2050s: −4 % to −16 % (low impact scenario) −15 % to −65 % (high impact scenario) Average number of hours suitable for snow-making in the 2050s: −3 %to −27 % (low impact scenario) −21 % to −82 % (high impact scenario)
Steiger and Mayer (2008)	Austria - Tyrol	The line of technical snow reliability is 700 m lower than the line of natural snow reliability. A warming of 2 °C would shift the line of technical snow reliability upwards by 500 to 600 m.

> be assumed that snowmaking costs are likely to rise disproportionately to the rising volumes. The economic limits of snowmaking might be reached (much) earlier than the technological limits [...]

In other words, as Abegg (2009) puts it, interesting research questions to be asked would be: 'Who can afford snowmaking? Who is going to pay the bill? Are snowmaking investments reasonable/cost-efficient?' While these questions are certainly interesting, especially from an economic point of view, they will not be covered further within this thesis for methodological reasons[6]. It should be emphasized though that in contrast to the first-generation of studies, the adaptation strategy of snow making is, among other strategies, implicitly included in the models applied in this thesis, as it influences the sensitivity on natural snow-conditions over time (see Subsection 4.2.5).

2.3 Impacts of Climate Variability on Tourism Demand

In recent years other limitations of these mainstream studies on climate change impacts on the ski industry have been pointed out e. g. by Shih, Nicholls and Holecek (2009) and Dawson, Scott and McBoyle (2009). On the one hand, these studies focus solely on climate, while other key factors influencing tourism demand, such as economic conditions, price levels, the availability of leisure time and changes in consumer behaviour are not considered. On the other hand, they do not look into the relationship between climate conditions and tourism demand. However, this would be absolutely essential as it is supposed that a decline in a climate index like skiing days does not lead to a proportional decline in the number of visitors or overnight stays. Consider for example the most obvious case of those areas which profit from poor snow conditions because of their comparatively snow reliable location, while other areas might lose disproportionally.

It is evident that these limitations of supply side studies can only be overcome by detailed demand analysis. In this section of the literature review I will therefore put attention on various approaches to quantify the impacts of climate variability on tourism demand. I will start with studies focussing on destination choice which incorporate climate regularly in form of average conditions. I will then turn to studies which concentrate more on of the temporal variability of climate and its impacts on tourism demand, applying either an analogue or regression approach. Being aware that not only climate impact researchers, but also a broad research community in the fields of both tourism

[6] As is evident, answering these research questions requires another methodological approach than the one further outlined in this thesis, namely a detailed cost benefits analysis of snowmaking investments. In order to conduct such an analysis, an understanding of the financing of these investments, the interaction between operating costs and climate conditions and the potential shifting of costs to customers is necessary. These research questions are expected to be discussed further in a research project (CC-Snow II) funded under the second call of the Austrian Climate Research Program (ACRP) by a team of climatologists and economists led by Prof. Ulrich Strasser.

and energy demand modelling and forecasting have carried out demand analyses, I will discuss implications from these studies for my own research in Section 2.4[7].

2.3.1 Destination Choice Studies

The *pooled travel cost model* has become popular for quantifying climate-induced changes in the number of trips to particular holiday destinations. Traditionally, travel cost models base on microeconomic theory and the idea of utility maximisation and are widely applied for estimating the recreation demand by taking into account travel costs and accommodation costs. Maddison (2001) adapts this methodology by incorporating climate variables and beach length in the statistical estimation of demand. When climate data is included, this needs to be done with a *pooled model*, because in contrast to travel costs the climate in a specific destination is the same for visitors from all origin countries. Thereby a single demand function is estimated pooling all of the observed visitation rates for the different destinations. From this demand function the trade-offs between climate and holiday expenditure can be analysed and the optimal climate for tourism can be identified[8].

The results from Maddison (2001) show that British tourists are attracted to climates which deviate little from an averaged quarterly daytime maximum of 30.7 °C. According to the author this corresponds to the current climate in the Caribbean. It would imply that Southern European countries like Greece and Spain benefit from higher temperatures, as they experience a lengthening and a flattening of the tourist season. Following this approach, several studies have been carried out. Lise and Tol (2002) find that an average quarterly temperature of about 21 °C is considered ideal for most international tourist. This preference is largely independent of the tourist's origin, but further analysis for Dutch tourists shows that it differs among age and income groups. Similarly, Hamilton (2003) uses monthly survey data on the destination choices of German tourists and estimates the optimal temperature for German tourists to be at 24 °C.

However, Hamilton, Maddison and Tol (2005) argue that the travel cost method might be unsuitable for a complete analysis of the effect of climate change on demand patterns. The absence of substitute site qualities and prices in such models makes it impossible

[7] Another related methodological approach, which I will not discuss in more detail, are survey-based studies, e. g. for Australia (König 1998), Switzerland (Behringer, Buerki and Fuhrer 2000), Canada (Dawson, Scott and McBoyle 2009) or Austria (Unbehaun, Proebstl and Haider 2008). All of these studies survey climate change impacts on destination choice, to estimate shifts in customer demand for winter sport activities. For example the survey by Unbehaun, Proebstl and Haider (2008) among 540 skiers from Vienna reveal a strong preference for destination attributes promising sufficient (natural) snow conditions. In snow-poor winters, areas in higher altitudes gain importance and travel distances lose some relevance. Furthermore this study shows that snow independent substitutes are accepted as a short time compensation but not for the whole winter holiday.

[8] The optimal temperature can be calculated in that the temperature is included into the regression equation both as a linear and quadratic term

to investigate the effects at more than one site and this limits their explanatory power, as climate change will not only affect one single country. Therefore the authors develop a *simulation model of international tourism* using basic data on departures and arrivals for 207 countries in the year 1995 and expand this model for changes in population, per capita income and climate. They find that in the medium to long term 'the change from climate change is smaller than from population and income changes'.

In a further simulation study Bigano, Hamilton and Tol (2006) investigate several influencing factors on holiday destination choice for tourists from 45 countries. They find that tourists are deterred by long traveling distances, political instability and poverty, while they are attracted to coasts and sunny yet mild climates. The optimal holiday destination has an average annual temperature of $16.2 \pm 1\,^{\circ}\mathrm{C}$, which corresponds to the current level in Mediterranean countries.[9] This indicates that the preferred holiday climate is rather the same for all tourists, independent of climate conditions in their home countries. However, concluding from the squared temperature, the authors find that people from warmer climates have more pronounced preferences, meaning that they are more sensitive to temperature.

In general it can be stated that whilst these destination choice studies are certainly fruitful for explaining changes in global demand patterns, they need to be supplemented by more detailed demand studies, because their current focus is solely on:

Cross-sectional data The time series characteristics are currently not exploited in these global studies, mostly because data is given for a single or only a few observations. If several years are available, e. g. in Lise and Tol (2002), data is still pooled together and treated as cross-section data.

National average climate Variations in regional climate condition are not taken into account in these studies. The broad range of conditions faced in many popular destinations such as Thailand, Italy, Spain or the US shows that this is a limitation for deriving national implications from these studies. In addition, climate is considered as average values (annual, quarterly, monthly). Climate variability and extremes are therefore not observed.

Temperature While some studies also include precipitation, the main focus is certainly on temperature, leaving out other climate elements potentially interesting for tourism, such as snow, wind or cloud cover.

Summer tourism Studies do not separately deal with tourism and recreational activities in winter months, which might be encouraged by cold temperatures, most notably skiing.

[9] It should be noted that according to the authors, results are not directly comparable to the earlier study by Lise and Tol (2002), as this study includes more origin and destination countries and data is aggregated on the annual level.

These limitations faced by destination choice studies on a more global level have been overcome by a series of approaches on the national, regional or local level, which are discussed in the subsequent subsections. In general, focussing on a particular country, region or case study area reduces the possibility to find general demand patterns. However, this is usually compensated by that better data availability allows in-depth analyses of the specific impacts of climate conditions on tourism demand for a certain market segment. These analyses rather focus on time series than on cross-sectional data. Hence all of the studies reviewed in the subsequent subsections deal in some form with the temporal evolution of the observed climate and tourism data.

2.3.2 The Analogue Approach

The so-called analogue approach takes an exceptional position among demand side studies for that it rather considers climate change analogue years instead of examining dependency structures between climate and tourism demand by some form of regression analysis. It has been applied in various fields of climate research, including impact assessments for the extreme warm and dry summer 1995 over a range of economic and social sectors (tourism, health, water supply etc.) in the UK (Giles and Perry 1998; Subak et al. 2000), and for several warm winters on the ski industry in Eastern North America (Scott 2005; Dawson, Scott and McBoyle 2009).

In principle, the analogue approach is used to compare diverse supply- and demand-side indicators for the performance of the tourism industry between climatically normal versus anomalous periods. Thereby, the anomalous periods are chosen in a way that they present analogues for normal climate conditions under future climate change conditions. Dawson, Scott and McBoyle (2009), for example, use ski season length, snowmaking conditions, total skier visits and operating profits in the ski industry as performance indicators and compare them between the winter seasons 2001/02 and 1998/99 (4.4 °C and 2.7 °C respectively above 1961-1990 average), and the climatically normal seasons 2000/01 and 2004/05. The major findings of this study are basically that reductions in the experienced season length, visits and profits differ dependent on ski area size and altitude. Interestingly, the authors also find that in recent years 'adaptations by ski businesses appear to have reduced the impacts of warm winters, as reductions in season length in the climate change analogue years were consistently lower than those projected in modelling-based studies' (see Subsection 2.2.4).

All in all, the analogue approach helps to overcome the major limitations of the supply-side studies, in that it examines how changes in physical indicators will affect demand patterns. Another key advantage is also that it captures the full range of both supply- and demand-side adaptations by the industry. However, limitations of the analogue approach include the possibility that no analogue situations can be found (like for the climate conditions in the second half of the 21st century) and its inability to consider other influencing conditions, such as changes in technology, behavioural responses, demographics and energy prices (Dawson, Scott and McBoyle 2009).

In addition, the selection of analogue years by climatological reasons might lead to the ignorance of trends in the tourism data. Although normal and analogue years are selected as close as possible, a non-inclusion of the time series characteristics of the underlying data might bias results to a great extent. Imagine for example the case of a region where the number of visitors decline continuously. The results of an analogue approach would differ dependent on whether a climatically normal year before or after the analogue year is chosen . Hence, it seems to be a good idea to supplement analogue analyses with more commonly applied times series and regression techniques.

2.3.3 Time Series and Regression Approaches

Several studies have been published which examine the relationship between weather and tourism demand indicators using time series and regression approaches. Most commonly, static regression models are applied for this, but also a range of alternatives have been presented in the literature. Table 2.3 gives an overview on respective studies for the ski industry and some further studies with noteworthy methodological contributions. While this subsection gives a summary on the dependent and explanatory variables and the results of these studies, a more technical discussion of the model specifications is presented in Section 2.6.

Generally, a distinction can be made between studies with a high temporal (daily, weekly) and spatial (local,regional) resolution, and studies using more aggregate spatial (provincial, national) and temporal (monthly, seasonal, annual) data. While the former studies directly assess visitor number or ticket sales and have more observations at hand, which gives more flexibility in the model choice, they are usually conducted for shorter time periods and only on the case study level, which does not allow conclusions on general demand patterns.

As can be seen in Table 2.3, skiing-specific studies on the local scale have currently been conducted for three US regions[10], using three different methodologies. All of these studies find some clear relationship between snow conditions (snow depth or snow fall) and the economic performance indicators. Notably, Hamilton, Brown and Keim (2007) also find evidence for the so called *backyard hypothesis*, namely that not only mountain snow conditions affect visitor numbers, but also snow conditions in surrounding urban areas[11].

[10]These three studies are Hamilton, Brown and Keim (2007); Shih, Nicholls and Holecek (2009); Englin and Moeltner (2004). Some other non-peer reviewed studies might have been conducted for other US and European regions, however to my knowledge, attempts of other researchers in the field have been of explorative nature so far. For example Shih, Nicholls and Holecek (2009) even claim to be the first to examine the relationship between skier attendance and weather conditions.

[11]Both examined areas in New England were within driving distance for day trippers from Boston (161 and 225 km).

Table 2.3: Time series and regression studies in order of their appearance

Author (Year)	Regions	Time series length and frequency	Dependent variable	Climate variables	Other variables	Methods
Meyer and Dewar (1999)	New Zealand 1 National Park visitor center	1095 days (1993-1995)	visitors	rainfall	day of the week, month, year	Dynamic linear regression, Transfer
Englin and Moeltner (2004)	US – Nevada 13 ski areas	25 weeks (1997-1998)	no. of trips (sample of 131 college students)	temperature, new snow	costs, snow-boarder, gender, age, income, slope size, holiday	Poisson, Negativ binomial
Bigano et al. (2005)	Italy 20 provinces	144 months (1983-1989, 1990-1995)	bed-nights, tourist arrivals	temperature, rainfall, sunshine	time trend, lagged dependent variable	ADL, Panel data (OLS, fixed effects)
Agnew and Palutikof (2006)	United Kingdom	domestic: 192 months (1980-1996) interna-tional: 16 years (1972-1996)	international: number of outward trips domestic: overnight stays	temperature, rainfall, sunshine	GDP, consumer prices, UK retail prices, exchange rates	ADL, Static regression (trend adjusted)
Hamilton, Brown and Keim (2007)	US – New England 2 ski areas	870/1030 days (area 1: 1997-2006/ area 2: 1999-2006)	skier attendance	snow depth, snow fall, temperature	day of the week, night time skiing	ARMAX time series model
Shih, Nicholls and Holecek (2009)	US – Michigan 2 ski areas	peak season: 559/1493 off-peak: 277/352 days (area 1: 1996-2004/ area 2: 1985-2003)	lift ticket sales	temperature, snow depth, snow fall, wind chill	consumer confidence index, holiday, weekend, year	Static regression (trend adjusted)
Bark, Colby and Dominguez (2009)	US – Arizona 2 ski areas	25 seasons (1982-2006)	visitors	snow depth, season length	-	Static regression

Some other not skiing specific studies have been conducted on the national and provincial scale within the EU project WISE (Weather Impacts on Natural Social and Economic Systems). Agnew and Palutikof (2006) apply time series regression models to look into the impacts of temperature, precipitation and sunshine in the UK on the demand for international and domestic tourism. In their approach models are either trend-adjusted or specified as autoregressive distributed lag (ADL) models and variables are then selected by a stepwise regression analysis. Considering the large number of variables in their model specifications, results seem not to show any clear relationship between UK weather and tourism demand. For outbound tourism, some dependencies on the conditions in the year prior to travel are found (positive for sunshine in July, negative for average annual rainfall). For domestic trips, drier- and warmer-than-average conditions seem to increase same-month domestic trips, but as the authors stress, a change in the direction of the association in subsequent months might indicate that domestic travel is rather inelastic to weather conditions in the UK.

Bigano et al. (2005) also apply the ADL model for tourism demand in Italian regions, and expand the regression models to fixed panel estimations. Their results indicate that temperature is positively correlated with Italian tourism demand in summer, and negatively with tourism demand in alpine regions in winter. The authors suggest that the latter effect may be due to the negative influence of high temperatures on the skiing season.

All in all, it becomes evident that, while there have been several attempts to model the relationship between climate and tourism demand, approaches have been heterogeneous and a comparison of results from different studies is hardly possible so far. However, as most of these studies use standard statistical methods, it seems to be a good idea to look on how these methods are applied in similar but more mature research fields. Doing so, I will give an overview on the experiences from the economic literature on both tourism and energy demand in the following section, which will be helpful for the modelling of weather dependencies in Chapter 4.

2.4 Modelling and Forecasting Tourism and Energy Demand

2.4.1 Tourism Demand

Worldwide tourism demand has increased rapidly in recent decades, and so have research efforts in modelling and forecasting tourism demand. Li, Song and Witt (2005) count 420 studies which have been published in the period 1960 to 2002, and more recent overviews mention more than 200 studies in the period 1990 to 2006 (Song, Witt and Li 2009, p. 13) and 119 studies in the period 2000 to 2006 (Song and Li 2008, p. 210).

In general, these studies predominantly rely on quantitative approaches, applying either non-causal time series models or causal econometric approaches[12].

Time-series models explain a variable with regard to its own past and a random disturbance term. Within the tourism demand forecasting literature the integrated autoregressive moving-average model (ARIMA) proposed by Box and Jenkins (1976) is most popular, with seasonal ARIMA (SARIMA) models being more and more deployed over the last few years. Other extensions include the application of multivariate models as well as the generalized autoregressive conditional heteroskedastic (GARCH) model. (Song and Li 2008, p. 210)

In contrast to time series models, causal econometric approaches identify the relationship between tourism demand and its influencing factors[13]. While some of the older studies rely on static regression models based on ordinary least squares (OLS), a range of modern econometric methods frequently appear in the recent literature. The most common among them are the Autoregressive Distributed Lag (ADL) model, the Error Correction Model (ECM), the Vector Autoregressive (VAR) model, the Time Varying Parameter (TVP) model or combinations of these approaches. In a few recent studies Panel approaches are also considered. Furthermore, system-of equations approaches like the Almost Ideal Demand System (AIDS) model are applied. (Song and Li 2008, p. 210)

Among the studies being reviewed by Song, Witt and Li (2009, p. 27), about two thirds employ annual, 25 % quarterly and less than 10 % monthly data on outbound and more frequently inbound tourism flows. In these studies the most popular measures of tourism demand are tourist arrivals, followed by tourist expenditure and overnight stays in registered accommodation. Most studies are based on aggregate data at the destination level (usually countries), however increasing research interest is on a more disaggregate level, e. g. different market segments.

The explanatory variables, which have the most significant effects on international tourism demand, are origin country income and relative tourism prices. Income is measured either by personal disposable income (PDI), national disposable income (NDI), gross domestic product (GDP), gross national product (GNP) or gross national income (GNI), all in constant prices. Tourism prices are commonly defined as exchange rate adjusted relative prices between the destination and the country of origin. Other variables include tourism prices in alternative destinations, travel costs, marketing expenditure and dummies for on-off events. Also noteworthy, the predominant functional form in tourism demand modelling studies has been double-logarithmic regression[14]. Comparat-

[12] In addition to time-series and econometric models, some forecasting studies also apply a number of new quantitative forecasting methods, such as artificial neural networks (ANNs), the rough set approach, the fuzzy time-series method, or genetic algorithms (GA). For more information about these methods see Song and Li (2008, p. 212).

[13] While I provide a brief summary of the applied models in this section, a more detailed technical illustration will be presented in Section 2.6.

[14] I will further discuss the reasons for this general preference in Section 4.2

ively few studies applied linear models without transformation, and even fewer employed non-linear and semi-log forms. (Song, Witt and Li 2009, p. 28f)

Interestingly, weather is not perceived to have an important impact on tourism flows in this economic demand literature. While tourism geography emphasizes the importance of climate conditions for destination choice, the inclusion of weather indexes is only reported in three economic studies (Jørgensen and Solvoll 1996; Jensen 1998; Goh, Law and Mok 2008). For Norway, Jørgensen and Solvoll (1996) include summer temperature in Norway to explain the demand for inclusive tour charters to other countries. Among other explanatory variables in their model (income level, expectations of income development, inclusive tour charter price level), the number of days with more than 20 °C proves to negatively influence demand. This means that Norwegians prefer (generally milder) destinations abroad, if summer weather conditions are unfavourable in their own country.[15]

More recently, Goh, Law and Mok (2008) include a tourism climate index in their rough set approach to explain variations in tourist arrivals to Hong Kong from the US and the UK. The climate index, originally proposed by Mieczkowski (1985), incorporates daily data on temperature, humidity, sunshine and wind, and is calculated on a monthly base. The authors emphasize that, at least for the examined origin countries, climate has a stronger impact on tourist arrivals than economic factors and should therefore be accounted for in future tourism forecasting. However, it needs to be stressed that the importance of climate in this approach seems to occur from intra-annual rather than inter-annual variability. In other words, Hong Kong's climate might simply be more unfavourable for US and UK citizens in some seasons of the year than in others, but it can be doubted that variations in actual weather conditions discourage long haul travellers.

2.4.2 Energy Demand

A large body of studies also deals with energy demand modelling and forecasting. Beside forecasting efforts, a major concern of these studies is to understand the relationship between demand and its determinants. For example, Dagher (2009, p.11)[16] counts 587 empirical studies in the period 1930 to 2007 which specifically estimate demand elasticities for electricity and natural gas.

Similar to tourism demand studies, the static model framework used in earlier studies has been replaced in these demand studies by more dynamic model specifications. The latter include Partial Adjustment (PA), Distributed Lag (DL) and Error Correction Models (ECM), which can all be seen as variations of the Autoregressive Distributed Lag

[15] Similarly, the study of Jensen (1998), which is not fully available to me, includes weather in the estimation of tourism demand for Denmark, but does not provide more details about relevant weather indices in the abstract.

[16] The reviewed studies were collected by Prof. Caroline Dahl, Colorado School of Mines

(ADL) model (see Section 2.6). While the dependent variable in these studies typically is some measure of energy use (e. g. kWh), the major explanatory variables are akin to those in tourism studies, namely the level of economic activity, the own price of the product and prices of substitute products. Additionally, studies in the literature regularly include variables to consider demographics, case-specific characteristics and weather. (Dagher 2009, p. 23 ff)

Weather is frequently included because it affects the energy use for heating in winter and the use of air-conditioning during the summer, especially in warmer climates[17]. Rather than directly including average temperatures studies transform them into heating degree days (HDD) and cooling degree days (CDD). Altogether, the major dependency of energy sales on weather was one of the major reasons for the emergence of the weather risk market in the recent decade, which will be discussed in the following section.

2.5 Weather Risk Management

Weather derivatives have become a heavily discussed and widely used financial instrument for hedging weather risks since their first application in 1997. According to a survey by PwC (2006), the total notional value of worldwide weather risk contracts was 45.2 billion US dollar in 2005/06. Although no recent market surveys have been published, it can be expected that trades have significantly lowered as a consequence of the global financial and economic crisis of the late 2000s. For example, Freeman (2009) reports that the trade volume in weather futures on the Chicago Mercantile Exchange (CME) has decreased by 54 54 % from January 2008 to January 2009. Still, most of the market volume is supposedly due to the listing of standardized weather products on the CME, where overwhelmingly HDD and CDD indices, but also frost, snowfall and hurricane indices are traded for US, European, Asian and Australian cities. In addition to this standardized trading, there exists a substantial over the counter (OTC) market, where risks are transferred from companies seeking protection to institutionalized sellers of derivatives. In this case, sellers and buyers have to bilaterally arrange contract parameters like the weather station and index, the contract period, the pay-off function and the payment modalities.[18]

[17] Interestingly, Austrian energy supply and demand is also heavily dependent on weather conditions and in addition to the traditional heating effect, a quickly emerging cooling effect can be observed for electricity in recent years. For a more detailed discussion on the impacts of weather on heating and cooling energy demand I would like to refer to some own previous work published in Toeglhofer et al. (2009)

[18] For an introduction to the basic principle of weather derivatives I would like to refer to the books of Dischel (2004); Jewson, Brix and Ziehmann (2005). A German version is also given in my diploma thesis (Toeglhofer 2007)

2.5.1 Valuation and Pricing

Simultaneously with the rise of the weather market, a substantial number of studies on the topic have been published. The majority of these studies deal with the valuation and pricing of temperature based derivatives (e. g. Alaton, Djehiche and Stillberger 2002; Cao and Wei 2004; Benth 2003; Benth and Benth 2005; Benth and Benth 2007; Svec and Stevenson 2007), while only a few studies cover the valuation of derivatives for other weather indices, like precipitation (Berg et al. 2004; Musshoff, Odening and Wei 2005) or wind (Leroy 2004).

In principle, there are three approaches for pricing weather derivatives: Actuarial, marked-based and arbitrage pricing. However, the second and third approach are only possible if there is an observable market, meaning that weather swaps are traded for the same location or some other location with a highly correlated weather index. As this is rarely the case currently, actuarial pricing is the only choice, especially for non-temperature indexes. Thereby, the valuation of single contracts can be done using either the historic values of the index (so called burn analysis) or some non-parametric (e. g. kernel smoothing) or parametric distribution modelling. The latter requires a modelling of either the index distribution itself or, less trivially, the daily observations of the underlying weather index.[19] (Jewson, Brix and Ziehmann 2005, p. 30 ff)

2.5.2 Identification and Quantification

Remarkably, the current literature heavily discusses the pricing and valuation of derivatives, but it rarely covers the often mentioned first step, namely the identification and quantification of the weather risks faced by companies. Even comprehensive books on weather derivatives (Dischel 2004; Jewson, Brix and Ziehmann 2005) give little information. This poor coverage of appropriate methods for risk measurement is seen to be a major limitation:

> [. . .] the value (in monetary units) of one point of a given weather index or the number of standardized contracts or tick value (according to practitioners) represents the fundamental parameter in building appropriate weather cover. If this parameter is too big, a case of over-hedging results and the premium for the cover is too large. This situation quite often gives the impression that weather derivatives are expensive. If the parameter is too small, possible pay-out will not completely cover possible losses. Efficiency of weather derivatives as weather covers can then be perceived as very low. Hence, the success of coming up with the correct hedge in most cases lies in the appropriate evaluation of the weather index point. (Preś 2009*b*, p. 425)

[19] I will discuss the merits and limitations of the different approaches in more details in Section 4.1.

According to Preś (2009*b*, p.433), currently there exist only a few approaches to estimate the tick value. The *best-worst approach*, mentioned by Clemmons and Radulski (2002), compares the weather index in the years with the best and the worst financial results. The *margin coefficient approach* described by Forrest (2002) is based on the average value of historical gross margins divided by historical weather indices. In addition, several uni- and multivariate *regression approaches* are applied (Clemmons and Radulski 2002; Berg et al. 2004; Vedenov and Barnett 2004; Preś 2009*b*). A more technical illustration of all these approaches is given in the following section.

All in all, the reasons for the modest coverage of this methodological issue seem to be plentiful:

1. Sellers of weather derivatives might think that companies themselves know best how dependent they are.

2. Estimating the weather impact requires sensitive business data and the results might also be confidential, therefore data, methods and results are rarely published.

3. In many cases complex price-quantity interactions as well as time-delayed effects make the estimation challenging.

4. From the weather industry's point of view, the application of more 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 risk and this may avert increasing awareness. Indeed, weather risk products have been used by far the most often in the energy sector, where the relationship between weather and the economic performance of companies is clear and well known, and profound statistical methods are already used for demand modelling, including the effects of weather anomalies. Therefore, the subsequent methodological considerations in this thesis might also be helpful for stakeholders in the weather risk management industry (even though they are not specifically targeted).

2.6 Model Specifications in the Literature

In this section I discuss the model specifications which have been used in previous studies to determine weather impacts on economic activities, and, if necessary, complement them by experiences from the tourism demand modelling literature. While the model considerations are very general in this section, they will be explained in more detail using empirical data in Chapter 4.

Note that the following model specifications are adapted to my research question from Song, Witt and Li (2009, p 48), Preś (2009*b*, p 433) and Heij et al. (2004, p 637). To keep things simple, it is assumed that the data is given on an annual basis and that (if not stated otherwise) the impact of one weather index x_t (e. g. snow days, temperature etc.) on one economic variable y_t (e. g. overnight stays, sales etc.) is examined. The *impact* is given as a change in y_t, if the weather x_t changes by one index point. In the case of regression models, the *impact* equals the respective values of the slope coefficients β.

2.6.1 Best-worst, Margin Coefficient and Analogue Approach

To start with, two simple, but intuitive approaches, namely the *best-worst approach* and the *analogue approach*[20] are discussed. Both approaches are similar in that they determine the impact of weather conditions on economic activities by comparing selected years only. However, although both approaches intend to do the same, they might come up with deviating results. This is because

1. the selection is based on different criteria. The *best-worst approach* focuses on the best and the worst financial year, which can be denoted as:

$$Impact = \frac{\Delta y}{\Delta x} = \frac{(y_{BestYear} - y_{WorstYear})}{(x_{BestYear} - x_{WorstYear})} \tag{2.1}$$

   In contrast, the *analogue approach* chooses years with outstanding weather conditions, which are seen to be representative for future climate conditions. This approach can be written as[21]:

$$Impact = \frac{\Delta y}{\Delta x} = \frac{(y_{NormalYear} - y_{AnalogueYear})}{(x_{NormalYear} - x_{AnalogueYear})} \tag{2.2}$$

2. the former approach takes the year with the best results for reference, while the latter compares to average conditions.

Another approach is called *margin coefficient approach*. Instead of selecting years with some notable financial or climatic outcome, the *margin coefficient approach*, captures the observations for one year, but for several cross-sectional units i (e. g. weather sensitive companies) and calculates the average sensitivity of total margins or some other financial variables to the given weather index x_i:

$$Impact = \sum_{i=1}^{n} (grossmargin_i / x_i)/n \tag{2.3}$$

[20]See also Subsection 2.3.2.

[21]Note that for the analogue approach sometimes only the numerator of this equation is used. Then the impact is given as the difference between an analogue and normal year and not as the effect of an one point change in the weather index.

This approach assumes a weather index of zero to equal a total margin of zero and that the relationship between the two variables is proportional. Thus, the omission of a constant variable in this approach might lead to an overestimation of the impact, which can be avoided in a regression approach. (Preś 2010)

Overall, all of these three approaches might be appealing for their simplicity, but there are several limitations to consider, as they

1. only allow to analyse one weather index at once,
2. do not deal with trends or autocorrelation in the data, and
3. do not allow to capture any other influencing factors on the examined economic variable.[22]

Hence, provided that there are enough observations at hand, regression approaches might be preferable, as they allow to deal with these limitations in various ways.

2.6.2 Static Regression Models

Simple static regression models have widely been used in the earlier tourism and energy demand modelling literature and have been regularly chosen for determining the weather impacts on economic indicators, e. g. more recently in Fleischhacker and Formayer (2007) and Bark, Colby and Dominguez (2009). Formally, if the impact of several weather indices x_{pt} on the economic variables y_t are examined, this can be denoted as:

$$y_t = \beta_0 + \sum_{p=1}^{k} \beta_p x_{pt} + \varepsilon_t \tag{2.4}$$

and similarly for one single weather index as:

$$y_t = \beta_0 + \beta_1 x_t + \varepsilon_t \tag{2.5}$$

Although this model is frequently deployed for analysing weather sensitivities, one should be cautious interpreting the results of respective studies, especially if obviously trending parameters are included and standard statistical diagnostic checking is not applied.[23] In general, the error terms in static tourism demand models have been found

[22] On the example of weather impacts on natural gas demand Preś (2009*a*) shows that these approaches might be less efficient for determining the optimum size of weather derivative contracts than simple linear regression approaches, even if none of these mentioned limitations is explicitly considered in the regression. When the author includes trends and seasonal variables in the regression model, its performance further improves.

[23] One obvious example for this approach in the Austrian context is Fleischhacker and Formayer (2007), where the impact of diverse climate parameters on summer 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, which is presumably the case for their data.

to be highly autocorrelated, which indicates that the demand relationships are likely to be spurious and that the standard t- and F-statistics are invalid (Song, Witt and Li 2009, p 48).

In order to correct for trends in the data, a series of studies (e. g. Subak et al. 2000; Lise and Tol 2002; Shih, Nicholls and Holecek 2009) either remove them from the time series and then use the adjusted series in the model, or include trend variables directly into the model. The estimated coefficients remain the same with both procedures (see Wooldridge 2006, p. 369). The inclusion of a linear time trend can be denoted as:

$$y_t = \beta_0 + \beta_1 x_t + \beta_2 trend_t + \varepsilon_t \tag{2.6}$$

However, when working with economic data this approach might still be unsatisfactory, as spurious correlation might still be an issue. The reason for this is that many economic time series remain non-stationary after the elimination of time trend, or in other words they are not *trend-stationary* and require differencing to become stationary[24]. While the econometric literature has extensively discussed methods to detect different types of non-stationarity and to deal with it appropriately, this issue has been left out in the examination of weather sensitivities so far[25].

Differencing of time series is seen as one possible approach to correct for non-stationarity and growth rate models might therefore be preferred to the undifferenced, static model. Formally, the first-differenced model can be written as:

$$\Delta y_t = \beta_0 + \beta_1 \Delta x_t + \varepsilon_t \tag{2.9}$$

Although the growth rate model overcomes the problem of spurious regression, it is rarely employed in the tourism demand literature, as the long-run properties of the

[24]Formally, time series that are trending can be characterized in the simplest case as either *trend stationary*:

$$x_t = \beta_0 + \beta_1 t + \varepsilon_t \tag{2.7}$$

or *difference stationary*:

$$x_t = \gamma + x_{t-1} + \varepsilon_t \tag{2.8}$$

where ε_t is stationary. Equation 2.7 says that the time series x_t is stationary except for a deterministic trend $E(x_t) - \beta_0 + \beta_1 t$ which varies with t. In contrast, Equation 2.8 says that the time series is a random walk with drift. The drift parameter γ in Equation 2.8 plays the same role as the β_1 parameter in Equation 2.7, since both cause x_t to trend upwards over time. A detrending is only valid if Equation 2.7 is true for every time series in a regression. On the other hand, Equation 2.8 requires differencing to obtain a stationary series. Detrending and differencing are two completely different remedies. What is valid for one model is not valid for the other. The choice between the model provided in Equation 2.7 and the model provided in Equation 2.8 is based on a test for the existence of a unit root. (Baltagi 2008, p 365)

[25]Tests for stationarity are conducted in Section 3.4.

economic model are lost due to data differencing (Song, Witt and Li 2009, p.49). Instead, studies frequently apply regression models with lags.

2.6.3 Regression Models with Lags

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 x_{t-i} is called *autoregressive distributed lag (ADL) model* or *autoregressive model with distributed lags*. It extends both the static regression model, which does not include autoregressive terms like y_{t-1} and the general AR model, which does not include explanatory variables like x_t. It is said that in the ADL model the effect of x_t on the dependent variable y_t is distributed over time. (Heij et al. 2004, p 637)

The ADL model is frequently deployed 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 impact of weather conditions on tourism demand (Agnew and Palutikof 2006; Bigano et al. 2005). For k explanatory variables and p lags the ADL model can be denoted as:

$$y_t = \beta_0 + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{k} \sum_{i=0}^{p} \beta_{ji+1} x_{jt-i} + \varepsilon_t \tag{2.10}$$

For the special case of one explanatory variable x_t and lags for only one time period the model can be expressed as:

$$y_t = \beta_0 + \phi_1 y_{t-1} + \beta_1 x_t + \beta_2 x_{t-1} + \varepsilon_t \tag{2.11}$$

In general, the inclusion of lagged dependent 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). Behaviour patterns are expected to be stable over time, 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)

Several special cases of the ADL model can be found in the literature. A *finite distributed lag model* is obtained if the restriction $\phi_1 = 0$ is imposed on the ADL model given in Equation 2.11. The underlying assumption of this model is that the weather in previous periods influences the current level of economic activities[26]. If only one lag of the weather variable is used, the *finite distributed lag model* can formally be denoted as:

[26]This model is e. g. applied in Subak et al. (2000), where lags of the predictor variables for up to 11 months enter the model.

$$y_t = \beta_0 + \beta_1 x_t + \beta_2 x_{t-1} + \varepsilon_t \tag{2.12}$$

Alternatively, if only lags of the dependent variable y_t are included, while restricting $\beta_2 = 0$, the model is called *partial adjustment model*. Formally, the inclusion of an autoregressive term for one time period $t-1$ can be written as:

$$y_t = \beta_0 + \phi_1 y_{t-1} + \beta_1 x_t + \varepsilon_t \tag{2.13}$$

The ADL model can also be rewritten in terms of the first difference of the variables $\Delta y_t = y_t - y_{t-1}$ and $\Delta x_t = x_t - x_{t-1}$, which leads to the so called *error correction model (ECM)*. By reformulating Equation 2.11 in that we subtract y_{t-1} from both sides of the equation, we obtain:

$$\Delta y_t = \beta_0 + (\phi_1 - 1)y_{t-1} + \beta_1 \Delta x_t + (\beta_1 + \beta_2)x_{t-1} + \varepsilon_t \tag{2.14}$$

The ECM appeared in the tourism demand literature in the mid-90s, but had already been applied in many other areas of economics in the mid-80s. The application of the ECM, e. g. when applying it in the Engle and Granger (1987) two-stage cointegration analysis, not only avoids 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.[27] (Song, Witt and Li 2009, p 51)

2.6.4 Further Models

Some other models have been applied in the literature so far for analysing weather impacts on economic activities. On the one hand, some studies focus on modelling *time series of count data* (Meyer and Dewar 1999; Englin and Moeltner 2004; Hamilton, Brown and Keim 2007). All of these studies have in common that they model daily or weekly visitor numbers, which means that they generally have a larger number of observations at hand compared to monthly or seasonal regression models. This gives them more degrees of freedom and supports them in choosing alternative functional forms and probability distributions (see Table 2.3). Note however, that in some cases, as the ARMAX model chosen by Hamilton, Brown and Keim (2007), the model specifications

[27] Note that in addition to the models discussed so far in this section there exist several more econometric models which can be derived from the ADL model given in Equation 2.11, e. g. the leading indicator model ($\beta_0 = \phi_0 = 0$), the common factor model ($\beta_1 = -\beta_0\phi_0$) and the dead start model ($\beta_0 = 0$).

do not significantly deviate from the ADL model presented before. Indeed, the only difference between the ARMAX and the ADL model is the moving average (MA) term.[28]

On the other hand, *panel data approaches* were introduced to the tourism and energy demand literature in recent years. Thereby a range of estimation techniques are applied, like the first-difference Generalized Method of Moments (Diff-GMM) proposed by Arellano and Bond (1991), which is, for example, used in Garin-Munoz (2006)[29]. Comparatively, a more basic model is applied in one weather impact study (Bigano et al. 2005) for estimating temperature impacts on Italian tourism demand, namely a fixed effect model with lags, which extends the ADL model presented in Equation 2.11. We can denote this model with one lag for both the dependent and the explanatory variable as:

$$y_{it} = \beta_0 + \phi_1 y_{it-1} + \beta_1 x_{it} + \beta_2 x_{it-1} + \varepsilon_{it} \tag{2.15}$$

One important advantage of *panel data models* over pure time series or cross-sectional modelling is the relatively large number of observations and the consequent increase in degrees of freedom. This reduces collinearity and improves the efficiency of estimates. However, it must be emphasized that the use of panel data is not unproblematic per se, since the 'choice of an appropriate model depends on the degree of homogeneity of the intercept and slope coefficients and the extent to which any individual cross-section effects are correlated with the explanatory variables'. (Song, Witt and Li 2009, p 149)[30]

2.7 Concluding Remarks

After having discussed the importance of climate for the winter tourism industry and the likely impacts of climate change, the main focus in this chapter has been on modelling the relationship between weather and economic indicators. It is shown that several approaches have been developed for estimating the impacts of climate variability on tourism demand in the literature: Destination choice approaches, the analogue approach, as well as time series and regression approaches. Indeed, the latter methods have also often been applied in the economic literature on modelling both tourism and energy demand, albeit weather impacts are of subordinate importance in these research fields. Similarly, regression approaches have been proposed in the fast growing literature on weather risk management in order to quantify weather risks faced by companies, although compared to the substantial efforts on the pricing and valuation of weather derivatives,

[28] For more information on count data time series and regression models and their specification I would like to refer to textbooks such as Kedem and Fokianos (2002).
[29] For more details on these approaches see Subsection 4.2.4.
[30] For more details on the merits and flaws of panel data methods compared to time series or cross-section regressions see Section 4.2.

only little attention has been on this issue so far. Altogether, despite their purpose has been different, the core approaches to model the statistical relationship between weather and economic indicators have been the same in the climate-oriented, economic-oriented and risk management-oriented literature. Therefore, a systematic overview of these approaches has been provided and the experience obtained will be used in the remainder of this thesis for introducing a risk management-oriented approach to measure weather risks.

3 Data and Methodology

In this chapter I introduce a methodological framework for assessing weather risks and describe the data which is necessary to apply this framework to the winter tourism industry in Austria. I start with explaining the general idea of the framework and outline the research issues arising from it (Section 3.1). Then, I turn to the selection and preparation of data (Section 3.2) and present the obtained data in full detail (Section 3.3). In addition, I give a summary of several data analysis steps (Section 3.4), like tests for unit roots, normality and multicollinearity, which are helpful for deciding on the modelling approach illustrated separately in Chapter 4.

Before presenting the data, methodology and results I would like to note that for data manipulation, calculation and graphical display I have used the programming language and software environment for statistical computing and graphics *R* (R Development Core Team 2008). *R* is similar to the *S* language and is available as free software under the terms of the Free Software Foundation's GNU General Public License in source code form. I have chosen *R* because it is an integrated suite of software facilities (*one-stop-shop*) that provides a wide variety of statistical (linear and nonlinear modelling, classical statistical tests, time-series analysis etc.) and graphical techniques (statistical and spatial graphics etc.) Furthermore, *R* can be extended easily via packages and it allows users to add additional functionality by defining new functions. While it must be emphasized that *R* comes with no warranty, the implemented basic statistical techniques are widely used, have been checked for reliability and validity by the *R* core team (R Foundation for Statistical Computing 2008) and are open to inspection by all users. In addition to the basic distribution of *R*, I have used several additional packages (Pebesma and Bivand 2005; Zeileis and Hothorn 2002; Bivand, Leisch and Maechler 2008; Venables and Ripley 2002; Lewin-Koh and Bivand 2008; McLeod 2005; Neuwirth 2007; Atkinson and Therneau 2008; Lumley 2008; Croissant and Millo 2008; Trapletti and Hornik 2009; Komsta and Novomestky 2007; Chan 2008; Zeileis et al. 2002). I refer to these packages in a separate part of the reference section.

3.1 Methodological Framework

This section describes the methodological framework of this thesis. In a first step, I outline a basic concept for examining weather risk, which requires an understanding of both the probability of adverse weather conditions and their potential impacts (Subsection 3.1.1). As weather is one out of many factors of risk faced by companies, it is of uttermost importance to see weather risk in the context of other corporate risks and how these risks are generally measured and managed (Subsection 3.1.2). Then, I specifically argue for a quantile based risk measure (Subsection 3.1.3). Based on these considerations, I finally outline a research agenda for the empirical work in this thesis (Subsection 3.1.4).

3.1.1 Assessing Weather and Climate Risks

Risk is a combination of the probability of an event and its potential impact. While this is generally well known, it seems that when it comes to empirical examinations of weather impacts on economic activities — and I have shown this especially for tourism in Chapter 2 — the focus is either on one of the two aspects or both aspects of risk separately, but not on an integrated assessment of both. However, this would be necessary to measure weather risks in a way that is informative and allows comparisons, an issue I give particular attention to within this thesis.

Prior to a more detailed discussion of the outlined methodological framework, which I refer to in a very general way as the *basic concept of weather and climate risks*, some issues related to its areas of application need to be pointed out:

Firstly, the focus within this work obviously is on *non-catastrophic risks*. However, in principle the basic concept could principally also be applied to *catastrophic risks*, but then particular attention would need to be paid on two differences. On the one hand, for *catastrophic risks* the appropriate modelling of the damage distribution and especially its tails (extreme values) is very critical. On the other hand, for modelling *catastrophic risks* damage data, e. g. from claims to insurers, can often be assessed directly, while a modelling of the relationship between weather indices and damage data might produce unsatisfactory results. This is in contrast to the modelling of *non-catastrophic risks*, which can be challenging for that data on impacts[1] is not available and needs to be estimated in some way.

Secondly, weather/climate impacts can either be determined by an enumerative or a statistical approach (see Tol 2009). While the former is frequently based on some combination of climate models, impact models and laboratory experiments, the latter directly estimates the impacts from weather/climate on economic activities with statistical methods. To give some examples, the impacts on agricultural production can either be determined by crop models or by regressing weather variables and historic crop yields. Similarly, the impacts on heating energy demand can either be estimated by building simulations or by determining the relationship between temperature indices and heating fuel sales. In winter tourism, impacts can either be assessed by assuming some threshold number of days with snow depth under which the operation of ski areas is not viable

[1] For *non-catastrophic risks* I usually prefer speaking about *impacts* rather than *damages*, because the term *impact* rather imply the possibility of positive as well as negative consequences from weather and climate compared to the negative connotation of *damage*.

any more, or by using observed variations in demand data. It needs to be emphasized that both approaches have their pros and cons, and which of them should be preferred highly depends on the field of application. Whereas the concept is certainly appropriate for both approaches, it is in the following demonstrated on the basis of the statistical approach, which is pursued in this thesis.

Thirdly, the time frame of interest influences the centre of attention. Assessments of weather and climate risks can focus on the past and/or the near and/or the long term future. When it comes to changes in the weather index, attention either is on learning from trends in past climate — an issue interesting for both climate research and the valuation of weather derivatives — or on the shift from past to future climate conditions modelled by climate scenarios, typically for future time horizons of 20 to 100 years. When it comes to the impacts of weather on economic activities, sensitivities are generally estimated for some past period and are then often held constant for the near future, e. g. for estimating the optimum size of weather derivatives, and sometimes even for the remote future, e. g. for climate change impact assessments. In both cases this assumption of constant sensitivities is highly questionable though. Therefore, in this thesis the focus is on explaining spatial and temporal patterns in the probability of adverse weather conditions as well as its impacts on economic indicators from past data. While this information is used to estimate current levels of weather risk, analyses have certainly further implications for forecasting risks both in the near and remote future, for which the concept would be easily extendible.

Against the background of these three focuses the basic concept and some of the associated research questions are presented in Figure 3.1. In order to illustrate the general idea behind this basic concept, it is illustrated in three steps (*Plot A, B and C*) and the plots are held as general as possible[2]:

Step 1: Statistical Modelling of the Weather Index *Plot A* focuses on the distribution of the weather index. The most frequent approaches are here to observe its empirical distribution (grey histogram), describing it by its mean μ and standard deviation σ and to fit a normal distribution to the data (dashed line). Obviously however, the distribution might be subject to changes in its mean value (red line in *Plot A1*), its variability and extreme values. Beside that, the normal distribution often inadequately describes the weather index. Therefore it is often a good idea to consider other symmetric (e. g. Cauchy) or non-symmetric distributions (e. g. Weibull) or to fit a non-parametric distribution (e. g. by Kernel smoothing), which is illustrated in *Plot A2*.

Step 2: Modelling of the Impact Function *Plot B* shows an often assumed linear relationship between the weather index and some economic or business indicator.

[2] *Plot A, B and C* are derived by generating random variables with $N = 100$, the weather index $x \sim \mathcal{N}(0, 1)$ and the economic or business indicator $y \sim x + \mathcal{N}(0, 1)$.

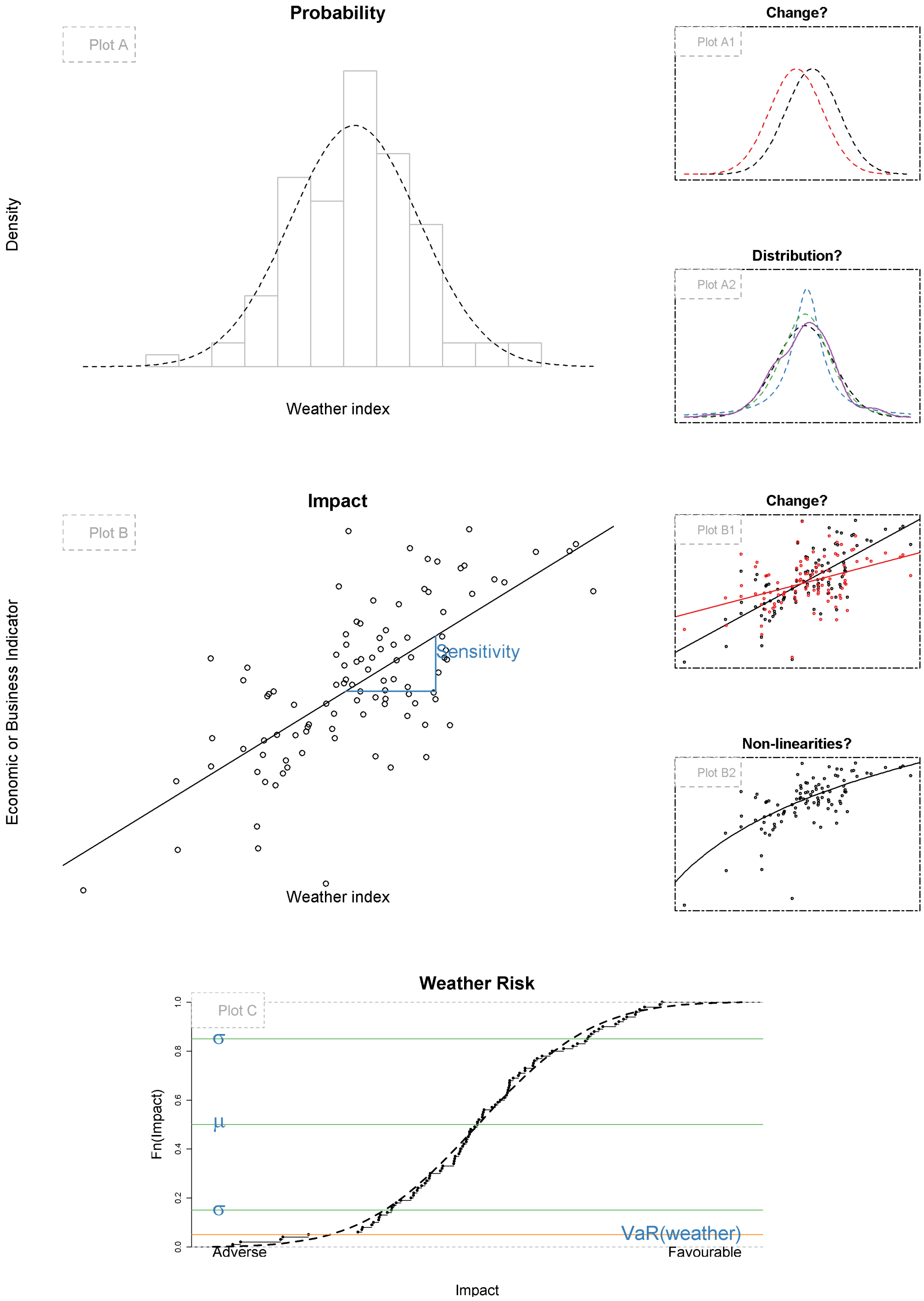

Figure 3.1: The basic concept of weather and climate risks (for details see step 1-3)

Under this assumption, the sensitivity of the economic or business indicator to a one unit change in the weather index is held constant. Of course, in general the economic or business indicator does not only depend on the weather index, but also on other factors, which need to be corrected for, too[3]. Furthermore, it needs to be asked whether the relationship described can be assumed to be constant over time (*Plot B1*) and whether the relationship is really linear (*Plot B2*).

Step 3: Risk Measurement If both the distribution of the weather index as well as its impact on the economic or business indicator have been modelled, the distribution of expected weather-related gains/losses can be given, which is illustrated in *Plot C* in form of a cumulative distribution function (CDF). Again this function can be described by μ and σ. In many cases however, one might not be interested in the mean value and positive impacts, but rather in the risk from negative weather impacts. One possibility to describe these downside risks is to give quantiles, e. g. the 5%-quantile[4], which describes the expected impact happening in one out of 20 years. Referring to the financial literature (e. g. Jorion 2007; Wolke 2007) and under several assumptions discussed in the following, this can also be denoted as Value at Risk (VaR) from adverse weather conditions or VaR(weather).

3.1.2 Weather Risk in the Context of Corporate Risks

Weather risk needs to be seen in the context of other risks faced by companies. Therefore, this subsection discusses how risks are generally measured and managed in a corporate environment and how weather risk can be classified in such a risk management framework. Based on these ideas, the subsequent subsection then specifically argues for a VaR alike risk measure for indicating impacts from adverse weather conditions. It needs to be emphasized that in these subsections particular attention is on *financial risk management*, while the term *risk management* is commonly used in a very broad sense, as indicated by the following definition:

> The term *risk management* is a relatively recent evolution of the term *insurance management*, and originated in the mid-1970s. [...] Risk management is the identification, appraisal, and prevention or minimization of exposures to accidental loss for an organization or individual. Since risk offers not only the opportunity for growth but also for harm, risk managers

[3]In principle, this can either be done prior to the analysis in that the respective indicator is adjusted in some form or it can be done simultaneously with the estimation of weather impacts, e. g. in a multiple linear regression, where the partial coefficient is then interpreted for the respective weather index.

[4]Note that if we consider negative and positive impacts, we are interested in the 5%-quantile of the distribution. However, if we consider damages, we usually denote them on a scale from 0 to some maximum damage. In this case we would be interested in the 95%-quantile.

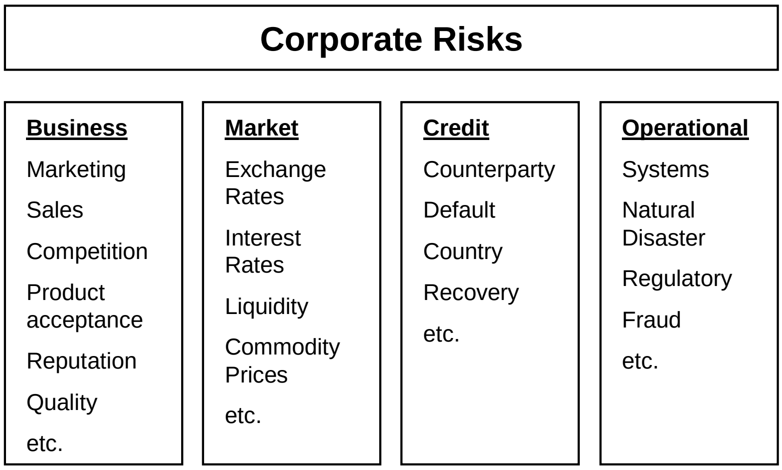

Figure 3.2: Types of risk in the corporate environment; Source: Lee et al. (1999, p 5)

> must predict and prevent or control any potential harm. Risk management is essential for companies to avoid costly mistakes and business losses. The practice of risk management utilizes many tools and techniques, including insurance, to manage a wide variety of risks facing any entity, from the largest corporation to the individual. The term *risk management* has usually referred to property and casualty exposures to loss but recently has come to include *financial risk management*, e. g. interest rates, foreign exchange rates, derivatives etc. (Encyclopedia of Business 1999)

While *financial risk management* and Value at Risk (VaR) methodologies developed for measuring downside risks were first applied by financial institutions (e. g. banks, insurance companies or investment funds), other companies have also been interested in applying *at Risk* concepts in the corporate environment. In contrast to financial institutions, for corporate managers financial results such as earnings and cash flows are generally more important than market value of portfolios of financial instruments, which are just a subset of the types of financial results that corporations care about. (Lee et al. 1999, p 3)

Indeed, a company's financial results can fluctuate because of many different factors of risks other than market risk, on which VaR methodologies typically focus on, and the relative importance of different risks varies across different industries and companies. Figure 3.2 gives an overview of risks in the corporate environment. In this classification, *business risks* are related to the business decisions that companies make and to the business environment in which companies operate. Basically, these are risks that companies are *paid to take* in order to generate profits. The term *market risk* refers to the uncertainty of future financial results that arises from market rate changes, *credit* *risk* relates to the possibility of not receiving payments promised by debtors and *operational risks* result from internal system failures, human errors or external disasters such as natural catastrophes. In contrast to *market risk*, these are risks companies typically seek to manage or mitigate. (Lee et al. 1999, p 5)

In general, weather risk might be classified to be an *operational risk*, although here a differentiation between catastrophic risks and non-catastrophic risks also seems necessary. In most cases, the centre of attention seems to be on weather-related risks which are *catastrophic* in nature, such as floods or storms. For example, the definition of the Basel Committee on Banking Supervision (2003) of what might be considered as an operational risk includes 'loss or damage to physical assets from natural disasters or other events'. These events have, like some other significant operational risks, low probabilities but potentially very large financial impacts. Not all risk events can be controlled (e.g., natural disasters), but risk mitigation tools or programmes can be used to reduce the exposure to, or frequency and/or severity of such events.

In contrast, the nature of risks from *non-catastrophic* weather events substantially differs from this traditional understanding of *operational risks* in several aspects. In fact, they seem to have a certain resemblance with market risks:

1. *Non-catastrophic* events may have positive financial impacts in case of favourable weather conditions and negative financial impacts in case of adverse weather conditions. Therefore, they do, unlike typical operational risks, not only generate losses but also potential gains, and are in this respect more similar to market risks.

2. There exist financial instruments for managing *non-catastrophic* weather risks, although compared to traditional products to manage market risks they are admittedly in their early stages of development (Section 2.5). Therefore, by using weather derivatives they can be transferred to other parties and this can be done using an exogenous source of data, namely some weather index. This possibility for risk transfer is in contrast to most other operational risks like fraud or system failures. Moreover, it opposes the idea that weather risks can be perceived as *business risk*, as companies can transfer weather risks and not necessarily need to take them to pursue their business.

3. Weather typically affects financial results such as earnings and cash flows over a longer period of time (e. g. quarterly, annual). For businesses, *non-catastrophic* weather risks are in this respect also similar to market risks.

4. Like market risks, *non-catastrophic* weather risks directly affect cash flows. This is in contrast to *catastrophic* events, which typically affect physical assets.

These arguments underline the similarity of weather risks and traditional market risks. Hence, an understanding of how market risks affect a company's financial results might also be beneficial for estimating weather risks: As illustrated in Figure 3.3, financial

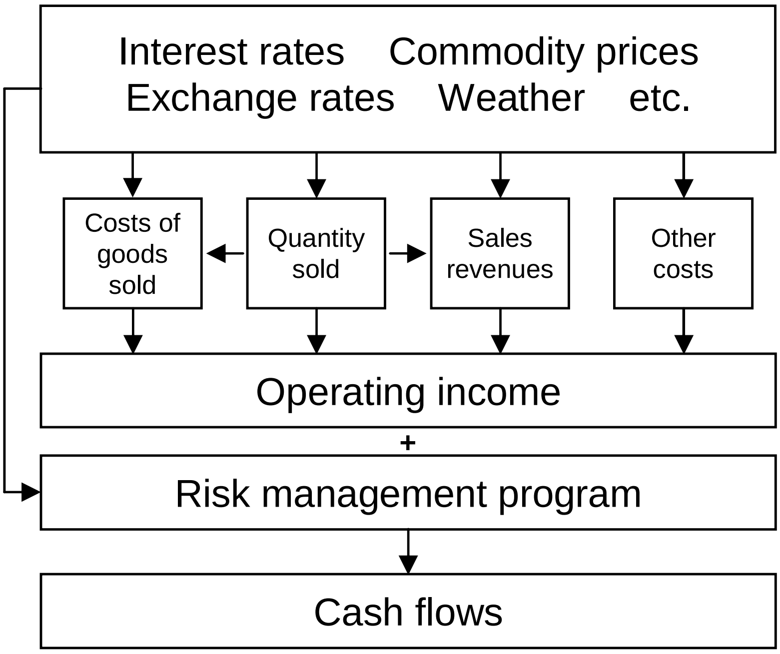

Figure 3.3: Impact of market and weather risks on cash flows
Adapted from: Jorion (2007)

variables affect operating cash flows through the costs of goods sold and other costs as well as through quantities sold or sales revenues (Jorion 2007, p 386). Likewise, weather might affect both the costs of goods as well as the quantities sold. What makes measuring risks in this framework most challenging is that quantities affect both costs and sale prices, and quantities and sales prices also depend on competition. However, measuring these risks — which will be explained in the following in more detail —, e. g. by using the VaR of the operating cash flows, is necessary to decide on a risk management program to lower risks.

In general, the purpose of applying VaR and alike concepts differs, dependent on the environment where they are used (financial versus corporate institutions), but also on how advanced and accepted their application is. According to Jorion (2007, p 379) *at Risk* concepts can be used to report risks to shareholders, management or regulators (passive), to control risks and set risk limits (defensive), or to allocate risks, e. g. when allocating capital or taking strategic business decisions (active). While reporting and measuring risks with a single risk measure that is easy to communicate was the original intention for establishing VaR, it has evolved into a risk-control tool and ultimately into an active risk management tool.

Different *at Risk* measures draw on the same basic methodological approach, but differ on the financial figures they target, which also implies some other obvious differences. For example, the measure Cash Flow at Risk (CFaR), being an attempt to create an analogue to VaR that can be useful for non-financial firms, focuses on cash flows and looks out over a horizon of a quarter or a year. In contrast, VaR focuses on asset values and is typically measured in days or weeks (Stein et al. 2001). Correspondingly, definitions and interpretations of these measures are identical except for the position at risk. For example, a general definition of VaR is:

> VaR summarizes the worst loss over a target horizon that will not be exceeded with a given level of confidence. More formally, VaR describes the quantile of the projected distribution of gains and losses over the target horizon. (Jorion 2007, p 17)

While this definition of VaR does not include the position at risk, it typically refers to a loss *in the portfolio value*. Therefore, a more specific definition includes the position at risk, e. g. cash flows:

> CFaR summarizes the worst loss *in cash flows* over a target horizon that will not be exceeded with a given level of confidence.

The idea behind the calculation of VaR and CFaR is shown in Figure 3.4, where both risk measures are illustrated on the example of the 95 % confidence level, which equals a quantile α of 5 %. Furthermore, for both risk measures also the expected shortfall, or respectively the conditional Value at Risk (cVaR) or conditional Cash Flow at Risk (cCFaR) is provided. Whereas VaR and CFaR ask 'how bad can things get' with a certain probability, cVaR and cCFaR ask 'what is the expected loss, if things do get bad', or in other words, what is the expected loss conditional on the loss being greater than the loss occurring with a probability of α (Hull 2007, p 197).

In addition to these risk measures, other risk measures are discussed in the literature. For example, the CFaR approach can be generalized to all earnings, in which case the risk measure is denoted as *Earnings at Risk (EaR)* (Jorion 2007, p 386) or *Earnings Per Share at Risk (EPSaR)* (Lee et al. 1999, p 10). Another risk measure related to VaR and cVaR is called *Lower Partial Moments (LPMs)*. *LPMs* are, like VaR, calculated based on the probability distribution of a position (e. g. the market value of a portfolio). However, *LPMs* reverse the idea behind VaR, in that they require first to define a loss limit and not a confidence level, and then to study the loss distribution for losses larger than this limit. (Wolke 2007, p 50)

Most important for risk measurement is a discrimination of *top-down* and *bottom-up* methods. *Top-down* approaches are simple, as they directly look at historical data, e. g. at the variability of operating cash flows. The obvious advantage of doing so is that this data should summarize the combined effect of all the relevant risks faced by a

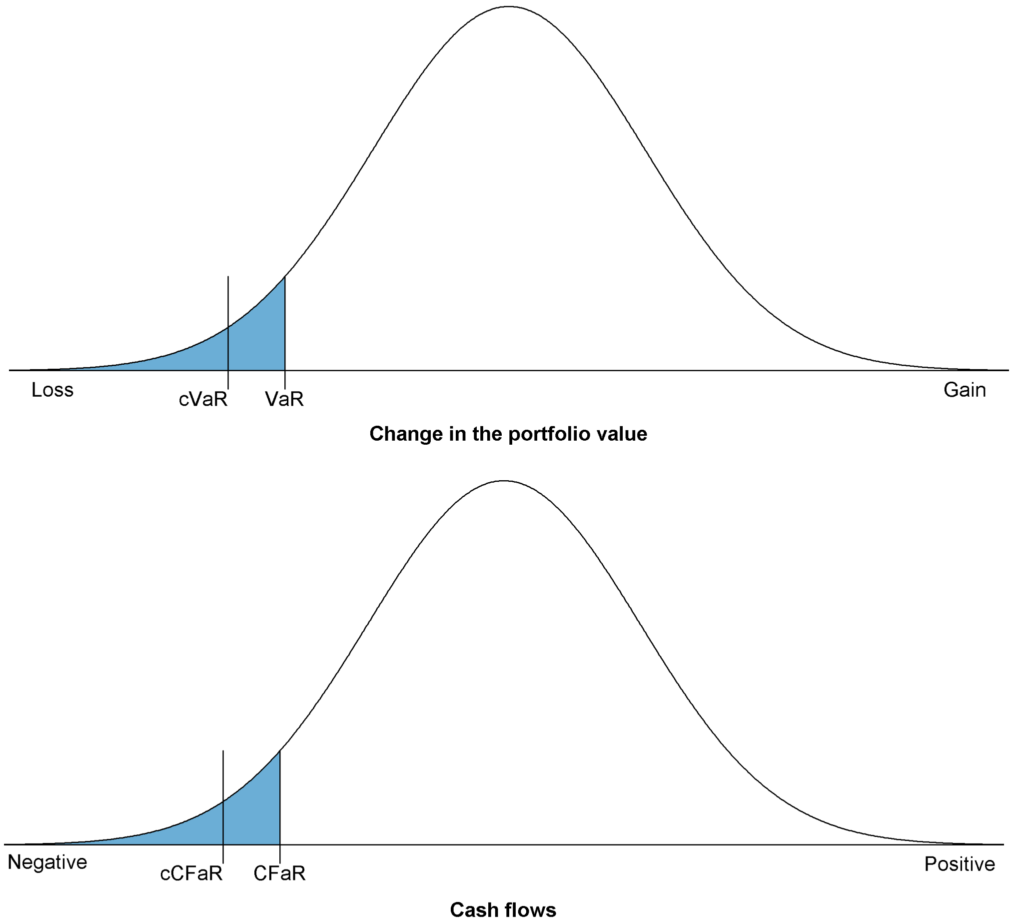

Figure 3.4: Calculation of VaR from the probability distribution of the change in the portfolio value and calculation of CFaR from the distribution of the expected cash flows respectively; The given level of confidence is 95 %; Adapted from: Hull (2007)

company and avoids the need to build a detailed model of the business from the ground up. As advocates of this approach highlight, this is in contrast to a *bottom-up* VaR analogue for measuring companies' risk, where there is a danger that it will 'simply leave out some important sources of risk, badly mismeasure others, and thus lead to a highly inaccurate estimate of overall CFaR' (Stein et al. 2001, p 9). However, as advocates of a *bottom-up* for measuring companies' risk argue, such a *top-down* 'is backward looking and include other risks such as business risks. [Therefore,] it provides little insight into the drivers of operational losses. On the other hand, *bottom up* approaches are more informative, like VaR.' (Jorion 2007, p 497)

As with the traditional VaR methods, measuring CFaR for a company can be done using a *bottom up* approach in three steps: (Jorion 2007, p 385)

- The first step requires delineating economic exposures, which represent the sensitivity of cash flows to movements in the prices of financial variables (e. g. exchange rates).
- The next step consists of describing the risk distribution of key financial variables. For example, this can be done via Monte Carlo simulations. The horizon is usually selected to match the business planning cycle.
- Finally, these financial variables need to be combined with economic exposures. This is akin to attaching a simulation engine to the business-cash flows.

Once all of these steps have been carried out, risk can be measured using the VaR of the operating cash flow.

Applying this principle to other types of risk (e. g. assets), companies might seek to use VaR for providing an aggregate measure of risk, which in particular requires considering correlations between different categories of risk. In other words, an aggregate VaR estimate is expected to be lower than the sum of its sub-aggregates due to diversification effects, which are the more pronounced, the lower the correlation coefficients are. In general, the basic principles of aggregation can not only be applied to different risk positions and types of risk, but also to different business units etc., which is seen as the major benefit of VaR:

> Perhaps the defining characteristic of Value at Risk (VaR) systems is large-scale aggregation. VaR models attempt to measure the total financial risk of an institution. (Jorion 2007, p 189)

However, VaR measures are no panacea and users must understand their limitations and dangers. The most obvious drawbacks, which are in generally recognised, are that

- VaR does not provide a measure of the absolute worst loss or of the losses exceeding the losses at some confidence level;

- VaR models based on historical data assume that the recent past is a good projection of future randomness;
- VaR models may be not effective in times of transition, e. g. if companies carry out organizational changes or expand into new markets;
- the use of VaR might be limited by data availability or the application of inappropriate models and statistical tools.

Furthermore, it has been argued that attempts to measure risk might also give a false impression of accuracy or that they might provoke stakeholders to behave even more risky. (Jorion 2007, p 542)

3.1.3 Measuring Weather Risks

While discussing all the merits and flaws of the VaR concept for measuring financial risk mentioned goes beyond the scope of this thesis[5], this subsection argues why a VaR alike risk measure, as introduced in more detail in Section 4.3, might be beneficial for measuring weather risk and how it is related to the ideas provided in the previous subsection.

First of all, from a specific corporate risk management point of view, a VaR alike risk measure might be beneficial to incorporate weather risk into existing risk management processes. This necessarily needs to be done using a *bottom-up* modelling approach where weather is one of the exposures affecting the financial result of interest.[6]

From a more general point of view, the main argument for introducing a weather risk measure comes from that currently it is not possible to compare adverse weather impacts calculated for different weather exposures, companies or regions, not to mention a possible aggregation of these impacts. As shown in Chapter 2, impacts are either indicated for one or several (observed) extreme years, a one unit or percentage change in the respective weather index or a climate change analogue. In order to allow comparability and aggregation, this thesis proposes a probability oriented approach, where the risk measure can be defined analogue to the traditional VaR in the most general form as VaR(weather):

> VaR(weather) summarizes the worst *weather-related loss* over a target horizon that will not be exceeded with a given level of confidence.

[5]For further discussions on this heavily debated issue see e. g. Dowd and Blake (2006); Jorion (2007); Taleb (2007); Wolke (2007); Hull (2007).

[6]As is evident, with a *top-down approach* one would not be able to distinguish weather effects from other effects.

This definition involves several aspects:

1. it refers to VaR as a general approach and term. Basically, VaR(weather) is understood as a quantile of some loss function and nothing more;[7]

2. for weather risks, using the term VaR instead of adapting it to the respective position at risk is convenient, as the position (e. g. quantities sold, revenues, sales, cash flow) might differ and therefore the definition would need to change. This somewhat also follows the convention used in Jorion (2007) or Wolke (2007), who use VaR referring to either a single position where cash flows are at risk (e. g. *VaR(oil)* to denote the exposure to oil prices), total operating cash flows (e. g. VaR from operating cash flows) or a company-wide aggregate risk;

3. as is evident, the term weather in parenthesis refers to the weather index the company is exposed to and which might have a negative impact on financial results;

4. the target horizon may be chosen dependent on the frequency the corresponding financial indicator is provided for (e. g. monthly sales or annual revenues);

5. the level of confidence of interest also depends on the frequency, but might for *non-catastrophic* events and a monthly to annual scale typically be chosen to be at 95 or 90 percent, indicating the risk from adverse weather conditions occurring in one out of 20 and 10 times respectively.

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[7] I use the term Value at Risk in this thesis because it is a simple and well known definition, without adding another risk measure to the manifold risk measures available and without necessarily using all the methodological tools often related to it, e. g. the Monte Carlo Method. In fact, the main effort in this work will be on how to estimate this loss function (or as I prefer: impact function) and thereby questioning some of the often implicit assumptions (e. g. of normally distributed variables etc.). In the sense of Dowd and Blake (2006) I am pragmatic in "naming the child", while spending a lot of attention on modelling the loss function and estimating quantiles.

> The subject of financial risk measurement has come a long way since the appearance of VaR in the early 1990s. In retrospect, it is clear that VaR was much overrated, and is now discredited as a "respectable" risk measure–despite the ostrich-like reluctance of many of its adherents to face up to this fact. Risk measurement has moved on, and we now have many "respectable" risk measures to choose from: these include coherent risk measures, spectral risk measures, distortion risk measures, and many others. Indeed, in some ways, we now have too many risk measures available to us, and there are (usually) no easy ways to determine which might be best: the most appropriate risk measure depends on the assumptions we make (e.g., whether we are prepared to "buy into" risk aversion theory, whether we prefer to work with distortion functions, etc.), and would appear also to be sometimes context-dependent. Any search for a single "best" risk measure–one that is best in all conceivable circumstances–would therefore appear to be futile, and practitioners should be pragmatic. De gustibus non disputandum est. (Dowd and Blake 2006, p.24)

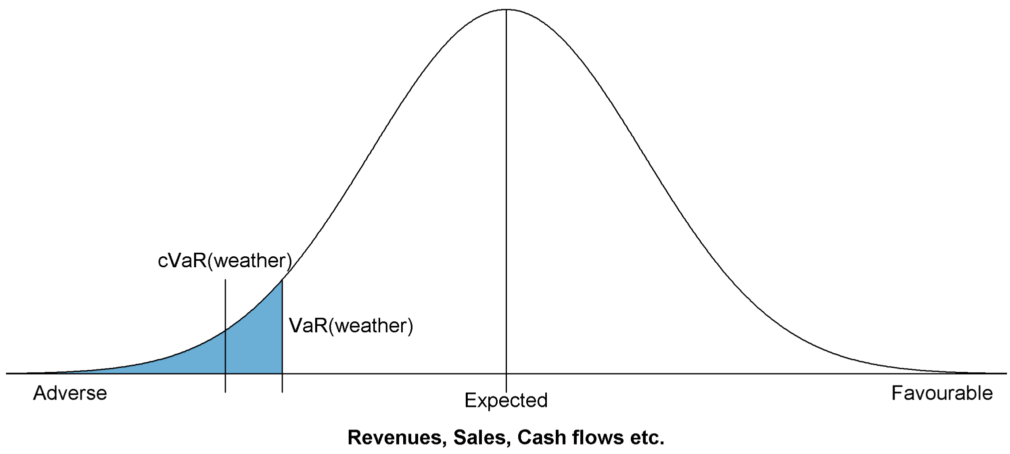


Figure 3.5: Calculation of *VaR(weather)* and *cVaR(weather)* from the probability distribution of weather impacts on the financial result of interest; The given level of confidence is 95 %

Figure 3.5 illustrates the idea behind VaR(weather) and simultaneously the idea to calculate a weather-related conditional Value at Risk, or in short cVaR(weather). It can be seen that the financial result of interest (or any other economic indicator) varies dependent on whether weather conditions in the target horizon are rather favourable or adverse. In addition, and this is a central point for estimating weather risk, one needs to define a target level of the financial result of interest under expected or normal weather conditions. This procedure is similar to determining the exposure e. g. of cash flows to changes in exchange rates, where the modelled distribution of exchange rates needs to be related to a reference scenario. Likewise, the distribution in weather needs to be related to cash flows under expected weather conditions. In contrast to exchange rates though, where a reference scenario might typically be based on some forecast, expectations on weather are in practice typically based on historical averages, which might be misleading under a warming climate though.

This leads to a discussion of the differences of traditional risk measurement and the measurement of weather risks. In principle, the three steps for measuring the VaR of the operating cash flow described in Subsection 3.1.2 are identical to the basic methodological framework outlined in Subsection 3.1.1. Both require a delineation of economic exposures, which means that the sensitivity of the financial result/business indicator of interest to financial or weather variables is determined, as well as a description of the risk distribution of financial or weather variables. In both cases, economic exposures and the risk distribution can then be combined in a consecutive step.

However, there exist several important differences. On the one hand, regarding the delineation of the economic exposure, there exists no deterministic relationship between weather and the financial result of interest, and so it needs to be estimated by some statistical procedure. On the other hand, the distribution of the weather variables may differ from those of financial variables and needs to be treated correspondingly. In addition, data availability and the low frequency of data for most economic indicators typically further reduce the set of methodological tools from financial risk management which can be taken for estimating weather risks. All in all, these differences reveal the necessity that in order to measure weather risks, traditional financial risk measurement techniques need to be complemented with experiences from other fields of research, such as applied climatology, weather derivatives valuation or econometric demand modelling.

3.1.4 Empirical Work

As outlined in Chapter 1, the primary objective of this thesis is to develop a methodological framework for assessing non-catastrophic weather risk and apply it on the winter tourism industry in Austria. While having described the methodological framework so far in a very general way, the empirical data has not yet been considered. In the remainder of this thesis, theoretical considerations are brought together with the empirical data. In order to achieve the research objective of quantifying weather risk, the focus will in particular be on the following issues, with the questions being structured in accordance with the three step approach presented in Subsection 3.1.1:

Step 1: Statistical Modelling of the Weather Index

- Observing several snow indices in order to find out the most appropriate index for describing ski areas specific exposure to weather conditions.
- Modelling the distributions of snow indices with different approaches.
- Considering trends in the snow conditions.

Step 2: Modelling of the Impact Function

- Testing several econometric model specifications in order to estimate the relationship between weather and tourism demand.
- Checking the stability of the impact over time with several methods considering either all seasons or extreme seasons only.

Step 3: Risk Measurement

- Describing weather risks with different risk measures.
- Comparing weather risks between individual ski areas.
- Aggregating weather risks of individual ski areas.
- Relating weather risks to other risk factors.

The modelling approach which is used to analyse these issues is described in more detail in Chapter 4. Before that, it is absolutely essential to get familiar with the data, as the nature of the data which is necessary to investigate these research questions also influences the chosen modelling approach.

3.2 Selection and Preparation of Data

In this section, I outline the selection of data for estimating ski areas' weather risk and the multiple steps needed for preparing it. In a first step, an overview is given on the main data sources and the reasons for selecting them. Then, I describe the classification of ski areas and the allocation of overnight stays to ski areas. In a next step, the preparation of the acquired weather data is discussed. In addition, I provide details on the economic and balance sheet data which is used for several analysis in this thesis.

3.2.1 Data selection

The selection of data is done in such a way that a loss of information due to aggregation and extrapolation of data is avoided. From a weather risk point of view it is desirable to estimate the weather dependency on the smallest scale for which good data is available. Especially in the tourism industry, stakeholders are frequently organized on a local level and are dependent on local weather risks. Therefore approaches on a more aggregate scale might be subject to the danger of averaging out weather risks, if, for example, several small ski areas with a substantial weather dependency and one large weather-independent area are considered jointly. However, as it is also important to know effects on the macro level, approaches on a local level should be conducted for as many locations as possible to dispel possible concerns on the extrapolation of values estimated for a limited number of locations (see Tol 2009).

As it can be seen from previous studies, basically there exist two sources for tourism indicators. On the one hand, it is possible to access tourism statistics, such as data on arrivals, overnight stays, capacity utilization (bed-nights) etc. For Austria this data is collected on the municipal level and is available on a seasonal since 1972 and also on a monthly level since 1995. On the other hand, visitor numbers or other business data can be requested from cable way companies or similar enterprises. While this data is frequently available on a daily level, it can often be obtained for short periods only. Furthermore, consistent data, e. g. on ski lift ticket sales, is generally only available for a limited number of areas. That is why previous studies examining the weather sensitivity with data on ski lift ticket sales (like Hamilton, Brown and Keim 2007; Shih, Nicholls and Holecek 2009) focus on case study data only. Hence, in order to draw conclusions on a more general level, the bulk of analysis in this thesis will be conducted using data from tourism statistics.

Even if tourism data is available on the local scale and for a larger number of observations, meteorological data is frequently not. In fact, the availability of adequate meteorological data is seen as a critical issue when examining the relation between economic activities and weather conditions. When analysing the snow sensitivity of skiing activities however, the availability of snow data becomes the most crucial issue. In Austria, consistent snow measurements for longer time series can only be obtained for a limited number of measurement stations, and do not cover regional snow variations and respective altitude of ski areas.[8] For this reason, this thesis utilizes data from a snow cover model, which has recently been developed by the Austrian Central Institute for Meteorology and Geodynamics (ZAMG 2009). This model allows to have meteorological data for each of the ski areas (see Subsection 3.2.4).

Furthermore, the literature on international tourism demand recognises origin country income and relative tourism prices to be important explanatory variables. While there are plenty estimations of these income and price effects on the national or provincial scale, this does not apply for the local scale. However, it might be expected that on this scale other local-specific effects are more important to explain demand changes. Therefore, these indices are considered when estimating effects on an aggregate scale, but are left out for estimations for individual ski areas within this thesis (see Section 4.2). Other explanatory variables suggested in some studies include tourism prices in alternative destinations, travel costs, marketing expenditure and dummies for on-off events. Again, these variables might be beneficial for estimations on the aggregate scale or for one or several individual areas, but difficult to obtain and construct for a large number of areas. Hence, they will not be considered within the underlying modelling framework.

Another data set from OHT (2008) on business indicators for hotels complements the available tourism statistics, as it includes data not only on overnight stays but also on key accounting ratios. As the nature of this data does not allow to analyse the impact of inter-annual variations in weather, it is not directly applied in the regression models, but is used to explore the interconnectedness between the sensitivity to snow conditions and the financial situation of the accommodation industry.

Table 3.1 summarizes the acquired data sets. As it can be seen, the data sets are given for different time horizons and frequencies and on different regional scales. In addition, the preparation of new data sets is necessary in order that the localized snow cover models can be run for individual ski areas. Therefore, in order to use the different kind of data inputs for the econometric and risk modelling a range of data preparation steps is needed, which are described in the following subsections.

[8]Therefore, previous studies (e. g. Schiman, Toeglhofer and Prettenthaler 2009; Falk 2010) are often restricted to those ski areas where meteorological stations are available, mostly in proximity to the valley stations of ski areas.

Data set	Source	Time series length	Time series frequency	Spatial resolution
Overnight stays	Statistics Austria (2008)	1972/73 - 2006/07	seasonal (winter)	municipalities
Tourist beds	Statistics Austria (2008)	1973 - 2007	annual (census in May)	municipalities
Overnight stays (by origin country)	Statistics Austria (2008)	2000 - 2007	monthly (winter season)	municipalities
Meteorological data	ZAMG (2009)	1971 - 2006	daily and monthly	1×1 km grid
Austrian ski resort database	Joanneum (2008), based on BMVIT (2003)	-	-	municipalities
Consumer Price Indices, Exchange Rates, Gross Domestic Products	OECD (2008)	1973-2007	quarterly and annual	origin countries of tourists
Balance sheet data for hotels	OHT (2008)	1999-2007	annual (different accounting dates)	postal codes

Table 3.1: Summary of the acquired data sets

3.2.2 Classification of Ski Areas

For the classification of ski areas, several datasets and web platforms are used. The main purpose is to define homogeneous ski areas in such a way that the availability of snow data for each of the ski areas as well as the availability of the number of overnight stays in the corresponding municipalities is ensured. Therefore, two tasks are carried out at the same time, namely the assignment of municipalities to ski areas, and the determination of the ski areas' altitudes and coordinates as an input for the meteorological model to provide localized snow data. In order to do this the following principles are applied:

- Similarly to Abegg et al. (2007), the currently most comprehensive skiing website www.bergfex.at (Bergfex GmbH 2009) is used to classify Austrian ski areas. If skiing municipalities have a common web presence on this platform, they are counted as one ski area (e. g. Serfaus-Fiss-Ladis). Exemptions from the common web presence criteria are made for large areas with a wide geographic spread (e.g. Skiwelt Wilder Kaiser Brixental), as in these cases homogeneity may not be given among municipalities. These areas are subdivided, depending on the interconnections within the area. Furthermore, municipalities with more than one independent ski area (e. g. Soelden and Hochgurgl-Obergurgl) are considered to be a single ski area, as data on overnight stays is not provided separately and guests generally have the possibility to choose between areas anyway, dependent on weather and snow conditions.

- For the determination of the size and altitudes of the ski areas a more comprehensive database which was created by Joanneum (2008)[9] is taken. In this dataset, information about cable cars, chair lifts and drag lifts from data collections as well as the public cable car statistics (BMVIT 2003)[10] has been allocated to each of the Austrian municipalities. It includes information about the number of transport facilities, their transport capacities[11], and, except for drag lifts, also the altitude of the valley and mountain stations of each transport facility.

- Areas are only counted if they provide more than five transport facilities or at least one cable car. This size restriction deviates from Abegg et al. (2007), who use a threshold of three transport facilities and at least 5 km of ski runs.

- The lowest (alt_0), mean (alt_{50}), and highest altitudes (alt_{100})[12] are determined for each of the ski areas. alt_{50} is calculated as the average of the mean altitudes of all the transport facilities (except drag lifts) in the area, weighted by transport capacities. This weighting supposedly provides more accurate information compared to the simple averaging of alt_0 and alt_{100} in previous studies, as many ski areas provide more transport capacities in higher lying regions. alt_0 and alt_{100} refer to the highest mountain station and the lowest valley station respectively. However, alt_{100} is adapted separately for areas where drag lifts obviously exceed the altitude given by the cable car statistics and alt_0 is changed for areas, where slopes are not usually provided to get to the lowest valley stations (as these transport facilities only support skiers to get to higher altitudes). In addition, for areas which solely rely on drag lifts, altitude information is taken from the coordinates matching (see Subsection 3.2.4).

- The geographic coordinates are determined for alt_0 and alt_{50}. Besides allowing to plot the data spatially, this is necessary for the meteorological model to provide snow data for each of the ski areas. The exact coordinates were determined based

[9] This data set is presented in full detail in Prettenthaler et al. (2009).

[10] Note that this dataset divides transport facilities in drag lifts (also called T-bar lifts) and other facilities like cable cars or chair lifts. I refer to this two groups as drag lifts DL and cable cars and chair lifts CC.

[11] The transport capacity (TC), measured in *person altitude meters per hour* (Pm/h), refers to the maximum number of persons, which can be transported within one hour, multiplied by the altitude difference of the transport facility. Note, that while the transport capacity is helpful for comparing the size of ski areas, it does not indicate the actual capacity utilization of the ski areas.

[12] For ski areas with more than 500 m difference between alt_{50} and alt_0 the coordinates are determined also for the 25 % and 75 % altitudes. While this data might be useful for other investigations, it is not considered further within this thesis.

on the information on alt_0 and alt_{50} by using the software *AMAP3D viewer* (BEV 2009). This software enables to view the map of Austria with a scale of up to 1:10 000, on which the transport facilities of ski areas are imaged (except recent extensions) and can be compared to the ski areas maps at www.bergfex.at. For the determination of the coordinates the technical specification of the meteorological model is taken into consideration. Since the model operates with a resolution of 1×1 km, it is important to find coordinates within the ski areas, for which the altitudes match as accurately as possible with the average altitude of the grid cells of the meteorological model. As the latter information is not known ex ante, several coordinates for different locations have been chosen for each ski area and altitude level. Furthermore, locations in the center of grid cells are preferred and steep declivity is avoided to minimize the difference between ski area and grid altitudes. In case one defined ski area includes several unconnected areas (e. g. Moelltaler-Gletscher: Flattach, where there is one glacial area, but also several lower lying lifts), coordinates for each of the different areas are determined in the corresponding altitude groups and are considered together.

This approach finally results in a total number of 202 ski areas, which will be further analysed in this thesis. In comparison, Abegg et al. (2007) base their analysis on 228 areas. A detailed list of the ski areas and the corresponding municipalities is given in Appendix A.

3.2.3 Allocation of Overnight Stays to Ski Areas

The 202 selected ski areas include 273 of the 603 municipalities which are listed in the Austrian ski resort database. The 330 excluded municipalities either provide very small transport facilities, which were eliminated by the size constraint, or transport facilities which are not used for winter sport purposes. In sum, the excluded transport facilities account for only 5 % of the total transport capacities. Moreover, it can be assumed that these excluded transport facilities predominantly attract day trippers, while national and international overnight stays are attributable to larger areas.

Beside the 273 municipalities where skiing activities take place, many more surrounding municipalities benefit from their close location to areas, especially to those who are internationally well known (Soelden, Arlberg, Saalbach-Hinterglemm, Kitzbuehel, Ziller valley etc.). Indeed, one can expect that the tourist stays in these municipalities are heavily related to those in the corresponding flag ship areas and their meteorological conditions.

Therefore, municipalities with indirect skiing activities are identified. In a first step this is done by limiting the Austrian municipalities to possible candidates, namely by listing municipalities that are either geographical neighbours of skiing municipalities, or are among the 110 non-skiing municipalities that account for the largest number in overnight stays. In a second step this selection is limited manually by excluding municipalities which evidently attracted tourist stays due to other reasons (spa tourism, city tourism etc.) than winter sport. The remaining municipalities are individually assessed on the basis of both, the proximity (by road connections) and attractiveness of the nearby areas. A municipality is selected when skiing activities in the nearby areas are thought to be the primary determinant of overnight stays in the corresponding community. The 72 selected municipalities are presented in Appendix A.

Furthermore, for the sake of simplicity, 17 ski areas with some missing observations in the dependent variable are removed before conducting the econometric analysis. This is done to avoid problems with missing values, especially when calculating with lags and differences.[13] The temporarily excluded areas are marked by an asterisk in Appendix A.

3.2.4 Meteorological Data

Because of the before mentioned lack of consistent snow measurements for the majority of ski areas, meteorological data is taken from a snow cover model, which uses temperature and precipitation data to reconstruct historic snow conditions for each of the given ski area coordinates on a daily basis. For this, the altogether 550 ski area coordinates have been provided to the Central Institute for Meteorology and Geodynamics (ZAMG). Then, several meteorological indices (mean snow depth; mean temperature; days with snow depth >1cm and days with snow depth >30cm)[14] have been calculated and aggregated on a monthly basis by ZAMG for each of the given coordinates 1×1 km grid cells. Of course, while this applied procedure creates a more consistent dataset, the underlying uncertainties regarding the extensive assumptions behind the snow model also need to be taken into account. For a more detailed discussion of the model see Beck et al. (2009).

Concerning the adequacy of the generated meteorological data for the selected ski areas it is important that the altitudes of the ski areas correspond to the mean grid altitude of the ZAMG grid. Since in mountainous areas the altitude can vary substantially within 1×1 km grid cells, it is expected that the mean grid altitudes deviate significantly from the ski area altitudes. Indeed, the altitudes vary for up to 500 m, with a mean deviance of 90 m. However, for each ski area and altitude level (alt_0 and alt_{50}) up to five coordinates are potentially available, which allows to exclude coordinates with a high deviance.

[13] Alternatively, when the number of missing observations is small, the missing observations could be filled by taking moving averages of the previous periods or similar methods. However, 7 out of the 17 areas have several missing values and the other concerned areas (except one) are of relatively small size anyway.

[14] All snow indices are also provided including assumptions on artificial snow production: If (1) the daily mean temperature is below −2 °C and (2) the snow depth on the previous day is smaller than 50 cm, then a production of 6 cm artificial snow is assumed. Note that this data will also be used in some analysis, but will not play a primary role due to methodological constraints, particularly because it is not known for individual ski areas since when, to what extent and with which technology snow making is utilized.

Hence, a procedure is developed for the generation of the snow indices to select the considered coordinates in such a way that the final altitude deviance is minimized for each ski area, while the number of included coordinates is kept as large as possible. The selection procedure is based on several considerations:

1. It is tried to include snow data from as many coordinates as possible, as these coordinates might refer to different local climatic conditions (e. g. because of slopes with different expositions). Thus, in case the absolute value of the mean deviation does not exceed 100 m, all coordinates are selected. For example, when the first altitude is 150 m higher and the second one 130 m below, both have been considered, because the mean deviation is then reduced to 10 m.

2. In case this 100-m-condition is not fulfilled, it is tested again after excluding one out of the coordinates (with $N-1$ possibilities to do so). If the condition is still not fulfilled for each of the possibilities it is continued excluding two coordinates etc.

3. At least one coordinate is provided for each area and altitude level, even if the absolute deviation of this coordinate was greater than 100 m.

The application of this selection procedure reduces the differences between ski area altitudes and the snow model grid altitudes. While still 204 out of 225 coordinates for alt_0 and 270 out of 325 coordinates for alt_{50} were considered, the mean deviance was reduced from 90 m for both altitude levels to 67 m for alt_0 and 73 m for alt_{50}. In addition, outliers have been substantially reduced, with only 55 areas deviating more than 100 m and 16 deviating more than 200 m for alt_0, and respectively 40 areas deviating more than 100 m and 8 deviating more than 200 m for alt_{50}.

3.2.5 Economic Data

Income and price variables, which are used for some analysis in this thesis are calculated using OECD data (OECD 2008) and by closely following Luzzi and Flückiger (2003). The income index is calculated by weighting the gross domestic products per capita (GDP) by the guests' origin[15] in each ski area. The price index represents the relative prices in Austria compared with the price level measured in the tourist country of origin, again weighted for each ski area by the guests' origin. It is calculated by adjusting consumer price indices (CPI)[16] by exchange rates between Austria and the respective country. Both

[15] Eastern European countries had to be excluded because income and price data is not available for the entire period. However, the share of Eastern European guests is negligible for the majority of the sample period, while it has strongly increased in some ski areas in recent years. Still, for the average ski area it was only approximately 5 % in the period 2000-2007.

[16] The CPI is used in the absence of a tourism price index, which would consider typical tourist expenditures instead of consumer prices, but is not be available for the sample period.

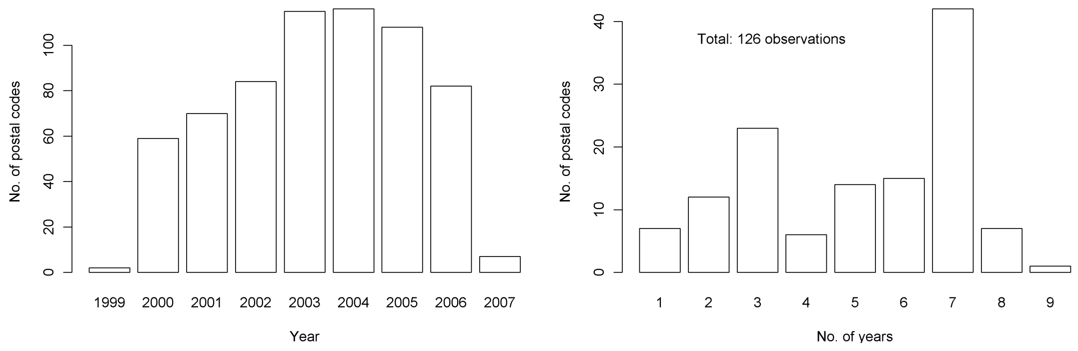


Figure 3.6: Sample size of the balance sheet data

for income and price indices, time-constant weights are taken, because when the weights are calculated for the entire period (average of the yearly weights), the variable is far more stable than if the weights are revised each year (Luzzi and Flückiger 2003).

3.2.6 Balance Sheet Data

Balance sheet data for Austrian hotels is provided by the 'Austrian hotel and tourism bank' (OHT 2008)[17] on a postal code level. Due to the data protection policy of the bank, data is delivered only for postal code areas with at least four clients. On the one hand, this minimum criteria means that the dataset is more robust to outliers, e. g. the performance of one particular hotel. On the other hand, it implies that observations are available for less postal codes and hence ski areas. Altogether, data is obtainable for 126 postal codes, of which 106 comprise one or several municipalities with skiing activities. In addition, it needs to be considered that the accounting dates of the banks' clients differ and that the data is given for different time periods, with 6 or less years available for the majority of areas (Figure 3.6).

For each of the postal codes, the dataset gives information on the number of hotels, the average number of overnight stays, sales, gross operating profits, energy costs, total assets and debts. From this data the sales per overnight stay and the following accounting ratios are calculated:

$$\text{Return on Investment (ROI)} = \frac{\text{Gross Operating Profit (GOP)}}{\text{Total Assets}} \tag{3.1}$$

$$\text{Profit Ratio} = \frac{\text{Gross Operating Profit (GOP)}}{\text{Sales}} \tag{3.2}$$

$$\text{Debt Ratio} = \frac{\text{Total debt}}{\text{Total assets}} \tag{3.3}$$

[17]The data has been processed for another research project by Alex Stomper, IHS Vienna and MIT Sloan School of Management.

For further analysis, also the temporal mean[18] and differences are calculated for all indicators, with differences only being considered for those years where the number of included hotels within a postal code remained stable. For ski area specific analysis the data is attributed to ski areas, which requires some assumptions, as the borders of postal codes do not coincide with the borders of municipalities. Therefore, for each ski area the postal codes of all included municipalities are considered, and the business indicators are weighted according to the number of overnight stays in the mean season[19].

3.3 Data Description

After having all the data transformed to the level of individual ski areas, I describe it in more detail in this section, while I provide further statistical analysis (tests for normality, stationarity and multicollinearity) in Section 3.4. These two sections will then be the basis for the modelling of weather risks in Chapter 4. Note that the data in this and the following sections is generally presented for the 185 ski areas without missing values in the overnight stays time series, as the estimation of weather risks will be conducted for these areas. However, in some cases where it is appropriate[20], I will also include the other 17 out of 202 areas for the sake of completeness.

3.3.1 Ski area data

Out of the information available for the individual ski areas, indicators for the altitude and size are of particular interest. As shown in Chapter 2, in previous studies the altitude of ski areas was frequently used as an indicator for the vulnerability of ski areas towards climate change, while indicators for the size of areas have largely been neglected. However, accounting for the size of areas seems to be beneficial when analysing impacts on the entire industry, as there exist distinctive differences in the size and altitude range of areas. What is more, for individual ski areas the acquired data allows to overcome the simplifying assumption that transport capacities are uniformly distributed between alt_0 and alt_{100}.

The size of an area is typically increasing with its altitude. This is well shown in Figure 3.7, where for each area the transport capacity (TC) is compared to the altitude range ($alt_{100} - alt_0$). Table 3.2 provides some more details in that the data is summarized

[18] Even if the number of observations varies amongst postal codes, the mean of all available seasons is chosen instead of the values for one particular season, as this meaning out of year-to-year variability should be more important than the disturbing effects of taking different time periods.

[19] This procedures means that the indicators should be roughly representative for the respective ski areas, with the underlying assumption that the more overnight stays are in a municipality, the more likely it is that a hotel is located in the given postal codes. However, it also imply that the sum of all ski areas should not be interpreted, as double counting is possible.

[20] For example, all 202 observations are considered for the description of ski areas altitude and size as well as of the performance indicators of hotels.

	No. of areas	∅ TC	Total TC	% TC	alt_{50} s	alt_{50}	alt_{50} s, w	alt_{50} w	% TC_{CC}	No. of CC/DL
altitude (m)										
$alt_{50} < 1200$	54	1.34	73	7.7	1027	1020	1107	1070	61.4	83/264
$1200 \leq alt_{50} < 1500$	68	4.32	294	31.0	1337	1371	1349	1393	77.7	323/528
$1500 \leq alt_{50} < 1800$	47	5.91	278	29.4	1575	1648	1537	1647	81.7	300/404
$alt_{50} \geq 1800$	33	9.14	302	31.9	1993	2030	2061	2089	85.7	323/288
area size $(10^6 Pm/h)$										
$TC < 1.4$	70	0.80	56	5.9	1162	1177	1182	1201	52.3	73/277
$1.5 \leq TC < 5$	71	2.92	207	21.9	1498	1532	1542	1579	71.3	230/449
$TC \geq 5$	61	11.19	682	72.2	1613	1666	1670	1729	85.1	726/758
province										
Carinthia	21	3.55	75	7.9	1496	1546	1563	1669	68.7	72/160
Lower Austria	13	1.32	17	1.8	1089	1086	1187	1179	68.7	24/52
Upper Austria	12	1.6	19	2.0	1059	1136	1161	1263	64.1	21/69
Salzburg	32	7.25	232	24.5	1401	1434	1507	1545	79.5	240/327
Styria	32	2.15	69	7.3	1324	1321	1368	1364	63.1	67/215
Tyrol	70	6.26	438	46.3	1580	1618	1761	1813	85.2	474/514
Vorarlberg	22	4.35	96	10.1	1368	1417	1573	1659	85.1	131/147
Total	202	4.68	946	100.0	1417	1450	1613	1665	80.2	1029/1484

w = weighted, s = simple mean, TC = transport capacity, CC = cable cars and chair lifts, DL = drag lifts

Table 3.2: Ski area data categorized according to altitude, area size and province

according to alt_{50}, area size and province. First of all, it can be observed that the average size ($\varnothing TC$) strongly increases with alt_{50}, e. g. areas where $alt_{50} \geq 1800m$ are seven times larger than areas where $alt_{50} < 1200m$. Thus the results of altitude analyses are influenced by whether the common or weighted mean is used, where the weight is the TC of ski areas. For example, the common mean of Austrian ski areas' altitude is 1450m (alt_{50}) while the weighted mean is 1665m ($alt_{50}w$).

Furthermore, there exist some differences in the area specific mean altitude, dependent on whether the simple mean between alt_0 and alt_{100} ($alt_{50}s$) or the weighted mean of individual transport facilities (alt_{50}) is considered. This is particularly true for larger areas, which have more capacities in higher lying regions than close to the valley station.[21]

Altogether, both of these effects ($alt_{50}s$ vs alt_{50} and alt_{50} vs $alt_{50}w$) influence the altitude distribution of Austrian ski areas, which is also shown in the cumulative distribution functions (CDFs) presented in Figure 3.8. For example, the mean altitude of 27 % of areas is below 1200 m, but these areas only make up 8 % of the TC. Therefore, this analysis leads to the conclusion that it is crucial to consider not only the total amount

[21] For 90 out of the 202 ski areas the simple mean altitude underestimates the weighted mean altitude, for 44 areas by more than 100 m. For 52 areas there exists an overestimation, with only 4 areas deviating by more than 100 m. For the remaining 60 areas both methods yield the same results, as only one transport facility is considered.

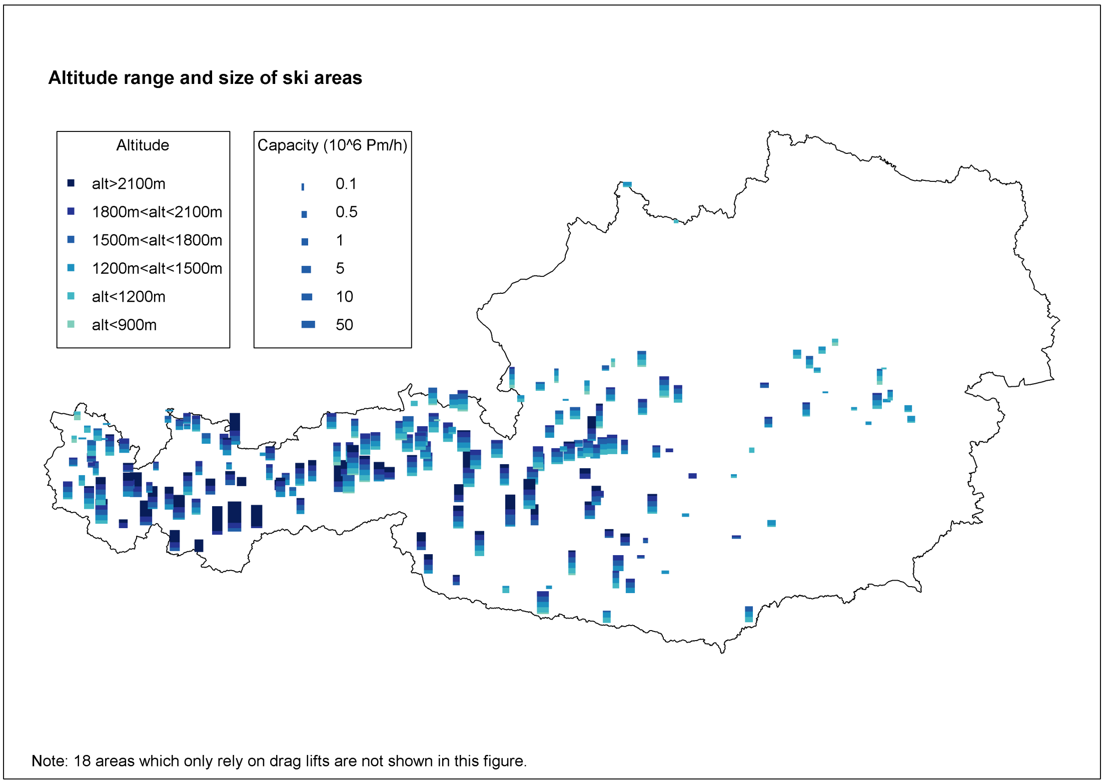


Figure 3.7: Altitude range and size of ski areas

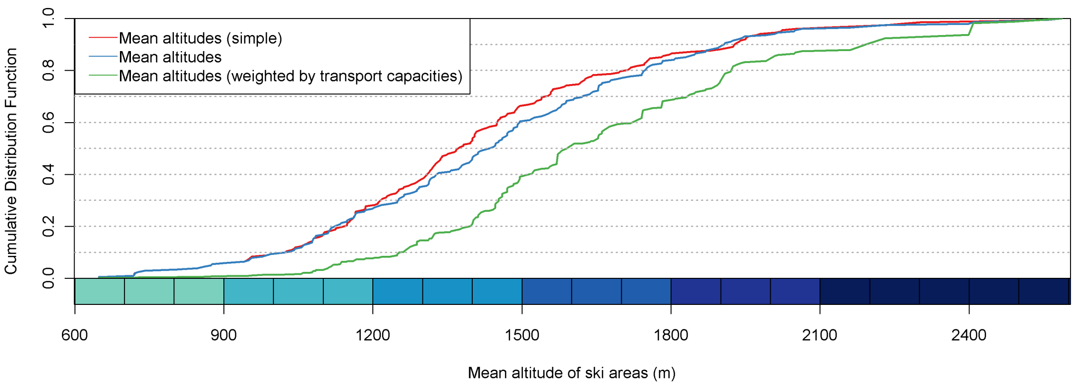


Figure 3.8: Cumulative distribution functions of the mean altitudes of Austrian ski areas

of ski areas but also their relative size. Furthermore, it is worth to have a look at the altitude distribution of all the transport facilities within an area, not only the maximum and minimum altitude.

In addition to the size and altitude of ski areas, Table 3.2 gives some information on the number and share of drag lifts (DL) and cable cars and chair lifts (CC) respectively. CC, while less abundant in numbers, account for 80 % of TCs ($\%TC_{CC}$), with higher shares in larger areas.

3.3.2 Meteorological Data

This subsection focuses on the description of the meteorological data, which has been matched to alt_{50}, alt_0 and also to the 5 largest Austrian cities (Vienna, Graz, Linz, Salzburg and Innsbruck), with indices being available for:

- days with snow depth >1cm ($Sday_1$)
- days with snow depth >30cm ($Sday_{30}$)
- mean snow depth (S_{mean})
- mean air temperature (T_{mean})
- artificial snow production included in each of the snow indices (e. g. $Sday_1(art)$)
- weighted average snow conditions [22] ($Sday_{AVG}$)

While analyses are conducted with each of these weather indices, descriptions in this section are, for the sake of brevity, mostly limited to the $Sday_1(alt_{50})$ index[23]. However,

[22] For this index $Sday_1$ are weighted by mean overnight stays in the respective ski areas, which are also taken as weights for further similar calculations (unless stated otherwise). Note that weighting by mean overnight stays produces extremely similar results as weighting by transport capacities.

[23] $Sday_1(alt_{50})$ are preferred to other indices for the following reasons:

Firstly, $Sday_1$ are chosen instead of $Sday_{30}$ — which are frequently deployed in other studies — because according to Dr. Wolfgang Schoener (ZAMG), who build the snow model, the model performs better with lower threshold definitions and higher ones may be more vulnerable to biased model outputs. Indeed, this can be seen when comparing the snow indices from the model with data for 17 areas, where measurement stations are close to the alt_0 of the ski areas and data is available for a sufficient period. The results from this analysis show that while the snow model underestimates the number of days with snow depth also for the 1 cm threshold (median area: −26 %) the bias is much worse for the 30 cm threshold (median area: −48 %). Furthermore, the seasonal correlations between measurement and model data are higher for $Sday_1$ (median area: 0.56) than for $Sday_{30}$.(median area: 0.51).

Secondly, $Sday_1$ are preferred to S_{mean}, since meaning can lead to the effect that high values in certain periods mask other periods with critical conditions. What is more, mean snow indices seem to be inefficient as from a certain threshold onwards, snow conditions should not influence skiers‘ behaviour any more.

more detailed descriptions (μ, σ, trends) for the other indices, both for alt_0 and alt_{50}, are available in Themessl, Gobiet and Toeglhofer (2009).

It can be seen from Figure 3.9 and Table 3.3 that the climatological mean μ and standard deviation σ for $Sday_1(alt_{50})$ vary substantially across ski areas, with higher lying areas generally exhibiting higher values and less data variability[24]. The latter can also be seen when correcting for the coefficient of variation σ/μ. Furthermore, the skewness γ_1 and kurtosis γ_2 vary substantially amongst areas, with γ_1 being negative (left-skewed) for the majority of areas, in particular those with higher μ. In contrast, γ_2 is not related with μ. All of those statistical properties are of particular interest for modelling the weather index, which will be discussed in more detail in Section 4.1.

	$Sday_1$					$Sday_1$ *trend*		$Sday_{30}$	S_{mean}	T_{mean}	$Sday_{1,art}$
	[d]	[d]				[d]	[%]	[d]	[cm]	[°C]	[d]
	μ	σ	σ/μ	γ_1	γ_2	p.a.	p.a.	μ	μ	μ	μ
Min.	40	7	0.04	-1.73	-1.76	-1.60	-1.55	0	2	-6.63	65
1st Qu.	111	17	0.13	-0.49	-0.60	-0.79	-0.61	24	12	-1.39	140
Median	131	21	0.16	-0.22	-0.15	-0.59	-0.45	43	18	-0.44	155
Mean	128	20	0.17	-0.25	-0.01	-0.55	-0.43	48	22	-0.62	151
3rd Qu.	145	22	0.20	0.02	0.32	-0.31	-0.27	66	28	0.38	165
Max.	176	33	0.43	0.98	4.05	0.55	0.73	148	92	3.94	179

σ/μ = *Coefficient of variation*, γ_1 = *Skewness*, γ_2 = *Kurtosis*
Min. = Minimum, Qu. = Quartile, Max. = Maximum (of all 185 ski areas)

Table 3.3: Summary statistics for the weather indices; Data correspond to the mean altitudes of ski areas in the winter seasons 1973-2006

Moreover, a declining trend can be found for $Sday_1(alt_{50})$ for the majority of ski areas. Using OLS, a negative trend can be observed for 172 out of 185 areas and trends are found to be statistically significant (5 %-level) for 76 of these areas. Trends are pronounced, e. g. with a -0.59 days (-0.45 %) annual change in days with snow depth >1cm for the median area (Table 3.3). Hence, a negative trend can also be observed for the weighted average snow conditions $Sday_{AVG}$ in alt_{50} as well as alt_0 of ski areas (Figure 3.9). However, a declining trend is surprisingly not the found for the average of the five largest cities, which represents urban snow conditions. In fact, more detailed studies by

Thirdly, snow conditions in alt_{50} are generally seen to be more relevant as those in alt_0. If snow conditions in the valleys are poor, guests can be carried to higher altitudes in many areas: 154 of the 185 included ski areas have five or more, 89 even ten or more transport facilities. These figures indicate the relatively high potential for shifting activities to higher altitudes in periods with unfavourable snow conditions.

[24] While σ decreases for $Sday_1(alt_{50})$ with alt_{50}, the opposite is true for $S_{mean}(alt_{50})$. Note also that, in contrast to snow indices, $\mu_{T_{mean}}$ obviously decrease with alt_{50}. These differences need to be considered when comparing estimation results with different indices.

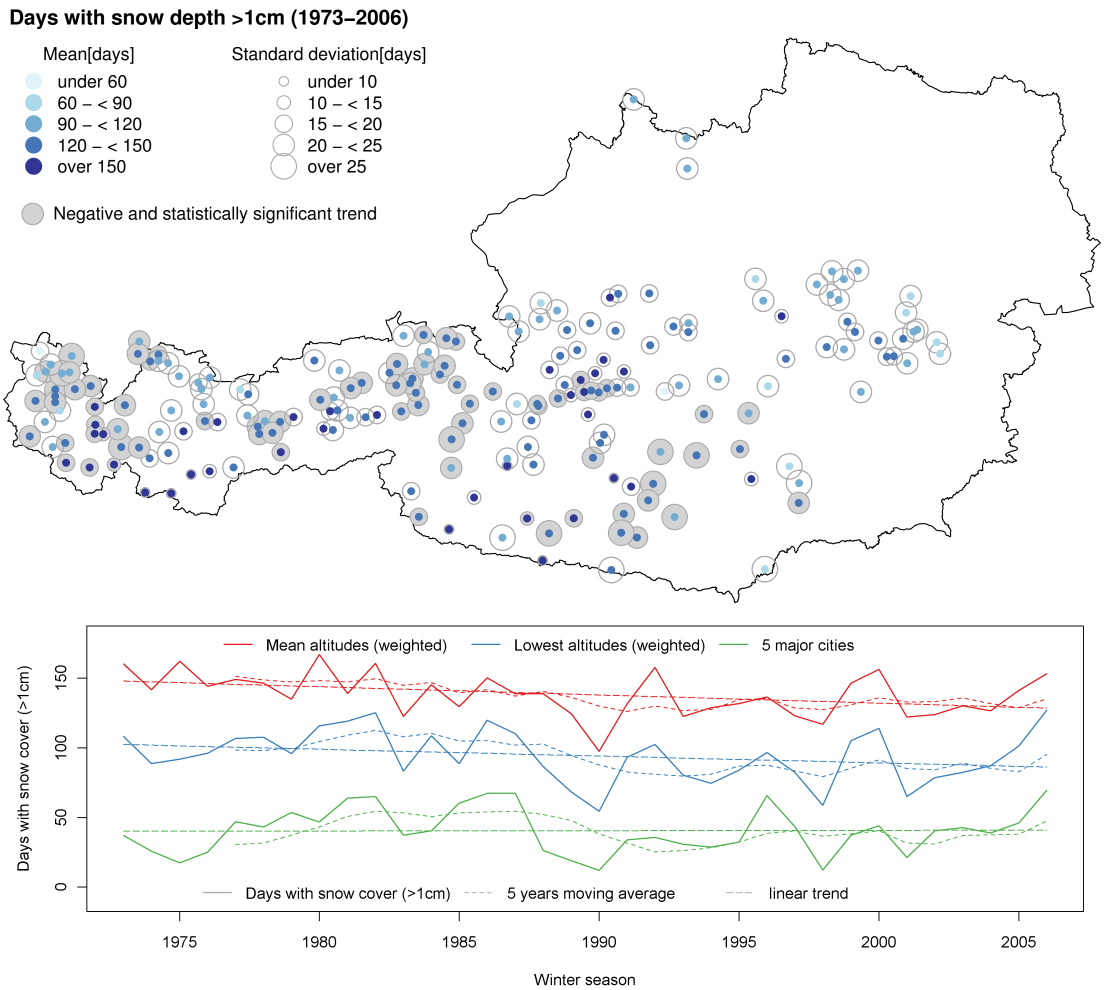


Figure 3.9: Climatological mean, standard deviation and trend for the mean altitudes of ski areas as well as the average development for the mean and lowest altitudes of ski areas and the five largest Austrian cities for days with snow depth >1cm in the winter seasons 1973-2006; *Data source:* ZAMG (2009)

Themessl, Gobiet and Toeglhofer (2009) show that — in strong contrast to the increase observed for all other seasons — winter temperatures have not changed for the period 1971-2006, with a slight decrease in northern and eastern Austria (where 4 out of the 5 cities are located) and a slight increase for the South. Similarly, winter precipitation sums have slightly increased in the northern provinces and decreased in the western provinces, but significantly decreased in Carinthia.

3.3.3 Overnight stays

Since the 1970s, the number of overnight stays has increased considerably in the winter season (November-April) in Austria, from around 25 to 60 million. This is in contrast to the summer season (May-October), where overnight stays have dropped from 75 million to around 60 million, with declines particularly in the 1990s. However, while both seasons account for approximately the same number of overnight stays nowadays, the winter season is considered to be more important as average turnovers are significantly higher[25].

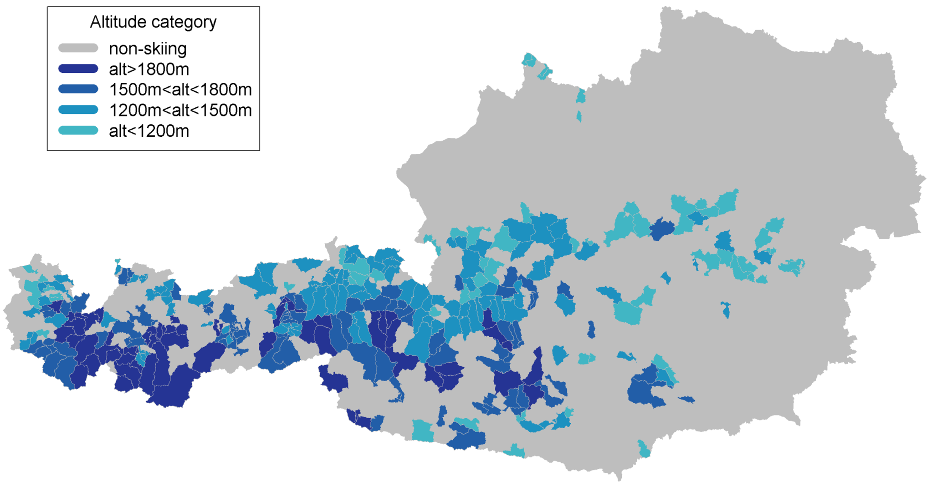
The overall development of overnight stays in the winter season is illustrated in the stack plot in Figure 3.10. It can be seen that the number of overnight stays has grown in 27 out of 34 seasons. Periods with a decline or weak growth can be found in the early 1980s, in the mid 1990s and the winter seasons 1989/90 and 2006/07. On the one hand, the stagnation in the early 1980s is — among the multiple other drivers for tourism demand — attributed to the weak economic growth in the aftermath of the second oil crisis. The most severe decline[26] in the mid 1990s is considered to be due to the rather weak economic growth in this period and most notably structural problems related to increasing competition from other alpine destinations as well as countries with mild winter temperatures (Lentz and Kraas 2003). On the other hand, the declines in the winter seasons 1989/90 and 2006/07 are often attributed to the adverse snow conditions in these two seasons, an effect which will be analysed in more detail later in Subsection 5.3.1.

All in all, the 345 included municipalities (273 with direct and 72 with indirect skiing activities) account for three fourths of the overnight stays in Austria in the winter season, and this share has remained relatively constant within the last 30 years (1973: 74 %, 1990: 76 %, 2006: 73 %)[27]. Within the federal provinces however, a remarkable

[25] According to T-MONA (2009) guests spend 135 € per day (incl. travel costs) in the winter season and respectively 109 € in the summer season.

[26] Note that although it is probably too early to judge, the impacts of the current financial and economic crisis, which are not analysed in more detail within this thesis, could result in the most severe crisis the Austrian tourism industry has seen in recent decades. According to Smeral (2009*b*) this might be less due to the short term effects of the crisis on overnight stays and more visibly turnovers, but rather due to longer term effects of the currently observed sharp decline in investments in the industry.

[27] Note that for consistency reasons comparisons like here and in the stack plot in Figure 3.10 are



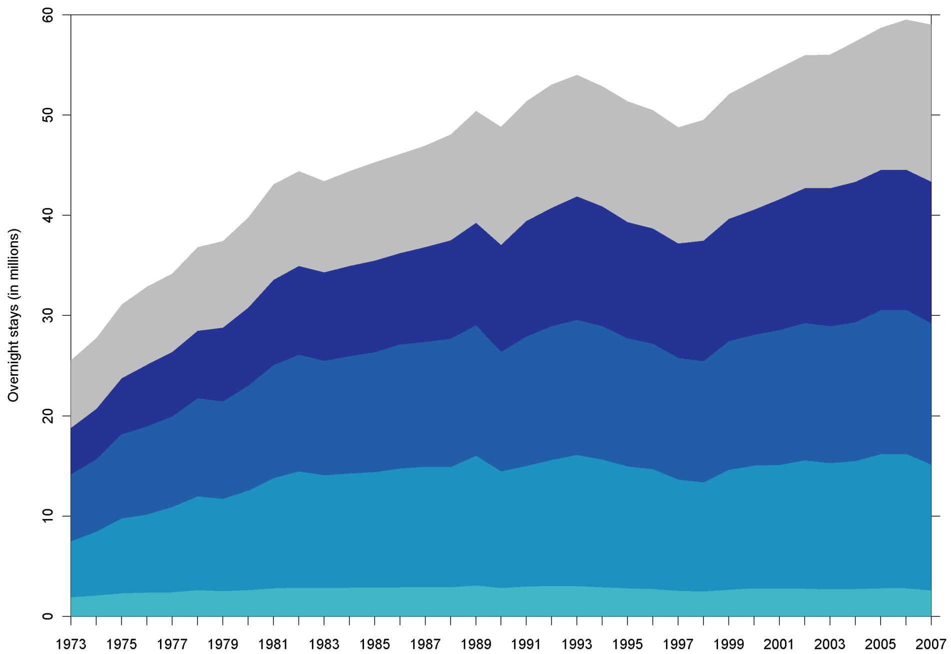


Figure 3.10: Development of overnight stays in the winter seasons 1973 to 2007 categorized according to the mean altitudes of ski areas in the respective municipalities; *Data source*: Statistics Austria (2008)

difference is observable between the core ski provinces Salzburg, Tyrol and Vorarlberg and the other provinces. While in the first mentioned the ski areas have by far the largest share in total overnight stays (Tyrol: 92 %) and thus determine the development of overnight stays, growth rates have decoupled especially in Styria, Lower Austria and Upper Austria. In these provinces an upward trend is observable in total overnight stays in the winter season, although the ski areas have grown only slowly (Styria), stagnated (Upper Austria) or decreased steadily (Lower Austria), which can also be seen in Table 3.5. For example in the case of Styria, ski areas have nowadays a share of less than 50 % in overnight stays, mainly due to the rising contributions of city, congress and spa tourism in the recent decade.

	Absolute values			Annual growth rate (in %)			
	μ	σ	σ/μ	1973-1983	1984-1994	1995-2006	1973-2006
Min.	982	592	0.07	-16.4	-5.7	-9.9	-5.3
1st Qu.	35 120	8 501	0.17	2.2	-0.4	-0.6	0.9
Median	95 080	19 420	0.24	6.0	1.0	0.4	2.4
Mean	188 700	43 670	0.27	6.2	1.2	0.6	2.5
3rd Qu.	236 200	51 200	0.32	9.0	2.8	1.8	3.9
Max.	1 580 000	410 000	0.81	26.1	13.6	11.3	9.9

μ = Mean (1973-2006) σ = Standard deviation, σ/μ = Coefficient of variation
Min. = Minimum, Qu. = Quartile, Max. = Maximum (of all 185 ski areas)

Table 3.4: Summary statistics for overnight stays in ski areas in the winter season

Within the sample of the 185 ski areas, there exist large differences in size and trends. The number of overnight stays in the average season range from 1 000 to 1 580 000 (Table 3.4) and the average annual growth rate deviates from -5 % to $+10$ %. Trends strongly differ over time and dependent on the province, altitude and size, which is illustrated in Figure 3.11 and summarized in Table 3.5. While until the mid of the 1980s nearly all ski areas and provinces (except Lower Austria) experienced considerable growth, this changed afterwards. Since then, little growth took place in the median area and the overwhelming part of growth could be attributed to large and higher lying areas, with the larger areas usually also being the higher lying ones. For example, the 58 areas with more than 200 000 overnight stays, which account for 77 % of overnight stays, increased on average by 2.5 %, whereas smaller areas with less than 50 000 overnight stays grew by 1 %. Similarly, overnight stays in areas with $alt_{50} \geq 1800m$ increased by 3.3 %, while areas with $alt_{50} < 1200m$ grew by 1.4 % only.

prepared by also including municipalities with some missing values, while for trend analysis like in Table 3.4 and Table 3.5 only the 185 ski areas without missing values are considered.

	No. of areas	Average size	Total (∅ season)	Share (%)	Annual growth rate (in %) 73/83	84/94	95/06	73/06
mean altitude (in m)								
<1200	44	57 000	2 498 000	7.2	4.0	0.1	0.3	1.4
1200 to <1500	65	168 000	10 930 000	31.3	6.6	1.0	0.8	2.6
1500 to <1800	45	260 000	11 712 000	33.6	5.0	1.1	1.0	2.3
≥1800	31	315 000	9 768 000	28.0	6.1	2.7	1.6	3.3
area size (in thousand overnight stays)								
small (<50)	65	26 000	1 688 000	4.8	2.9	0.4	0.0	1.0
medium (50 to<200)	62	104 000	6 422 000	18.4	6.1	1.4	0.7	2.6
large (≥200)	58	462 000	26 798 000	76.8	5.8	1.5	1.2	2.7
province								
Carinthia	14	129 000	1 812 000	5.2	4.1	3.5	1.8	3.2
Lower Austria	10	34 000	343 000	1.0	-1.0	-1.0	-0.3	-0.8
Upper Austria	12	49 000	586 000	1.7	2.2	1.6	-0.8	0.7
Salzburg	32	290 000	9 278 000	26.6	6.2	1.4	1.0	2.7
Styria	29	67 000	1 937 000	5.6	3.8	0.5	0.7	1.5
Tyrol	68	253 000	17 230 000	49.4	6.5	1.5	1.3	3.0
Vorarlberg	20	186 000	3 722 000	10.7	4.3	0.8	0.3	1.6
Total	185	180 000	34 908 000	100.0	5.7	1.4	1.1	2.6

Table 3.5: Overnight stays in ski areas categorized according to altitude, area size and province

Another indicator which describes the supply of tourism capacities are tourist beds. In principle, their development is very similar to the development of overnight stays[28]. While tourist beds could be used to construct bed-nights as an indicator for capacity utilization, for which weather impacts could be examined (see e. g. Bigano et al. 2005), this is not recommendable for Austrian data. The reason for this is that the time series for beds exhibit considerable jumps, whereby the most obvious one in the year 1986 can be attributed to changes in the method of data collection[29].

3.3.4 Economic Data

The time series for the income and relative price index for the average ski area are depicted in Figure 3.12[30]. It can be seen that for ski areas the income index[31] has grown in the observed period, but growth has been comparatively slower in the last two decades.

[28] This can also be seen when examining potential multicollinearity (see Figure 3.15).

[29] Tourist beds are however used as a control variable for the panel data approach, which is in general less sensitive to jumps in the data and in particular to potential multicollinearity (see Subsection 4.2.4)

[30] Both indices are used for the panel estimations (see Subsection 4.2.4) and are also of interest in their own right.

[31] The income index is shown in logarithms, so that the slope of the line illustrates the rate of growth.

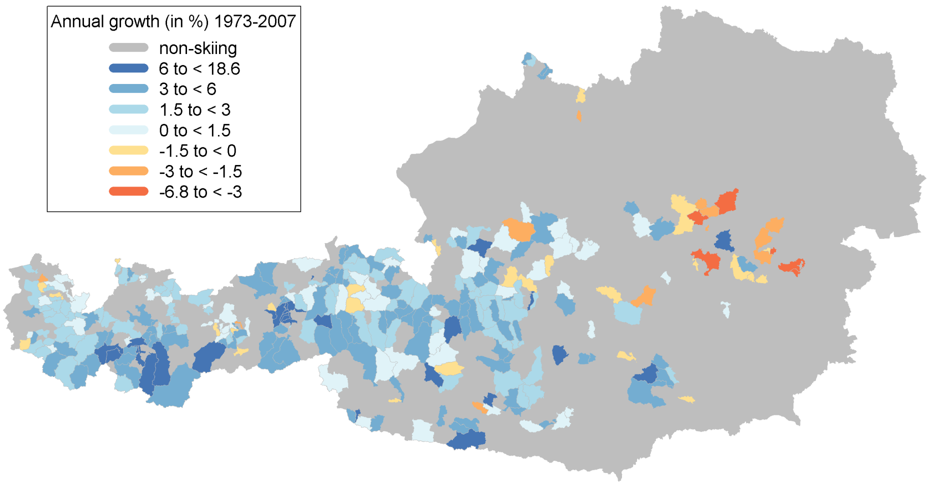


Figure 3.11: Annual growth in overnight stays in the winter seasons 1973 to 2007 (in %); *Data source*: Statistics Austria (2008)

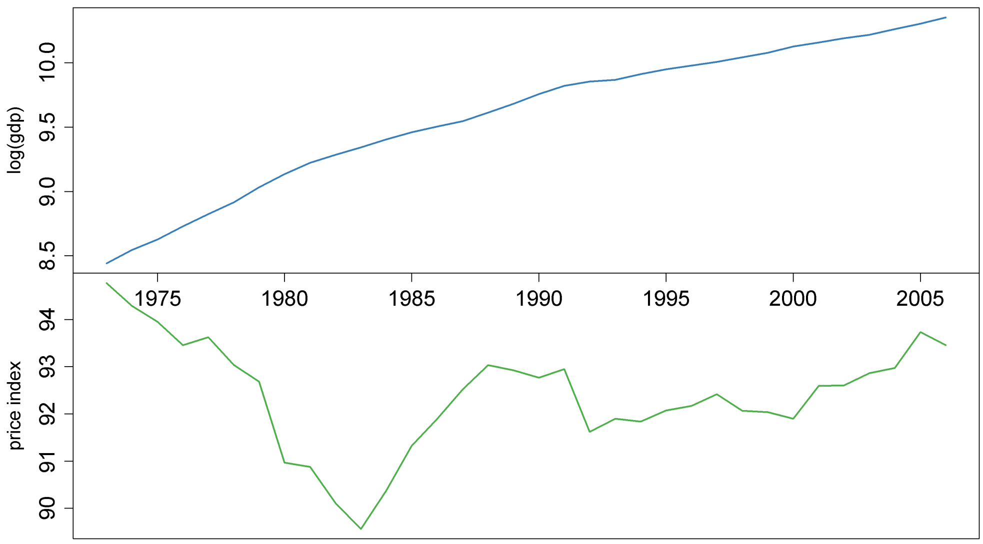


Figure 3.12: Time series for income (in €, per capita, log) and relative prices (Austria=100); Values are indicated for the (weighted)-average ski area and are for individual ski areas dependent on the tourist's origin countries

The relative price index exhibits little variation, especially in the last two decades. This is supposedly due to very similar price developments in the two main source markets, namely Germany and the Netherlands, as well as the fact that more than 90 % of the guests in ski areas come from the Euro zone.

	DE	AT	NE	UK	CH	BE	IT	CZ	PL
%-share (ski areas)	54.4	16.9	8.5	3.5	2.6	2.4	1.4	1.3	1.2
%-share (total)	45.4	23.1	8.9	3.4	2.5	2.1	1.9	1.2	1.1
Income	93.6	(100)	96.8	88.4	118.5	96.0	88.5	-	-
Prices	96.5	(100)	97.3	126.4	95.9	103.0	164.1	-	-
	HU	DK	FR	US	RU	RO	ES	JP	other
%-share (ski areas)	1.2	1.1	0.8	0.4	0.3	0.1	0.1	0.1	3.8
%-share (total)	1.2	1.3	1.0	0.8	0.3	0.2	0.3	0.3	5.1
Income	-	98.8	88.7	119.9	-	-	72.1	91.2	-
Prices	-	114.5	111.9	113.3	-	-	167.7	89.6	-

Table 3.6: Origin countries of tourists in the winter season (average 2000-2007) and the respective income and price indices (average 1973-2006, Austria=100)

Table 3.6 provides more details on the tourists' origin country in the winter season, as well as the calculated income and price indices for the respective countries. It can be seen that the share of German guests is much higher for ski areas than for the total of overnight stays in the winter season, while it is comparatively lower for domestic guests, which represent the second largest group.

All in all, higher income levels are expected to influence tourism demand positively, while for the relative price index lower levels are expected to stimulate tourism demand. Therefore, in the period 1973-2007 conditions have generally been favourable for Swiss or US tourists, while stays in Austria were relatively expansive for guests from Spain or Italy.

3.3.5 Balance Sheet Data

Operating figures derived from the balance sheet data are available for 88 out of 202 ski areas, which however account for 77 % of total transport capacities. Therefore, it can be said that the presented data is rather representative for larger areas.

Figure 3.13 illustrates the calculated averages of the indicators for each of the ski areas as well as the median for ski areas and for non-ski areas. It can be seen that the average hotel size is larger in non-ski areas than in ski areas, which can be expected as the non-ski areas include many cities. Although average sales per night do not seem

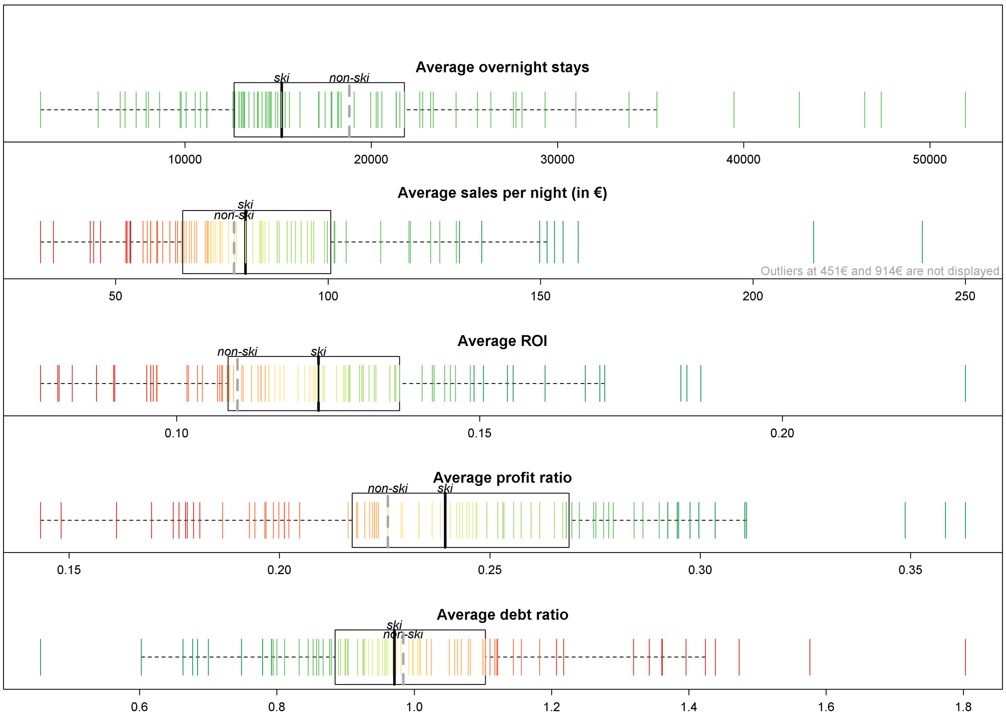


Figure 3.13: Operating figures of hotels in ski areas compared to non-ski areas
Data source: OHT (2008)

to be significantly higher in ski areas compared to non-ski areas, the range between ski areas is quite wide[32]. Highest sales per night are observed in well known areas on the Arlberg (Sankt Anton, Lech) in the Silvretta group (Ischgl, Silvretta Montafon) and in the Oetztaler Alps (Soelden).

More interestingly, operating figures indicate that ski areas exhibit higher ROIs and profit ratios, while the average debt ratio is slightly smaller. Altogether however, with debt ratios around and in many cases above 100 %, the data points out the high vulnerability of the tourism industry, for which the availability of equity capital has traditionally been considered as a weak point.[33]

Apart from that, another issue of interest is the interaction between the different indicators. If the differences over time are highly correlated, there might be inference

[32] It needs to highlighted though that this can partly also be explained by the business strategies of different areas, which is not indicated in the data. While some areas primarily focus on the winter season and close down in other seasons, some try to attract guests all over the year, with supposedly lower average sales per night.

[33] The debt ratio has also become more important in recent years, particularly because of it's increasing role in credit ratings in the course of the introduction of Basel II (see e. g. Hartl 2002).

from one indicator to others. If for example a change in overnight stays would go along with changes in the debt or profit ratio, the impacts of snow conditions on overnight stays could also be related to these business indicators. Not surprisingly however, given the manifold factors which impact these indicators, analyses clearly show that such dependencies are not deducible from the given data.

3.4 Data Analysis

In this section I provide some more analysis on the data and test it for normality, stationarity and multicollinearity. For this purpose, I use the following convention on notation in this and the following sections:

- The variable $nights_t$ denotes the overnight stays either in the respective ski area or on a more aggregate scale (province, altitude or size category, all ski areas). In most cases the level of aggregation should be clear, otherwise I will refer to the level of aggregation with a subscript.

- The variable $snow_t$ symbolizes the snow index examined, usually the $Sday_1(alt_{50})$ index for individual areas or $Sday_{AVG}$ on the aggregated scale. Otherwise, e. g. for comparing several snow indices, the notation follows the convention given in Subsection 3.3.2.

- The variables gdp_t and pp_t denote the income and price variables weighted by the guest's origin country, the variable $beds_t$ symbolizes tourist beds and the variable tc_t equals the transport capacity over time.

3.4.1 Testing for Normality

In a first step, normality tests are applied in order to get an idea whether the meteorological data can be modelled by the frequently deployed normal distribution or not. This is particularly important for the weather index modelling in Section 4.1 and could also give a hint whether the indices should be transformed to their logarithm prior to the modelling of the impact function in Section 4.2. It needs to be emphasized that due to the relatively low number of observations over time ($T = 34$) particular caution is necessary when interpreting the results of the normality tests. For this sample size the Shapiro-Wilk test (Shapiro and Wilk 1965) seems to be a good choice. In addition, the tests suggested by Lilliefors (1969) and Jarque and Bera (1980) are conducted.

The results from the normality tests presented in Table 3.7 show that the $Sday_1$ and T_{mean} indices can be well approximated by a normal distribution for most of the ski areas.[34] However, when transforming $Sday_1$ to logarithms this is less often the case. In

[34] All tests also indicate normality for average and urban snow indices.

Test	$Sday_1$ alt_{50}	S_{mean} alt_{50}	$Sday_{30}$ alt_{50}	$Sday_{1,art}$ alt_{50}	T_{mean} alt_{50}	$Sday_1$ alt_0	S_{mean} alt_0	$Sday_{30}$ alt_0
Shapiro-Wilk	171	39	46	157	180	177	11	14
Jarque-Bera	174	91	114	168	185	179	44	54
Lilliefors	178	87	75	161	181	175	29	22
Logarithms:								
Shapiro-Wilk	118	165	-	142	180	96	173	-
Jarque-Bera	116	179	-	155	185	110	182	-
Lilliefors	162	163	-	157	181	155	170	-

All tests are based on a 5 % level of significance

Table 3.7: Number of cases (total=185) where statistical tests do not reject the hypothesis of a normally distributed weather index; Weather indices are also converted to a logarithmic scale

comparison the S_{mean} and $Sday_{30}$ indices hardly follow a normal distribution, but for the former this can be overcome by taking the logarithms[35]. Overall, the results suggest that, at least, it might be a good idea to consider a normal distribution in addition to the other approaches for modelling the distribution (Section 4.1).

3.4.2 Testing for Stationarity

A time series is called stationary if its statistical properties remain constant over time. In order to understand the relationship between two or more variables using multiple regression analysis for time series data, stationarity needs to be assumed. Otherwise regression analysis might indicate a relationship between variables simply because each has a trend, is an integrated time series, or both, a phenomenon widely known as spurious regression problem. (Wooldridge 2006, p. 381)

Two unit root tests are applied to test the data for level and trend stationarity (see also Subsection 2.6.2), namely the Augmented Dickey Fuller (ADF) test (Dickey and Fuller 1979), which tests the null hypotheses of a unit root against the alternative of stationarity and the KPSS-test (Kwiatkowski et al. 1992), which reverses the test hypotheses and thus provides additional insight. Tests are conducted to test for stationarity both before (level stationarity) and after the removal of a deterministic trend (trend stationarity).

The results of the unit root tests are shown in Table 3.8. In principle, they show that overnight stays $nights_t$ and other tourism or economic variables like $beds_t$, gdp_t and pp_t are non-stationary for most of the ski areas and this also does not change when removing deterministic trends. In comparison, $snow_t$ is stationary for the majority but not all ski

[35]It should be noted that when changing to logarithms, the problem with zeros and negative values can easily be solved for temperature data in transforming it from Celsius to Kelvin. However, adding a constant would be more disturbing for count indices with zero values such as the $Sday_{30}$ indices.

Variable	KPSS-Test for Level Stationarity[1] Yes	No	KPSS-Test for Trend Stationarity[1] Yes	No	ADF-Test for Trend Stationarity[2] Yes	No
$nights_t$	30	148	37	155	20	165
$snow_t$	107	78	134	51	116	69
$beds_t$	25	160	54	131	20	165
gdp_t	0	185	28	157	0	185
pp_t	16	169	31	154	22	163
$\Delta nights_t$	159	26	174	11	153	32
$\Delta^2 nights_t$	185	0	185	0	185	0
$\Delta snow_t$	185	0	185	0	172	13

[1] Non-Stationarity is indicated, if p-value< 0.05
[2] Non-Stationarity is indicated, if p-value> 0.05

Table 3.8: Number of cases (total=185) where unit root tests indicate level/trend stationarity for the respective variable

areas, especially after trend removal. After first-differencing of the variables (integration of order one), the test results indicate level and trend stationarity for almost all areas. For the remaining areas second-differencing may be a good idea, as it is indicated for $nights_t$.

The effects on the time series from either removing deterministic trends or from differencing can also be observed by visual inspection. Figure 3.14 illustrates the effects of these transformations both on total overnight stays in ski areas and weighted-average snow conditions. On the one hand, removing a linear trend[36] still leaves some strong autoregressive behaviour for $nights_t$, while it is supposed to be a good idea for $snow_t$, as it eliminates the observed downward trend discussed before. On the other hand, differencing seems to be beneficial for $nights_t$ rather than for $snow_t$. For $nights_t$ first-differencing clearly reduces autocorrelation and the trending behaviour. On the example of the snow deficient winter season 1989/90 it can be seen that it brings out the large decline in this season, in fact the most severe decline observed in the sample period. However, for $snow_t$ differencing has the effect that this season does not stand out any more, for the reason that it is compared to the previous season, which has been below average as well.

Moreover, the residuals of an AR(1) model for both time series are displayed in Figure 3.14. The variable $snow_t$ can not be well described by an autoregressive model and hence the series is almost identical to the non-transformed one. In contrast, for $nights_t$ removing the autoregressive part leaves us with a series which is extremely similar to the first-differenced one. This is not surprising at all, given the importance of autore-

[36]This also does not change after removing other than linear trends.

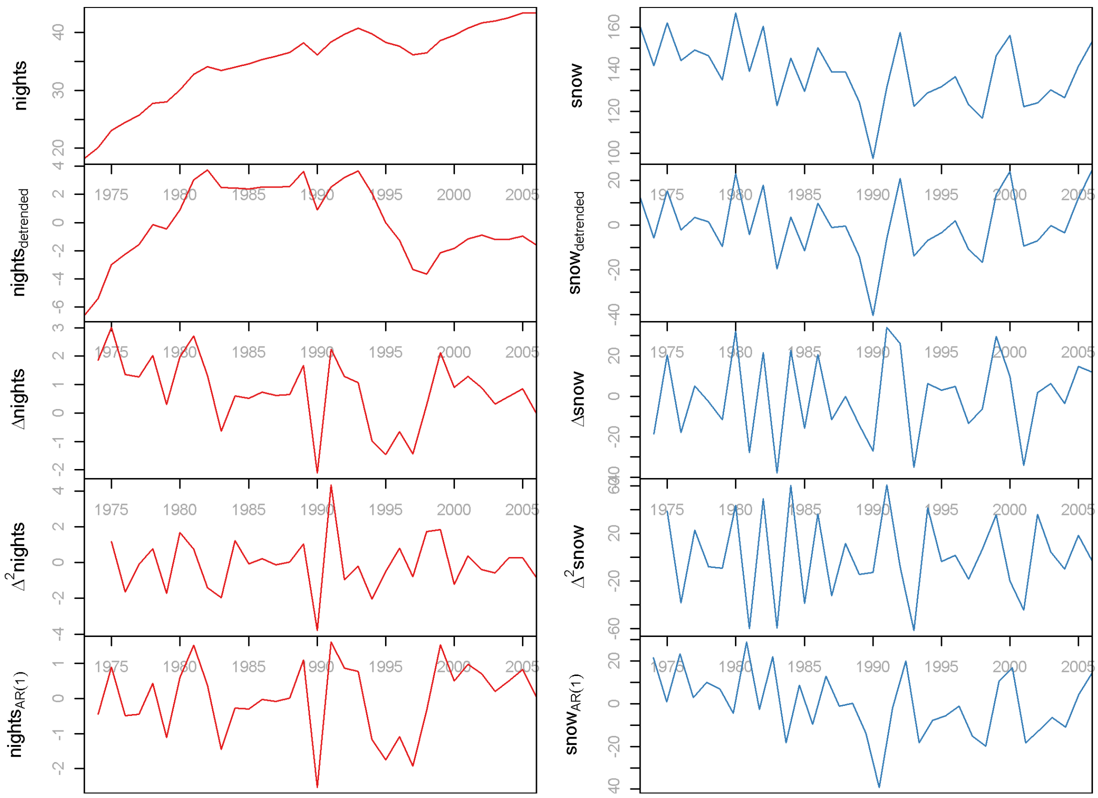


Figure 3.14: Time series of total overnight stays (in million) and snow conditions after de-trending, first and second order differencing, and correcting for AR(1)

gressive processes in tourism demand indicators, which has frequently been confirmed in previous studies (see Subsection 2.6.3). The implications from this strong autoregressive behaviour of $nights_t$ on model choice will be discussed in more detail in Section 4.2.

3.4.3 Testing for Multicollinearity

If in a multiple regression one or several predictor variables are strongly correlated, this affects the calculation of individual predictors. The standard errors increase and even small changes in the data may have a large effect on the estimated coefficients. As a general rule of thumb, multicollinearity may cause problems if the absolute value of the correlation coefficient ρ exceeds 0.5.

Figure 3.15 summarizes the correlations between different potential predictor variables for all ski areas. It can be seen that multicollinearity is definitely not a problem if the variable $snow_t$ is included together with lagged overnight stays $nights_{t-1}$ or other

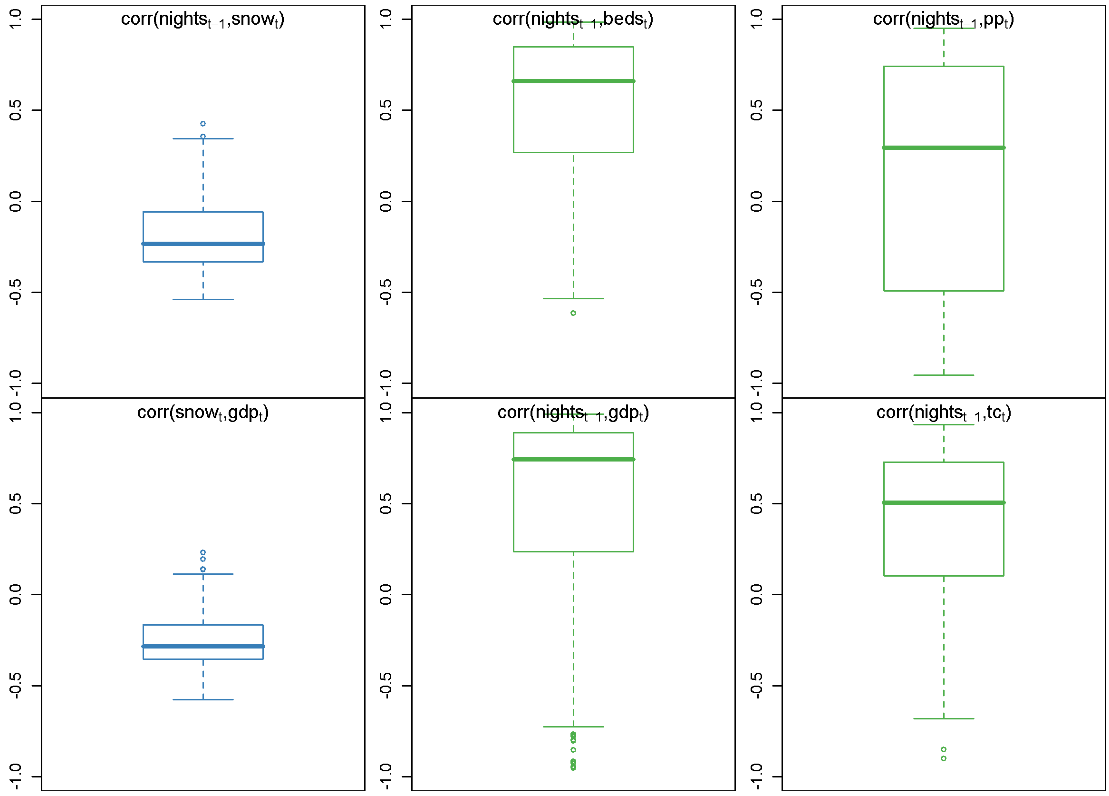


Figure 3.15: Summary of correlation coefficients ρ between different potential predictors

economic variables like gdp_t. However, if several tourism or economic variables like $nights_{t-1}$, $beds_t$, tc_t, gdp_t or pp_t are included in the models, the supposedly spurious impact of collinearity among these variables will complicate the estimation of individual predictors. The implications of this for the modelling will be discussed in more detail in Section 4.2.

Checking for collinearity amongst the different weather indices can also yield interesting insights. A frequently applied strategy in the literature is to put several indices into the regression models and then interprete the results either for variables with significant coefficients or for those selected by stepwise regression (see Table 2.3). However, especially when using the first approach, multicollinearity might affect the coefficients.

Figure 3.16 reveals that with a few exceptions, weather indices are highly correlated and in case of applying the before mentioned modelling strategies including several of them could cause problems with multicollinearity. When checking for collinearity amongst the variables for the same altitude alt_{50} (blue boxplots), it can be seen that

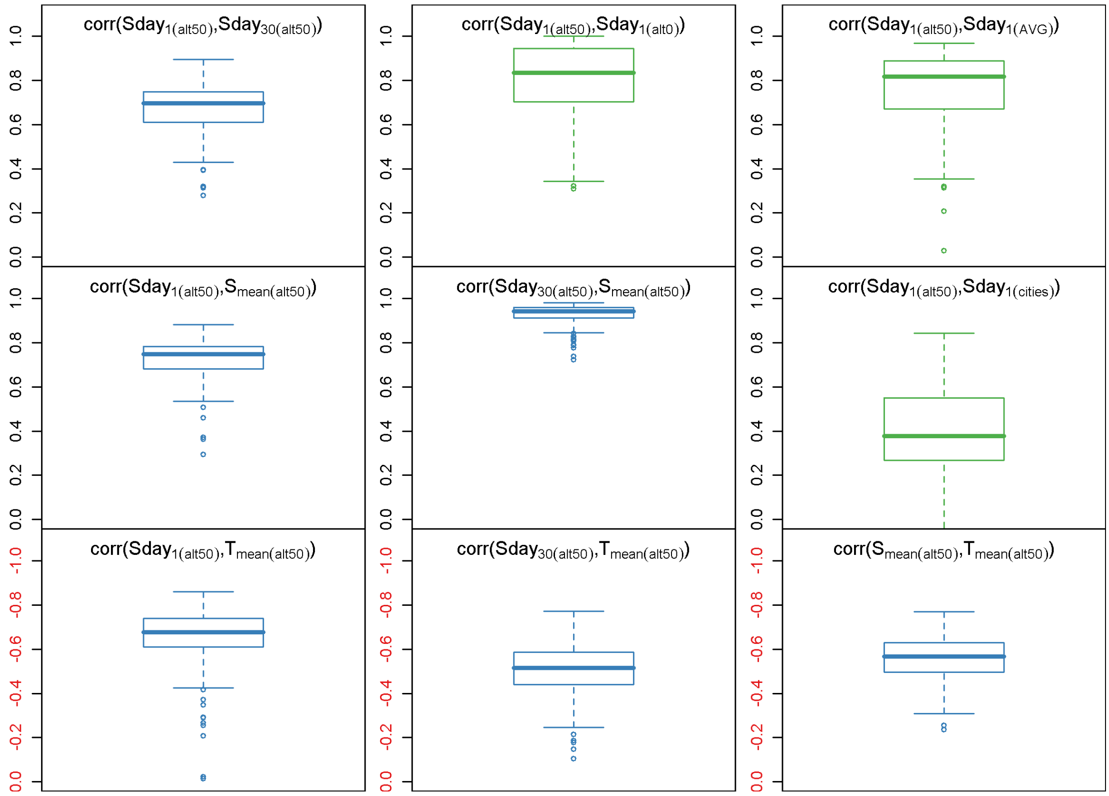


Figure 3.16: Summary of correlation coefficients ρ between different weather indices

especially the S_{mean} and $Sday_{30}$ indices strongly correlate, while $Sday_1$ and not surprisingly T_{mean}[37] show less stronger but still clear correlations with the other indices.

Likewise, as the green boxplots in Figure 3.16 show, $Sday_1(alt_{50})$ highly correlate with $Sday_1(alt_{50})$ and notably also with the weighted-average ski area snow conditions $Sday_{AVG}$. Even average urban snow conditions $Sday_{cities}$ are, with a few exceptions, positively related to ski area snow conditions. Altogether, these observations heavily suggest that it needs to be dealt with this collinearity amongst weather indices in the time series regression models (see Section 4.2).

[37]Note that because temperature and the snow indices are negatively correlated, scales are shown inverted (red axis labels) in Figure 3.16.

3.5 Concluding Remarks

While having described the methodological framework for estimating weather risks at the beginning of this chapter, the focus has then been on the empirical data. It was shown that data is in general not readily available for risk modelling and that it is hard to obtain data with a sufficient number of observations over time, at least if weather risk calculations should go beyond single case studies. Furthermore, data has been analysed statistically. It has been demonstrated that not all weather indices can be approximated by a normal distribution and especially tourism and economic indicators exhibit non-stationarity. In addition, correlations between weather indices are frequently high, and this is also the case for some other potential predictor variables. For all of these reasons, methods from tourism demand modelling, financial risk management and climatology need to be adapted to the nature of the data in order to quantify weather risks in the tourism industry, as will be discussed in the following chapter.

4 Modelling Approach

In this chapter I give details on how the methodological framework presented in Section 3.1 can be applied on the empirical data. The structure of this chapter closely follows STEPS 1-3 of the framework, namely the modelling of the weather index (STEP 1) and of the impact function (STEP 2) as well as the corresponding measurement of weather risk (STEP 3). In order to provide answers to the outlined research issues, I do calculations in a way that allows for comparability between the weather risks in different ski areas and for analysing the sensitivity of results to the choice of the weather index, weather index modelling approach and model specification.

Therefore, I choose the following sequence of modelling activities. First, one reference case with one weather index, model specification and risk measure is established and calculated for the $N = 185$ ski areas. Then, the modelling of the weather index, the impact function and the calculation of the different risk measures is repeated for 15 weather indices[1], 6 different approaches to model the weather index, and 6 different model specifications. This is done both for individual ski areas and on the aggregated scale[2] and allows to carry out the above mentioned sensitivity analysis. It also provides the basis to finally decide on which of the possible constellations[3] should be taken into account for calculating best estimates of ski areas' weather risks.

For the sake of simplicity and clarity I use the following conventions on notations in this chapter:

- Except stated otherwise, equations are the same for i in $1, ..., N$ ski areas and therefore it is convenient not to notate the subscript i in any of the equations.

- As already mentioned before, the variable $snow_t$ always symbolizes one of the 15 weather indices under consideration. In many cases it is useful to standardize it, or in other words to convert it to its z-score. Thereby $snow_t$ is corrected for μ and σ observed over time t and the transformed index is denoted as WI_t.

[1] 9 out of these 15 indices are different for each area, namely $Sday_1$, $Sday_{30}$, S_{mean} (each both for alt_0 and alt_{50}),$Sday_1(art)$,$Sday_{30}(art)$ and T_{mean} (each for alt_{50} only). The other 6 indices are identical for each area, with $Sday_{AVG}$ representing the weighted average conditions for $Sday_1(alt_{50})$ and $Sday_{Vienna}$, $Sday_{Linz}$, $Sday_{Graz}$, $Sday_{Innsbruck}$, $Sday_{Salzburg}$ the $Sday_1$ index in the respective cities.

[2] Data is accumulated for all Austrian ski areas, the seven federal provinces with skiing activities, four altitude and three size categories (see Subsection 4.2.4)

[3] $540^{185} \approx 10^{505}$ constellations are possible if no restriction is given to combinations of approaches to model the weather index, different weather indices and model specifications in each of the areas.

This transformation can also be done for the logarithms of the respective indices ($lnWI_t$).[4] Formally it can be written as:

$$WI_t = \frac{snow_t - \mu_{snow}}{\sigma_{snow}} \tag{4.1}$$

$$lnWI_t = \frac{ln(snow_t) - \mu_{ln(snow)}}{\sigma_{ln(snow)}} \tag{4.2}$$

- Similarly, models are written in such a way that β_1 interchangeably represents the estimated impact of WI_t on $nights_t$ for area i. Of course, its value changes when calculations are repeated with different weather indices and model specifications (Equation 4.9 to Equation 4.14).

4.1 Modelling the Weather Index

In this section I describe the modelling of the weather index, which corresponds to Step 1 of the modelling framework outlined in Section 3.1. First, I discuss the historical distribution and other potential approaches to model the weather index distribution. I then focus on two of these approaches and explain them in more detail. Last but not least, I illustrate the incorporation of time trends in the weather indices for all of these approaches.

4.1.1 Historical Distribution

The most basic approach is to consider the historical distribution of WI_t, which would be a discrete distribution with $T = 34$ observations for each area i for the empirical data. To emphasize that the time order is not of importance for the resulting distribution and that WI_{hist} is a function $\mathcal{G}$[5] it is formally written as:

$$WI_{hist} = WI = \mathcal{G}(WI_t) \tag{4.3}$$

While this frequently employed approach is easy to apply, it has some major flaws. Due to the usually low number of observations, the assumption that the historical index time series is statistically consistent with the weather that will occur in the period of interest needs to be challenged. Apart from trends in the historical series, this particularly

[4] Equation 4.2 highlights that $lnWI_t$ is not equal to $ln(WI_t)$. This difference is important to understand for the risk modelling.

[5] This notation is chosen to be consistent with the other distribution modelling approaches, which is important when describing the later modelling steps.

concerns the accuracy of extrapolation of extremes. How critical this assumption is can be easily observed when changing either the sample size or the sample period. In both cases, the distribution might change substantially. To overcome some of the limitations of the historical approach, several alternatives are conceivable[6]:

Distribution modelling The weather index can be modelled by either using a *non-parametric* (e. g. kernel smoothing) or *parametric* (e. g. normal) distribution. While, analogous to the historical approach, sample changes will also lead to changes in the parameters of the distribution, both approaches help to interpolate between points on the historical distribution function and extrapolate at the extremes. In general, the *non-parametric* approach thereby constrains the shape of the fitted distribution to a much lesser degree than *parametric* methods, but it is more difficult to validate. *Parametric* distributions more likely capture possible extremes which have not been observed in the sample period, but their accuracy crucially depend on the goodness of the fit.

Numerical simulation Another possibility is to simulate the weather index (e. g. by the Monte Carlo method). In this case, pseudo-random numbers are generated from the index distribution, and this usually large number of simulated values can then be used for further modelling steps.

Daily Index Modelling Instead of cumulated indices like HDD or $Sday_1$, the underlying climate element is modelled stochastically on a daily basis. This approach is appealing for the reason that a more complete use of the available historical data enhances the accuracy of the index distribution and the extrapolation of extremes. However, daily models are significantly more complex than other index modelling methods even for temperature, which is currently the only climate element with promising applications[7].

Multivariate Index Modelling The intention behind this approach is to enhance the number of observations by using weather indices for several locations instead of one single location. The use of additional locations might be beneficial under two conditions: On the one hand, the statistical properties of the weather indices in the two locations should be similar, otherwise taking extra data would not increase the accuracy of the joint index distribution. On the other hand, the indices should not be perfectly identical, as there would not be any additional information available then.

[6] All except the last approach are described in more detail in Jewson, Brix and Ziehmann (2005).

[7] See for example Benth and Benth (2005) for the stochastic modelling of temperature variations with an Ornstein-Uhlenbeck process.

Finally, from all of these approaches two have been selected, namely the multivariate and the parametric index modelling approach, and their application will be explained in more detail in the following.

4.1.2 Multivariate Non-parametric Distribution

In order to give a distribution of the weather index WI_{nonpar} for each ski area i, which includes not only information on the distribution of the weather index WI in the ski area itself, but also on the distribution of the weather index WI in other ski areas j, it has to be decided on how to select these areas j. For the given research question it seems to be a good idea to include information from other areas with a similar snow reliability, which does not necessarily mean that the snow conditions exhibit the same development over time. Technically speaking, this means that μ_{snow} as a measure of snow reliability[8] and not ρ or some other measure of dependency[9] is used as a criterion to decide how much weight is given to the empirical distribution of WI in area j for describing the distribution of WI in area i.

Instead of defining some on/off threshold (e. g. by selecting only areas j with a μ_{snow_j} that lies between $\mu_{snow} - \sigma_{snow}$ and $\mu_{snow} + \sigma_{snow}$) for each area i, a normally distributed weighting function $\mathcal{N}(\mu_{snow}, \sigma^2_{snow})$ is used. This means that the farther μ_{snow_j} is away from μ_{snow}, the less weight is given to the distribution of WI in area j. Moreover, due to the characteristics of the normal distribution weights quickly decrease with increasing differences to avoid a unreasonably high influence of areas with a different snow reliability.

Formally, for each ski area i the weight ω_j for the snow conditions in area j can be written as:

$$\omega_j = \phi_{\mu_{snow}, \sigma^2_{snow}}(\mu_{snow_j}) \tag{4.4}$$

As $\sum_{j=1}^{N} \omega_j$ is different for each area i and each weight ω_j is used for T seasons, the weights are corrected so that $\sum_{t=1}^{T} \sum_{j=1}^{N} \omega_{j,t} = 1$. The obtained normalized weights $\omega_{j,normalized}$ can be denoted as:

[8] Of course, even if μ is identical in several areas, a higher volatility in one of them would mean that it is less snow reliable. However, as μ is strongly correlated with σ anyway, I do not consider σ for creating the weighting function, as it would add some additional complexity.

[9] Indeed, using ρ might be generally out of question. Consider the case of two areas where $snow_t$ is highly correlated because they are influenced by the same weather currents. In this case, the distributions would be alike and little information would be gained from considering both areas.

$$\omega_{j,normalized} = \frac{\omega_j}{T \sum_{j=1}^{N} \omega_j} \tag{4.5}$$

As a result, for each area i a discrete distribution $\mathcal{G}$ with $N * T$ jumps is available for $N * T$ observations of $WI_{j,t}$ and the respective weights $\omega_{j,normalized}$:

$$WI_{nonpar} = \mathcal{G}(WI_{j,t}, \omega_{j,normalized}) \tag{4.6}$$

It needs to be emphasized that WI_{nonpar} seems to be helpful for estimating the snow risk of ski areas compared to the historic distribution WI, as it captures extremes and other characteristics of the distribution which might have been observed not in the area itself but for some other area. Its comparative advantage is therefore determined by the spatial dependencies in the data and should outweigh concerns on whether the distributions in the other areas j are really representative for area i. Of course, similar to the historical distribution, its shape might be substantially influenced by the choice of the sample period.

4.1.3 Parametric distribution

As shown in Subsection 3.4.1, the distributions for most of the weather indices in most of the ski areas can be quite well described by a normal distribution $\mathcal{N}$[10]. Therefore, in addition to the two approaches introduced so far, a normal distribution is fitted, which is identical for each area i due to the use of standardized weather indices WI:

$$WI_{norm} = \mathcal{N}(\mu_{WI}, \sigma^2_{WI}) = \mathcal{N}(0, 1) \tag{4.7}$$

4.1.4 Trend adjustments

The meteorological data contains quite remarkable time trends for many ski areas, an issue already discussed in Subsection 3.3.2. Therefore, it is interesting to capture these trends and repeat the three modelling approaches with trend adjusted weather indices WI_{trend}. For this, a constant is added to WI, which equals the slope of the trend line obtained by OLS ($trend_{WI}$), multiplied by $(\frac{T}{2} + 1)$, corresponding to the expected distribution for the year after the sample period[11].

[10] It is conceivable not only to consider a normal distribution, but rather compare the fit of several different distribution forms and choose the most appropriate one. However, this would add some complexity to the modelling and particularly for the reason that for $T = 34$ results might be questionable anyway, I do not spend further attention on this approach.

[11] Another issue is, of course, whether not only μ but also σ changes with time. However, it is evident that for a period of $T = 34$ years it is not reasonable to interpret changes in σ.

$$WI_{trend} = WI + (\frac{T}{2} + 1)trend_{WI} \tag{4.8}$$

4.2 Econometric Modelling

In this section I explain the empirical modelling of the impact functions. This basically covers STEP 2 of the modelling framework outlined in Section 3.1, namely the estimation of the relationship between the demand indicator $nights_t$ and the respective weather index WI_t. Therefore, econometric models are estimated, and statistically tested in order to detect violations of model assumptions.

4.2.1 Model Choice

From the models suggested in the literature (see Section 2.6), an Autoregressive Distributed Lag (ADL) model is applied for the bulk of analysis in this thesis for the reasons outlined in this subsection. In principle, it has the same form as the models used in Bigano et al. (2005) and Agnew and Palutikof (2006) for estimating weather impacts on tourism demand in Italy and the UK. However, calculations are done on the local rather than on the national or provincial scale and are therefore repeated for a large number of cases, which influences the choice of the model and the modelling approach.

First of all, the ADL model is preferred to panel data methods, which are applied in some recent tourism demand studies, mainly because of the specific interest in weather impacts for individual ski areas. Individual effects can only be obtained when specifying the panel as variable coefficient model and results should then largely correspond to those obtained from an ADL model. Moreover, panel techniques seem to be less appropriate for several reasons. Firstly, the homogeneity assumption may not hold and is very likely to be more critical for weather than price or income variables. Indeed, in a panel of several ski areas, some might profit and some might lose from the same weather index. Secondly, different ski areas are supposedly dependent on different weather indices, e. g. lower lying ski areas might be affected by $Sday_1$ while higher lying ones by S_{mean} or $Sday_{1,AVG}$. It seems challenging to deal with these two issues in a panel setup. In addition, panel techniques are more complex than time series regressions, and many of the estimation procedures have only be developed recently and are not implemented as a standard in statistical software. For all of these reasons, panel estimations are not conducted within this thesis, but it is possible and highly interesting to compare ADL results on the aggregate level with panel estimation results obtained for the same data set in another study (see Subsection 4.2.4)[12].

[12]Panel data estimations are conducted by a colleague with a background in statistics and econometrics. Results of these estimations are thoroughly discussed in Eigner, Toeglhofer and Prettenthaler (2009).

Furthermore, the ADL model is preferred to static regression models because dynamic modelling by including lagged dependent variables in the regression is recommendable in the presence of temporal autocorrelation in the residuals and/or high persistency in the dependent variable. The inclusion of a lagged dependent variable then reduces the amount of potential spurious regression, which may lead to wrong inferences and potential inconsistent estimation. While another way to avoid problems with spurious regressions would be to conduct regressions with first or second-order differenced variables (Hamilton, J. D. 1994, p. 561), the ADL model is generally more popular for estimating tourism demand relationships, as the obtained autoregressive coefficients are of interest by themselves (Song, Witt and Li 2009, p. 49). Therefore the ADL model will be used in this thesis, but a regression model with differenced variables will also be considered for comparison reasons.

In an ADL setup where the variables tend to be non-stationarity, one strategy is to test for co-integration and use an error correction model (ECM) in the presence of a co-integrating relationship. Two recent studies for Austria have done this on an aggregated scale. For their panel data set on 28 ski areas Falk (2010) finds a co-integrating relationship between overnight stays, weighted GDP per capita, accommodation prices and S_{mean}. In comparison, Schiman, Toeglhofer and Prettenthaler (2009) consider data for the 7 winter sport provinces and find the economic variables to be co-integrated for 6 out of 7 provinces, while they suggest to deal separately with the trend-stationary $Sday_{30}$ indices. In this thesis however, an error correction framework is not considered for the reason that, as explained below, income and price variables are not included in the model specifications for individual areas and meteorological indices are mostly stationary anyway (see Subsection 3.4.2).[13]

It needs to be emphasized that one major restriction for the use of time series regression models of any kind is the given number of observations ($T = 34$). As a general rule of thumb, the number of structural parameters to allow in a regression model should be approximately $N/10$ (Burnham and Anderson 2002, p. 245). In order to limit the number of variables, one popular approach is to apply a general-to-specific modelling approach, which works in the following way: A general demand model with a large number of explanatory variables, including the lagged dependent and lagged explanatory variables, is constructed in the form of an ADL model, which is then restricted by considering the t, F and Wald statistics to achieve a simple but statistically significant specification (Song, Witt and Li 2009, p.59). However, because comparability might not be given between individual ski areas if the model specifications are different for each of them, this approach is not chosen.

Instead, the number of variables is kept the same for all calculations and is constrained to four (plus the intercept) by the following:

[13] Above that, some empirical studies show that the ADL and the cointegration/ECM approach give very similar results (see e. g. Bentzen and Engsted 2001).

1. Unlike other similar studies (e. g. Agnew and Palutikof 2006), the calculations were assessed using only one weather index at once and were then repeated for all indices. This might be preferential because if variables are highly collinear, which is the case for most of the considered weather indices (see Subsection 3.4.3), the use of selection criteria is problematic per se.

2. Income gdp_t and price variables pp_t are not considered, as for the development of overnight stays in individual ski areas it is expected that a change of national GDP and CPI, which are taken to construct these indices, are less important than a series of local-specific effects. Indeed, exploratory analyses show that very similar results are obtained by simply including a deterministic trend component instead of the income index gdp_t into the model specification (Equation 4.12). Therefore, the inclusion of a trend is pursued instead of taking into account the for local studies supposedly inadequate income index, as explained in more detail in Subsection 4.2.2. What is more, the variable pp_t shows comparatively very little variations (see Subsection 3.3.4) and is therefore unlikely to heavily influence tourism demand on the local scale.

4.2.2 Model Specifications

Based on the before mentioned considerations, several model specifications are considered in this thesis. For the bulk of analysis a semi-logarithmic ADL model is chosen (Equation 4.9). However, additional insights are expected from comparing this model to other specifications (Equation 4.10 to Equation 4.14).

Following the recommendations from empirical studies on tourism demand (e. g. Song, Wong and Chon 2003), the dependent variable enters the equation with two lags ($nights_{t-1}$, $nights_{t-2}$). A lag is also considered for the weather index (WI_t), as it might be the case that because of pre-bookings and the terms of cancellation adverse weather conditions might not affect demand in the same, but in the following year. Furthermore, the logarithm of overnight stays is taken. This is common in the literature for tourism demand data, because transforming to logarithms produces time series with approximately constant variance over time. Otherwise it is often the case that the higher the level of a series rises, the greater the variation observed around that level (Cryer and Chan 2008). Accordingly, the model can be written for each of the $1, ..., N$ ski areas as:

$$ln(nights_t) = \beta_0 + \phi_1 ln(nights_{t-1}) + \phi_2 ln(nights_{t-2}) + \beta_1 WI_t + \beta_2 WI_{t-1} + \varepsilon_t \qquad (4.9)$$

In addition to the semi-logarithmic reference model given in Equation 4.9, it is interesting to consider a double-logarithmic model specification (Equation 4.10), where also WI_t and WI_{t-1} are considered in logarithms. This specification might be helpful if the relationship between overnight stays and the weather index is non-linear[14]. Other model specifications of interest are a linear model without transformation (Equation 4.11) and a model including a time trend (Equation 4.12).

$$ln(nights_t) = \beta_0 + \phi_1 ln(nights_{t-1}) + \phi_2 ln(nights_{t-2}) + \beta_1 lnWI_t + \beta_2 lnWI_{t-1} + \varepsilon_t \quad (4.10)$$
$$nights_t = \beta_0 + \phi_1 nights_{t-1} + \phi_2 nights_{t-2} + \beta_1 WI_t + \beta_2 WI_{t-1} + \varepsilon_t \quad (4.11)$$
$$ln(nights_t) = \beta_0 + \phi_1 ln(nights_{t-1}) + \phi_2 ln(nights_{t-2}) + \beta_1 WI_t + \beta_2 WI_{t-1} + \beta_3 tr_t + \varepsilon_t \quad (4.12)$$

$$\Delta^2 nights_t = \beta_0 + \beta_1 \Delta WI_t + \varepsilon_t \quad (4.13)$$
$$ln(nights_t) = \beta_0 + \beta_1 WI_t + \varepsilon_t \quad (4.14)$$

Furthermore, a regression model with differenced variables (Equation 4.13) and a static regression model (Equation 4.14) are calculated for comparison reasons.

4.2.3 Diagnostic Checking

All results from time-series regression models are tested for residual autocorrelation, functional form, heteroscedasticity and the distribution of the residuals. A model can be considered as statistically acceptable if none of the applied tests indicate a violation of the underlying assumptions. All of the following tests are conducted with a significance level of 5 %:

- The Breusch-Godfrey test (Breusch 1978; Godfrey 1978) is an LM(Lagrange Multiplier)-test on serial correlation. In presence of lagged values of the dependent variable it should be preferred to the Durbin-Watson test (Durbin and Watson 1951) to check whether the residuals are serially uncorrelated (Heij et al. 2004, p. 362).

- The *regression specification error test* (RESET), introduced by Ramsey (1969), has proven to be useful to detect general functional form misspecification. The RESET has the advantage that it does not require the specification of alternative models. However, this also means that it does not provide any direction on how to proceed if the model is rejected. Furthermore it needs to be emphasized that the test has no power for detecting omitted variables whenever they have expectations that are linear in the included independent variables in the model (Wooldridge 2006, p. 309).

- The Breusch-Pagan test (Breusch and Pagan 1979) is a test for heteroskedasticity where the squared OLS residuals are regressed on the explanatory variables in

[14] The log-log specification also enables to interpret coefficients from the regression models as elasticities. However, for doing so it would be necessary to run regressions with the non-standardized weather index $snow_t$ instead of WI_t

the model (Wooldridge 2006, p. 860). Residuals are regarded as heteroskedastic when they have different variances depending on the value of one or more of the explanatory variables.

- Two tests are applied to test whether the distribution of the residuals is close to normality, namely the Lilliefors test (Lilliefors 1969) and the Jarque-Bera test (Jarque and Bera 1980).

In accordance with other tourism demand studies (e. g. Song, Wong and Chon 2003), tests are conducted in order to point out violations of the model assumptions and test statistics will be presented together with the regression results, but individual regressions will not be adapted, e. g. by calculating hetereoskedasticity corrected standard errors.

4.2.4 Aggregated models

In addition to the estimates obtained for individual ski areas, effects are also of interest on a more aggregate level. For that, results are provided for the seven federal provinces with skiing activities, four altitude and three size categories as well as for the entire Austrian ski industry. Principally aggregate estimations can be done with different methodological approaches:

1. Data is accumulated for each of the provinces, altitude and size categories before estimating the models using the model specifications presented in Subsection 4.2.2. For $nights_t$ this can be done by using the sum, for $snow_t$ by using the weighted average (by μ_{nights}) of the respective category.

2. Calculations are done for individual ski areas, but impacts are then added up, considering also the dependency structure between areas. This approach is appealing as it allows to incorporate different weather indices for each of the areas. It can be implemented directly based on the individual impact functions and is described in full detail in Subsection 4.3.3.

3. In Eigner, Toeglhofer and Prettenthaler (2009) the ADL model as used for the time series regressions before (Equation 4.10) is also applied on the whole data set by a panel data model. As this model gives more degrees of freedom, additional variables for the supply of accommodation ($beds_{it}$), income (gdp_{it}) and prices (pp_{it}) are included. Accordingly, the general model setup for the panel data estimations is:

$$\begin{aligned} ln(nights_{it}) = \beta_0 + \phi_1 ln(nights_{it-1}) + \phi_2 ln(nights_{it-2}) + \beta_1 ln(snow_{it}) + \\ \beta_2 ln(beds_{it}) + \beta_3 ln(gdp_{it}) + \beta_4 ln(pp_{it}) + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{4.15}$$

where the impact of the unobserved heterogeneity and the common time trend is captured by μ_i and λ_t respectively. Results are obtained by using several different estimation procedures:

- a pooled model (OLS), which assumes that all coefficients including the intercept are constant for all ski areas and over time.[15]
- a two-way fixed effects model to include individual fixed effects, which captures all remaining time-constant (fixed) determinants of tourism not yet controlled for in the model.
- a bias-corrected fixed effects model (Bruno 2005), which allows to calculate a consistent corrected estimator based on additive bias correction.
- the first-difference generalized method of moments (*DIFF_GMM*) proposed by Arellano and Bond (1991), which delivers asymptotically efficient estimates and instruments the differenced variables that are not strictly exogenous with all their available lags in levels.
- the System-GMM, which is an augmented version of the first-difference GMM (Arellano and Bover 1995; Blundell and Bond 1998).[16]

A summary of the applied estimation procedures is given in Table 4.1. Estimated models are distinguished according to the transformation method they use to remove unobserved effects or according to their consistency properties. For the sake of brevity, a detailed discussion on the methodological issues concerning the different panel data estimators is left out, but can be found in full detail in Eigner, Toeglhofer and Prettenthaler (2009).

4.2.5 Analysing Time Varying Effects

The approaches discussed so far rely on the assumption that the impacts of snow conditions on overnight stays are constant over time, an assumption which is also common in the literature dealing with weather impacts on tourism demand. However, a more detailed analysis of this temporal dimension seems to be fruitful and could provide additional insights, especially as for the case of winter tourism it is questionable whether this assumption holds. Therefore, in order to study the extent to which the sensitivity of the respective economic indicator to adverse weather conditions varies over time, several different approaches are applied:

[15] This model is only estimated for purposes of comparison, since unobserved individual effects are expected to be highly significant, and estimates of the pooled model will therefore be inconsistent and biased.

[16] In addition to its standard version, the System-GMM is calculated using only lag 4 to 7 of the dependent variable as GMM-instrumentals to fulfill the overidentifying restriction test (*System_GMM_v*) as well as in a version where the GDP is not treated as standard but as GMM style instrumental variable (*System_GMM_g*) to overcome the assumption of strict exogeneity.

Model (*Abbreviation*)	Trans-formation	Regressors	Consistency
Pooled (*Pooled*)	-	$y_{it-1}, x_i, 1, \lambda_t$	inconsistent/biased
Fixed effects (*FE*)	Within	$y_{it-1}, x_i, 1, \mu_i$	inconsistent/biased
Two-way fixed effects (*FE_tw*)	Within	$y_{it-1}, x_i, 1, \mu_i\lambda_t$	inconsistent/biased
Bias corrected FE_tw (*FE_tw_bc*)	Within	$y_{it-1}, x_i, 1, \mu_i\lambda_t$	consistent/unbiased
One-step first-difference GMM (*DIFF_GMM*)	Δ	$\Delta y_{it-1}, \Delta x_i, 1, \lambda_t$	consistent/unbiased
One-step System GMM (*SYS_GMM*)	Δ	$\Delta y_{it-1}, \Delta x_i, y_{it-1}, 1, \lambda_t$	consistent/unbiased

Source: Eigner, Toeglhofer and Prettenthaler (2009)

Table 4.1: Summary of the panel data estimation procedures

1. Effects are analysed separately for two extreme seasons, namely the warm and relatively snowless winter seasons 1989/90 and 2006/07[17]. In these seasons $Sday_1$ were 22 % and 29 % respectively below average which corresponds to $-1.5\,\sigma$ and $-1.9\,\sigma$ respectively. To overcome one major pitfall related to the analogue and similar approaches used to study extreme seasons (see Subsection 2.6.1), namely that trends in the underlying economic data are not accounted for, the performance of individual ski areas in these two seasons is compared to previous seasons by interpreting changes in the growth rates of overnight stays. Of course, while with this approach the underlying differencing of the economic data should reduce the influence of general trends on the results, it can not be ruled out that other factors than adverse snow conditions have contributed to the change in growth rates in the respective seasons.

2. Time-varying effects are considered by observing changes in the estimates from the dynamic regression models. Following Zeileis et al. (2002), empirical fluctuation processes are defined on the basis of estimates of the unknown regression coefficients given in Equation 4.9. Doing so, the β coefficients can either be estimated recursively with a growing number of observations or with a moving data window of constant bandwidth h, and are then compared to the estimates based on the whole sample[18]. In this thesis the latter mentioned approach, also known as moving estimates (ME) process (see Chu, Hornik and Kuan 1995), is taken. Bandwidths of $h = 0.2$ and $h = 0.4$ are chosen, which give estimates for 28 and 21

[17] According to Steiger and Mayer (2008), the extraordinary warm season 2006/07 with winter temperatures in Tyrol being 3.5 °C above the 30-year average 1971-2000 represents an average season in the PRUDENCE regional climate model projections (+2.0 to +4.0 °C in the Alps) for the period 2071-2100.

[18] These approaches follow the same idea as CUSUM (cumulative sums of residuals) or MOSUM (moving sum of residuals) type processes, but base on fluctuations in the estimates instead of the residuals.

intervals respectively.

3. Changes in the estimates from cross-section regression models are compared over time. This approach utilizes the idea to learn from the cross-section of observations amongst ski areas for each season t instead of time series regressions for each ski area i as presented in Equation 4.9. Thereby, for t in $1, ..., T-1$ time points the following model is estimated:

$$\%\Delta nights_i = \beta_0 + \beta_1 \%\Delta snow_i + \varepsilon_i \tag{4.16}$$

If in this model the β_1 coefficient decreases/increases over time, this could mean that changes in snow conditions have less/more of an impact on overnight stays.

4. In Eigner, Toeglhofer and Prettenthaler (2009) panel data models are recalculated using sub-panels for 3 periods consisting of 10, 11 and 11 seasons respectively[19]. Separate models are estimated for each time period, using the *FE_tw_bc* and the *System_GMM_GDP* model. For these separate models with only 10 and 11 time points respectively, the relatively large cross-section dimension of 185 makes the GMM estimator used for the *System_GMM_GDP* model preferable to the *FE_tw_bc* model.

4.3 Risk Measurement

In this section I give details on how the weather risk can be measured both for individual areas and on the aggregated scale. This basically corresponds to Step 3 of the modelling framework outlined in Section 3.1. First, I discuss the assumptions behind a probabilistic modelling of weather risks. Second, I explain how impact functions are obtained by considering both the estimated coefficients from the econometric models and the modelled distributions of the weather indices, and how these impact functions are then used to determine the Value at Risk from adverse weather conditions. Third, I cover different approaches to aggregate risk estimates obtained for individual areas. I end this chapter on the modelling approach by illustrating a possible way to choose from the variety of approaches discussed in order to obtain best estimates of ski areas' weather risks.

4.3.1 Assumptions behind Weather Risk Calculation

So far, the estimations of the impact of weather on economic indicators described in the literature have been conducted using one of the methods discussed in Section 2.6. In these estimations impacts have — mainly dependent on the choice of the approach and model specification — usually been provided for:

[19] The lagged dependent variables make it necessary to dispense with 2 out of the 34 time points.

- one or several (observed) extreme years;
- a one unit change in the respective weather index (e. g. by using a lin-lin or log-lin model specification);
- a percentage change in the respective weather index (e. g. by using a log-log model specification to calculate elasticities);
- a climate change analogue (e. g. by an analogue approach or by multiplying the results from regression models with the results from climate change scenarios for a specific period).

From a risk point of view — with the focus being on (short-term) weather risks rather than (long-term) climate change risks — such interpretations basically concentrate only on one side of the coin, namely on the impact side. Yet, the other side of the coin, the probability side, is largely neglected. The likelihood of a one unit or one percentage change in a weather index might deviate between regions and especially between different weather indices, obviously being dependent on the variability observed in the respective data. Hence, a comparability either between different regions or weather risks originating from different exposures is not given for these approaches.

Using the standard deviation σ as a risk measure[20] somewhat helps to overcome this problem, in that the probability that a certain impact occurs is under consideration as well. However, the probability of a standard deviation change crucially depends on the distribution of the weather index. For example under a normal distribution, the probability for a winter with a higher than one standard deviation decrease in the weather index would be 15.8 %, but for the empirical data, the estimated probabilities basically vary with the skewness and kurtosis of the respective indices.

As an alternative a probabilistic (statistical) approach can be used. With such an approach two questions are considered at the same time, namely how much could be lost in a period with adverse weather conditions, and how likely it is that losses will exceed this amount. In fact, a probabilistic approach might provide the same risk measure as it is commonly given for catastrophic events, even if the method for calculating it might differentiate (see Subsection 3.1.1). As discussed before, an event with e. g. a 5 % probability could be referred to as a *1 in 20 year event*, or in the language of financial risk management as *95-% Value at Risk* from adverse weather conditions or $\mathrm{VaR}(weather)_{0.95}$.

The quality of the weather risk estimates for a certain period provided by such a probabilistic approach fundamentally depends on how well the following statistical assump-

[20]This can be done by standardizing the weather indices before running the regression models, as it is also done in this thesis, or by multiplying regression coefficients obtained with unstandardized weather indices by σ of the respective indices.

tions, which also must be made for the classical VaR calculation (see Allen, Boudoukh and Saunders 2004, p. 8), are fulfilled[21]:

1. The *stationarity requirement* demands that a 1 % fluctuation in returns is equally likely to occur at any time point. For weather risk calculations this means that the expected impact does not change over time (see below).

2. A related assumption is the *random walk assumption of inter-temporal unpredictability.* For weather risks, this assumption could be interpreted in a way that the day-to-day, season-to-season or year-to-year fluctuations in the weather index are independent. Under this assumption there is no relevant information available to forecast from period t to period $t + 1$. Typically, this assumption will not hold when using high-frequency time series, but may hold for seasonal or annual data (see below).

3. The *non-negativity assumption* requires that the underlying economic indicator is not allowed to attain negative values.

4. The *distributional assumption* is of particular importance, as the focus is on the tails of the distribution of weather-related returns. In the standard case it is assumed that continuous return fluctuations follow a normal distribution with $\mu = 0$ and $\sigma = 1$, an assumption which might be challenged when estimating weather-related risks (see below).

In general, the accuracy of these assumptions for calculating weather risks seems to depend heavily on the specific risks examined, the time interval and the geographic region. For the special case of weather risks faced by the winter tourism industry in Austria, empirical estimates seem to be mainly influenced by the following:

1. The *stationarity requirement* is certainly the most challenging assumption. For the empirical models it implies that the sensitivity parameter β_1 is assumed to be constant over time. Indeed, this assumption is difficult to test when low-frequency time series with small samples are available, which is usually the case for the weather-sensitive financial or economic indicators of interest. Therefore, it is questionable from a statistical perspective if changes in the impact of weather on the

[21] Note that these assumptions have been adapted from the classical VaR calculation for the special case of weather risks. While the former approach focuses on fluctuations in returns, but does not consider the multifaceted causes which lead to these fluctuations, the latter approach concentrates on the fluctuations caused by one specific risk factor on the underlying returns, namely the weather. Nevertheless the underlying assumptions for calculating the former approach should also be valid for the latter.

respective indicators might be estimated with a sufficient accuracy[22]. It seems to be difficult to replace the simplifying assumption that historical experiences are representative for estimating weather risk for some (near) future period by some more sophisticated set of assumptions.

2. The *random walk assumption of inter-temporal unpredictability* implies two issues. On the one hand, unlike stock returns or other economic indicators, the levels of seasonal weather indices generally do not depend on previous seasons, but these indices rather contain some deterministic time trend (see also Subsection 3.4.2). Therefore, not incorporating this trend would affect the weather risk estimate and it seems to be beneficial to take it into account in the estimation. On the other hand, weather forecasts could, if available, be incorporated in risk estimations. However, at least on a seasonal basis and for the European Alps, prediction skills are currently rather low. This is e. g. in contrast to the Western US, where variability is linked to the El Niño Southern Oscillation (ENSO). For this region, ENSO warm phases typically indicate a good ski season and vice versa (see Bark, Colby and Dominguez 2009).

3. The *non-negativity assumption* needs to be assessed from case to case. For instance, it is obvious that for overnight stays or sales there can be no negative values and thus a VaR estimate should not indicate more than in what a total loss in overnight stays or sales would result.

4. The *distributional assumption* is of crucial importance for the estimation of weather risks. For the empirical modelling the standard assumptions will be modified in two respects: The inclusion of time trends shifts the expected mean away from 0, and other distribution modelling approaches like the introduced non-parametric approach complement the assumption of a normally distributed weather index.

4.3.2 Risks for Individual Areas

Based on the assumptions discussed in the previous subsection, the calculation of weather risk using a probabilistic approach is now outlined in a more formal way. As discussed in Subsection 3.1.3, the used risk measure is denoted as $VaR(weather)_{1-\alpha}$[23] and indicates the expected maximum loss from weather which is not exceeded with a given level of confidence $1-\alpha$ over a given period of time t. In order to calculate the $VaR(weather)_{1-\alpha}$, both the impact of weather on overnight stays given by β_1 and the modelled distribution

[22] If it is believed that only for recent years the relationship between weather and the economic indicator can be determined accurately, estimations could be done for a shorter period. But then, the number of observations T decreases, and so does the reliability of the statistical model. For individual ski areas, the *ME* approach introduced in Subsection 4.2.5 bases on this principle. When using this approach, the lower the bandwidth h is chosen, the higher are uncertainties.

[23] As already mentioned, this equals a 1 in $1/\alpha$ year (or any other given period of time) event.

of the respective weather index WI are put in one impact function, which can be written as:

$$impact = \beta_1 WI \tag{4.17}$$

It needs to be emphasized that this simple multiplication is only possible due to the definitions previously made for the modelling of the weather index and its relationship with overnight stays. On the one hand, WI is for all of the weather index modelling approaches defined as a function where WI either stands for WI_{hist} (Equation 4.3), WI_{nonpar} (Equation 4.6), WI_{normal} (Equation 4.7) or the respective trend adjusted functions WI_{trend} (Equation 4.8). On the other hand, the relationship between the weather index and overnight stays is assumed to be linear which means that β_1 is not dependent on the level of WI. This is the case even in a log-log model specification, but only under the condition that the distribution of WI is also modelled in logarithms (Equation 4.2).

With this approach it is easy to see that the prefix of β_1 determines whether the upper or lower tail of WI is of interest for calculating $VaR(weather)_{1-\alpha}$. If β_1 is negative, meaning that overnight stays depend negatively on weather conditions, the focus is on above-average weather conditions (upper tail) as impacts are most severe here. In contrast, a positive β_1 infers that below-average weather conditions (lower tail) lead to unfavourable economic results. However, formulating the impact function as in Equation 4.17 does automatically allow an adjustment to the prefix of β_1 and to focus on the lower tail of the impact function.

Having formulated the impact function, the $VaR(weather)_{1-\alpha}$ can directly be obtained from the inverse impact function, or, which is the more commonly used convention, to consider the $1-\alpha$-quantile of the inverse loss function[24]. The loss function simply equals the impact function multiplied by minus 1, and therefore $VaR(weather)_{1-\alpha}$ can be expressed as the $1-\alpha$-quantile of either the negative impact distribution or of the loss distribution[25]:

$$VaR(weather)_{1-\alpha} = F^{-1}_{-impact}(1-\alpha) = F^{-1}_{loss}(1-\alpha) \tag{4.19}$$

[24] In contrast to an impact function, in a loss function it is common to denote negative impacts in positive numbers and positive impacts in negative numbers.

[25] Alternatively, if the impact function is not transformed by minus 1, the interest is on the α-quantile of the impact distribution. Then, in order to match the convention that VaR is usually denoted as a positive number while impacts on the lower tail of the impact function are typically negative, a minus is added on the right hand side of Equation 4.18 and Equation 4.19 can be expressed as:

$$VaR(weather)_{1-\alpha} = -F^{-1}_{impact}(\alpha) \tag{4.18}$$

Which convention is chosen is a matter of taste, but does not affect $VaR(weather)_{1-\alpha}$ estimates.

Furthermore, for the empirical data it is important to note that $VaR(weather)_{1-\alpha}$ based on a log-lin model specification can typically be interpreted as the %-decrease in overnight stays due to adverse weather conditions occurring with an α-probability. Therefore, for most of the analysis a relative VaR will be indicated, which is in general also more intuitive to compare between different ski areas than absolute values. However, it is easy to derive a €-VaR by multiplying the relative VaR by some indicator for the economic losses faced by a one percentage change, e. g. a change in sales (see Subsection 4.3.4).

Another technical issue for calculating $VaR(weather)_{1-\alpha}$ arises from how to approximate it from discrete impact functions. For WI_{hist} with T= 34 observations and respectively 34 steps in the impact function, $VaR(weather)_{1-\alpha}$ can be approximated by quantile estimation. The procedure applied in this thesis follows Hyndman and Fan (1996), using quantile estimates that are approximately median-unbiased regardless of the distribution of WI_{hist}[26]. For WI_{nonpar} with 6290 (though unequally weighted) observations, the approximation is done by using the mean between the two estimates for which the CDF is nearest (above and below) $1-\alpha$.

Last but not least, the outlined probabilistic approach gives the flexibility to provide some other risk measure than $VaR(weather)_{1-\alpha}$. For example, the conditional Value at Risk, in short $cVaR(weather)_{1-\alpha}$, can be calculated. Instead of measuring the expected maximum loss from weather impacts which is not exceeded with a probability of α, $cVaR_{1-\alpha}$ indicates the expected loss for the worst α% of the cases. Therefore, $cVaR_{1-\alpha}$ must in any case be greater than (or equal) $VaR_{1-\alpha}$.[27]

4.3.3 Aggregated Risks

Indicating risks for more than one ski area[28] requires to think about how to aggregate individual risks. In the following, three options for doing so are presented *(Option A,B and C)*. The simplest way is to accumulate the data for individual areas for a certain region before conducting the risk assessment (option A). In this case the impact function is already estimated on the aggregate level ($impact_{agg}$), and the corresponding $VaR(weather_{agg})^{A}_{1-\alpha}$ can then be written as:

$$VaR(weather_{agg})^{A}_{1-\alpha} = F^{-1}_{-impact_{agg}}(1-\alpha) = F^{-1}_{loss_{agg}}(1-\alpha) \tag{4.20}$$

[26] Be aware that particularly for a low number of observations at hand, quantile estimations may remarkably differ between estimation procedures implemented in different statistical software solutions as a standard routine (see Hyndman and Fan 1996).

[27] Alternatively, the expected value could be calculated for any probability range or, the other way round, for any range of the respective weather index.

[28] More generally, the issue here is how to aggregate specific risks from the smallest entity — which are ski areas here, but could for example also be companies — to some larger level. Basically, the same principle could be applied to add up the VaRs estimated for different risk factors etc.

This procedure has two obvious drawbacks, namely that information is lost due to the aggregation of data and that it is not possible to take into account different weather exposures of different areas. An alternative to this approach would be to add up the estimates for individual areas. However, this can not be done by simply summing up the $VaR(weather)_{1-\alpha}$ for individual areas, as the underlying impacts are interrelated as well. In other words, for different locations adverse weather impacts do not occur at the same time and with the same intensity. Therefore, a procedure is needed to incorporate the relationship between the impacts occurring in different areas.

One approach to do so is to apply standard considerations from portfolio theory (Markowitz 1952) and, so to say, to jointly look at a portfolio of weather risks. Using the variance-covariance technique (option B), the portfolio $VaR(weather_{agg})^{B}_{1-\alpha}$ is calculated by multiplying the portfolio standard deviation σ_{agg}, which is estimated based on all covariances of the estimated historic impacts, by the z-score $z_{1-\alpha}$:

$$VaR(weather_{agg})^{B}_{1-\alpha} = z_{1-\alpha}\sigma_{agg} = z_{1-\alpha}\sqrt{\sum_{i=1}^{N}\sum_{j=1}^{N} Cov(impact_i, impact_j)} \tag{4.21}$$

The variance-covariance approach illustrated in Equation 4.21 is based on the assumption of normally distributed impacts. This assumption can be relaxed in that $VaR(weather)_{1-\alpha}$ is calculated for individual ski areas in a first step, possibly using other than the normal distribution (option C). Then, the individual $VaR(weather)_{1-\alpha}$ are aggregated to $VaR(weather_{agg})^{C}_{1-\alpha}$ based on the correlation matrix as follows[29]:

$$VaR(weather_{agg})^{C}_{1-\alpha} = \sqrt{\sum_{i=1}^{N}\sum_{j=1}^{N} \rho_{impact_i, impact_j} VaR(weather_i)_{1-\alpha} VaR(weather_j)_{1-\alpha}} \tag{4.22}$$

4.3.4 Best Estimates of Weather Risk

Doing analysis as outlined so far with different weather indices, different approaches to model the weather index, and different model specifications and restrictions allows to determine the sensitivity of weather risk estimates to these parameters and assumptions. In addition to such an analysis, it seems to be beneficial to provide an approach which allows to present results in a more comprehensive way and hence to reduce complexity from the large set of weather risk estimates obtained.

[29] It is easy to see that Equation 4.21 and Equation 4.22 deliver identical results, if for Equation 4.22 only the parametric modelling approach with normally distributed weather indices WI_{normal} and respectively normally distributed impact functions is used.

One approach would be to summarize estimates, either by providing a range of these estimates or simply the median or mean estimate. However, it is highly questionable whether such an approach would really provide accurate information on the weather risks faced by individual areas, as not all possible estimates are equally reasonable. Take the example of different weather indices. Some of them might better, some might not at all be suitable to describe the risk exposure faced by an area. Taking the mean estimate obtained from different indices would very likely result in underestimating weather risk.

Therefore, instead of summarizing information from all possible constellations, results are in a final step reduced to a best set of assumptions, providing a deterministic best estimate of weather risk which is as efficient as possible in describing ski areas' risk due to adverse weather conditions. In this sense, the term best estimate is applied as it is frequently used in the actuarial literature (Blum and Otto 1998): A best estimate attempts to define one specific point within a range of *reasonable* estimates. A *reasonable* estimate is defined simply as an estimate based on reasonable assumptions and methods. However, the term best estimate does not refer to statistical efficiency, where it is applied to unbiased estimates which have a minimum variance.

One needs to be aware that due to methodological and data restrictions, it is not possible to avoid any kind of bias in such an estimate. More specifically, such a best estimate approach raises a range of issues related to uncertainty, which will be outlined in the following for the case of ski areas' weather risks:

1. The use of 'imperfect' weather indices supposedly leads to an severe underestimation of weather risk, as will be explained in the following. Indeed, basis risk, which means that the pay-offs of a given hedging instrument do not correspond to shortfalls in the underlying exposure, has already been cited as a primary concern for the implementation of weather hedges (Woodard and Garcia 2007). However, and this is particularly important for interpreting the results from this thesis, a high basis risk also leads to a likely downward bias in the weather risk estimate, as the estimations do not display the 'true' weather risk faced by the industry from the corresponding exposure.[30]

[30] From a theoretical point of view, it is straightforward to show that the estimated coefficient $\hat{\beta}_1$ is expected to be lower than the 'true' β_1, which describes the impact from a perfect weather index x_t^* on the underlying economic indicator y_t:

$$y_t = \beta_0 + \beta_1 x_t^* + \varepsilon_t. \tag{4.23}$$

Adding some disturbance η (e. g. geographic basis risk) to x_t^*, so that the imperfect weather index $x_t = x_t^* + \eta_t$, increases variance and therefore influence $\hat{\beta}_1$:

$$\hat{\beta}_1 = \frac{cov(y_t, x_t)}{var(x_t)} = \frac{\beta_1 var(x_t^*)}{var(x_t^*) + var(\eta_t).} \tag{4.24}$$

This effect can also be shown empirically by simply adding a disturbance term η_t to WI_t before ADL model calculations. Assuming $\eta_t \sim \mathcal{N}(0, \sigma)$, the larger the chosen σ is, the lower should the expected

Sources of potential basis risk which affect estimates and hedging effectiveness in the winter tourism industry are[31]:

- *Geographic basis risk* occurs because the location where the weather index is measured is different to the location where the risk exposure occurs. While the chosen approach of using interpolated, gridded weather data instead of measurement data reduces this sort of basis risk, it supposedly still leaves a substantial level of basis risk due to the high relevance of altitude in alpine areas and the respective effects of deviances between ski area altitudes and the snow model grid altitudes (see Subsection 3.2.2).

- *Product basis risk* refers to the fact that hedging effectiveness is lower, when using less suitable weather indices. Considering snow indices is supposedly more effective for the ski industry than temperature indices and this effect should also be noticeable in the estimated sensitivities. In addition, it comprises all sort of risks related to the weather index construction. For example, the extensive assumptions behind snow cover modelling do increase product basis risk and might to a certain extent counterbalance the reduction of geographic basis risk.

  Local basis risk captures the remaining effect that because of an imperfect link between weather and tourists' behaviour constructing a perfect index for estimating impacts or hedging risks is simply not possible.

2. The possibly substantial downward bias related to basis risk from weather index construction is opposed to a possible upward bias, dependent on the chosen statistical modelling approach. As it is very often not possible to theoretically determine which weather index might display the relationship between weather and the underlying economic indicator best, several indices are tested and the weather index with highest (and generally most significant) impact, or respectively the model with the best statistical properties is taken. However, if the number of considered indices is large, there is an increased chance that this procedure comes up with significant weather effects by random.[32]

$\hat{\beta}_1$ become, which is confirmed by some exploratory analyses for the empirical data and under the reference assumptions. For this analysis, η_t is randomly generated 100 times for each ski area and for 5 different values of σ (0.5, 1.0, 1.5, 2.0 ,2.5) and for each simulation the $\hat{\beta}_1$ is then compared to β_1 from the original regression (Equation 4.9). Results show that for $\sigma = 0.5$ the median $\hat{\beta}_1$ is $0.91 \times \beta_1$, for $\sigma = 1.0$ it is $0.84 \times \beta_1$ and for larger values of σ it is around $0.82 \times \beta_1$. Of course, the results from this simulation depend on how representative the used WI_t is, as it already contains some (presumably substantial) basis risk. However, as is evident, the true extent of the estimation bias between a perfect weather index and the used imperfect WI_t can not be determined.

[31] Classification is carried out in accordance with Woodard and Garcia (2007), who examine basis risk for agricultural weather derivatives.

[32] As is evident, when considering independent weather indices, from taking e. g. 20 indices it can be

3. While the first two arguments deal with the construction and choice of an appropriate weather index, the statistical properties of such an index are of importance for estimating weather risks. This specifically concerns the assumptions on intertemporal unpredictability and the distribution of the index (see Subsection 4.3.1). Dependent on the direction of the relationship between the weather index and the economic indicator of interest, the direction of a possible time trend and the shape of the distribution, estimates might over- or underestimate the 'true' weather risk.

4. The stationary requirement (see Subsection 4.3.1) is of utmost relevance to the accuracy of the weather risk estimate. If there is evidence that the current sensitivity of the examined economic indicator to weather conditions is below the average in the study period, then the given estimate overestimates the current level of weather risk and vice versa.

It is evident that it is not always possible to identify and control for these potential sources of biases. However, for providing best estimates of ski areas' weather risk it is tried to deal with them accordingly, which is described in more detail in Section 5.4, right after a discussion of the general results.

For finally providing a monetary quantification of best estimates of weather-related declines in overnight stays, the *direct cost evaluation method* is used. This method assumes that 'the welfare change induced by the weather extremes can be approximated by the quantity change in the relevant variable times its price' (Bigano et al. 2005).[33] For doing so, the best available price indicator on the level of individual ski areas supposedly is sales per night in the accommodation industry as provided by OHT (2008) (see Subsection 3.3.5).[34]

4.4 Concluding Remarks

While a methodological framework and data for assessing weather risks in the winter tourism industry was discussed in the previous chapter, this chapter has focused on describing the modelling approach. Firstly, the modelling of the weather index distribution was illustrated. It was shown that approaches discussed in the weather risk management

expected to find 1 significant relationship at the 0.05 and respectively 2 at the 0.1 level. However, if indices are highly intercorrelated, which is usually the case, it is likely to either find a significant relationship for all or none of them.

[33] Indeed, while this method is based on the assumption that weather only effects quantities and not prices, which might not be the case, it is in the light of the non-availability of disaggregated price data the only choice.

[34] This information is available for 88 out of 185 areas, which however account for 77 % of TC. For other areas, interpolation is chosen according to the size of the areas, as their exists a clear relationship between average sales and size. Note that interpolation is also chosen for two areas with data availability, but concerns about the plausibility of data (Mariazeller Buergeralpe and Kreischberg).

literature might be adapted for modelling the snow index distribution. In addition, a non-parametric approach was introduced which uses weather indices for several locations instead of one single location. Particular attention was also paid to the incorporation of time trends. Secondly, the estimation of the relationship between weather indices and overnight stays, which serve as an indicator for tourism demand, by means of econometric methods was illustrated. Details were provided on the use of these methods, which are generally available from the literature on tourism demand modelling. Thirdly, the measuring and aggregation of weather risks was discussed. Considerations were based on methods from financial risk management, which needed to be adapted for several reasons to the specific nature of weather risk. Finally in this chapter and discussing aspects of all three modelling steps together, an approach for obtaining best estimates of weather risk was outlined which helps to summarize detailed results in a comprehensive way. Detailed results for each of the modelling steps as well as best estimates will be presented in the following chapter.

5 Results

In this chapter I present the empirical results, which are organized into four sections. In Section 5.1 I thoroughly discuss the results for individual ski areas, with a focus on comparing results obtained for different weather indices, different approaches to model these weather indices and different model specifications. In Section 5.2 I analyse effects on the aggregate level (provinces, altitude and size categories) in more detail, with a particular focus on comparing different procedures for such an analysis. Section 5.3 is dedicated to the question whether the sensitivity of overnight stays on snow conditions is constant over time or not. Finally, I give best estimates of current weather risk in Section 5.4, where estimated weather risks will be expressed in monetary terms and related to other risk factors in the accommodation industry. Results are then discussed in a broader context in Chapter 6.

5.1 Individual Ski Areas

The structure of this section, which provides results for individual ski areas, closely follows Steps 1-3 of the methodological framework presented in Section 3.1. In addition, I conduct a sensitivity analysis where I compare results obtained for different weather indices, different approaches to model these weather indices and different model specifications in Subsection 5.1.4. Larger tables and plots which illustrate the results for individual ski areas in full detail can be found in Appendix B to D, but are referenced separately in this section.

For the sake of clearness, I choose one ski area to explain modelling steps in more detail, namely Kitzbuehel. Kitzbuehel is well known and has also been taken as a case study region in a range of previous studies. A comparison of overnight stays[1] and transport capacities shows that Kitzbuehel is among the major Austrian ski areas (Table 5.1). With an average of 90.4 € per night, sales in the hotels being part of the sample (see Subsection 3.2.6) are considerably above average. Kitzbuehel has one of the lowest alt_0 of ski areas in Austria[2], while its alt_{50} and alt_{100} are above the median ski area. This is also reflected in the rank provided for the corresponding snow indices. Most interestingly

[1]Note that overnight stays in the neighbouring municipalities of Aurach bei Kitzbuehel and Reith bei Kitzbuehel are also included. Both municipalities exhibit less than 10 % of overnight stays in Kitzbuehel itself.

[2]This low alt_0 and its supposedly low snow-reliability is also often the main reason why it has been selected for previous studies.

however — and this provides an excellent reason for Kitzbuehel to be chosen as a case study region — the snow conditions in Kitzbuehel and neighbouring areas like Jochberg[3] correlate higher with snow conditions in other ski areas than it is the case for any other area. Therefore, a good winter season in Kitzbuehel usually goes in line with a good season in most other Austrian areas and vice versa.[4]

Indicator		**All areas**		**Kitzbuehel**	
	Min.[1]	Median[1]	Max.[1]	Value	Rank[2]
Overnight stays (mean season)	1 000	95 000	1 580 000	582 000	14/185
Transport capacity (in 10^6 Pm/h)	0.2	3.1	41.8	8.9	31/185
Sales per night[3] (2000-2006, annual)	32.3 €	75.6 €	239.8 €	90.4 €	31/185
Share of foreign guests (2000-2007)	3.2 %	79.3 %	99.6 %	78.4 %	94/185
alt_0	419 m	933 m	2150 m	770 m	141/185
alt_{50}	648 m	1446 m	2587 m	1500 m	77/185
alt_{100}	807 m	1898 m	3440 m	1973 m	75/170
μ $Sday_1(alt_0)$[4]	20 *days*	93 *days*	174 *days*	79 *days*	133/185
μ $Sday_1(alt_{50})$[4]	40 *days*	131 *days*	176 *days*	135 *days*	84/185
ρ with other areas (median)	-0.006	0.676	0.779	0.777	**2/185**

[1] Min. = Minimum, Median, Max. = Maximum (of all ski areas where data is available)
[2] Rank of Kitzbuehel among ski areas (1 = maximum value)/ Number of areas with data
[3] Data available for 88 mostly larger ski areas and interpolated for others (rank may differ)
[4] Values from snow cover model: They likely exhibit a downward bias (see Subsection 3.3.2)

Table 5.1: Indicators for Kitzbuehel compared to other ski areas

5.1.1 Weather Index Modelling

To begin with, some key aspects of the weather index modelling outlined in Section 4.1 are presented in this subsection. Results are in a first step illustrated on the example of Kitzbuehel and for the reference weather index $Sday_1(alt_{50})$. Figure 5.1 provides details on the development of the snow index over time (upper part of figure) and the respective distribution functions of the index (lower part). The x-axis interchangeably provides the number of $Sday_1(alt_{50})$ and the standardized weather index WI.

[3] Indeed, Jochberg is the number one in the ranking provided in Table 5.1.
[4] To name just two obvious reasons for this, Kitzbuehel is both in the heart of the Austrian ski industry (geographic longitude) and is located, like most other areas, on the northern side of the main chain of the Alps.

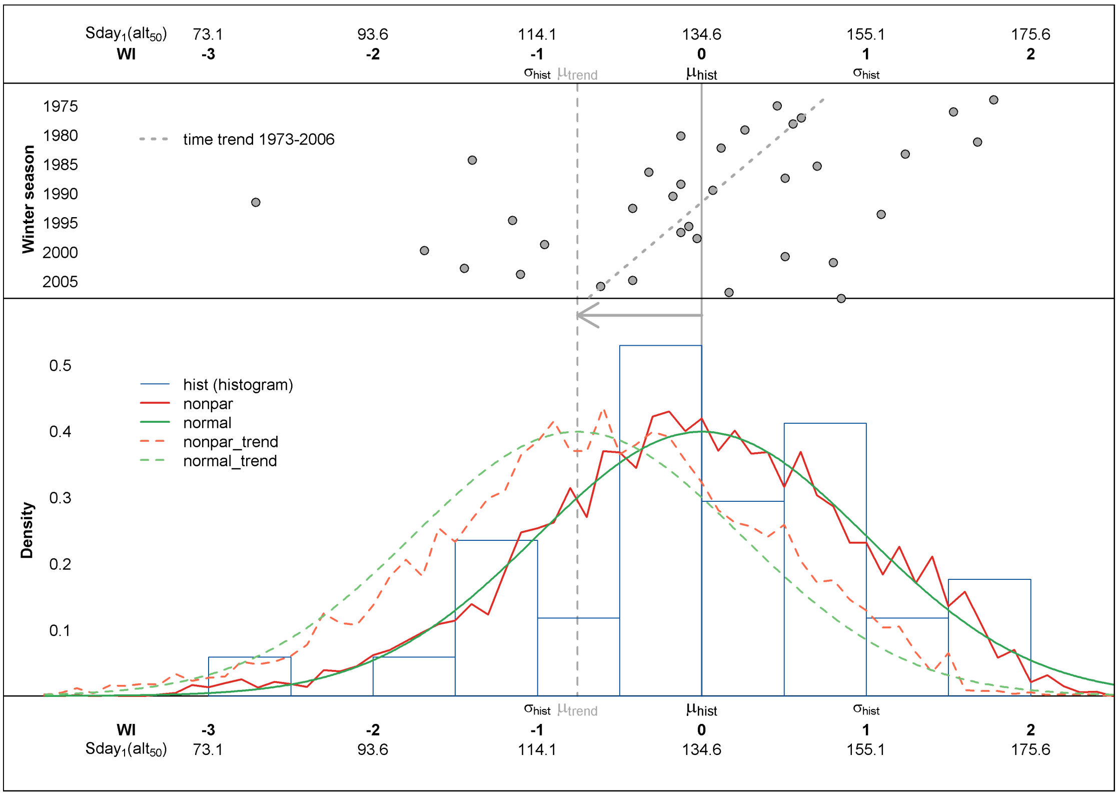


Figure 5.1: Weather index modelling on the example of Kitzbuehel with and without including time trends

For Kitzbuehel, the historical distribution WI_{hist} (blue-lined histogram) is — like for the majority of other areas — slightly left-skewed ($\gamma_1 = -0.47$), which is predominantly caused by the outstanding winter season 1989/90. Furthermore, the excess kurtosis is similar to a normal distribution ($\gamma_2 = +0.22$) and none of the three applied tests for normality rejects the assumption of a normal distribution. In fact, visual inspection of the normal distribution WI_{normal} (green line) indicates at first sight that it holds fairly well. However, when looking closer at the lower tail of the distribution, the problematic nature of assuming the comparatively thin-tailed normal distribution is revealed. To name one example, the probability of a winter season exceeding the 1989/90 season ($-2.7\,\sigma$) would be 0.33 %, or in other words such a season would occur in 1 out of 300 years.

The non-parametric modelling approach WI_{nonpar}, which is also based on historical distributions in other ski areas with a similar snow-reliability, shows a distribution with a close resemblance to the normal distribution, except that the left-skewness caused by the extreme winter season 1989/90 leads to higher probability levels in the lower tail ($-2.5\,\sigma$ to $-3.5\,\sigma$). Therefore, for the specific case of Kitzbuehel, the estimated probability of a winter season exceeding the 1989/90 season would be 0.78 %, a 1 in 127 year event.[5]

Including the linear time trend observed in the period 1973-2007 — and this is the main message of Figure 5.1 and the index modelling — substantially changes the estimated distributions and respective probability levels. Estimating again the probability of a season as bad as 1989/90 or even worse, for $WI_{normal,trend}$ the $-0.73\,\sigma$ shift[6] in the mean of the distribution leads to a probability of 2.53 % (1 in 40 year event). The estimate for $WI_{nonpar,trend}$ is still higher (3.03 % - 1 in 33 year event) than the one for $WI_{normal,trend}$, but compared to the approaches without time trends, the difference is much less pronounced. This is due to the fact that for other areas less strong negative trends in the snow index are observed.

Altogether, incorporating time trends heavily influences the expected means and probabilities for the vast majority of ski areas. While this can be expected in the context of climate change and is supported by other similar studies for the winter tourism industry (e. g. Olefs, Fischer and Lang 2010), the magnitude of the effect is surprising. As Figure 5.2 illustrates, there are substantial deviations between what one would expect when modelling the weather index distribution by a normal distribution without (WI_{normal}) and with considering trends ($WI_{normal,trend}$). The expected mean after de-trending is lower for most areas (upper left plot), particularly those with an average number of 100 to 150 $Sday_1$ (lower left plot). For the median area, the probability that $Sday_1$ are below the historical mean is 70.5 % (upper right plot), while for the tails of the distribution the inclusion of trend increases the probability of a 5%-event to 13.5 % (middle right plot) and that of a 95%-event to 98.5 % (lower right plot).

To sum up, the choice of the weather index modelling approach, and in particular the decision whether to account for trends in the underlying meteorological data or not, influences the estimated likelihood for the occurrence of adverse weather conditions. As a consequence, this substantially affects the weather risks estimated for individual ski areas, which will be shown in more detail in Subsection 5.1.3 and Subsection 5.1.4.

5.1.2 Impacts

In this subsection the results from the econometric modelling described in Section 4.2 will be presented, first briefly on the example of Kitzbuehel and then for all ski areas. Detailed results are given based on the log-lin reference model for a standard deviation change in $Sday_1(alt_{50})$. These results are also compared to the results obtained with

[5] Of course, and this is obviously one drawback with a non-parametric approach, the probability estimate for other areas which have been affected worse in this extreme season would be much smaller due to a lack of historical analogues.

[6] The trend estimate for Kitzbuehel is highly significant (p-value = 0.013).

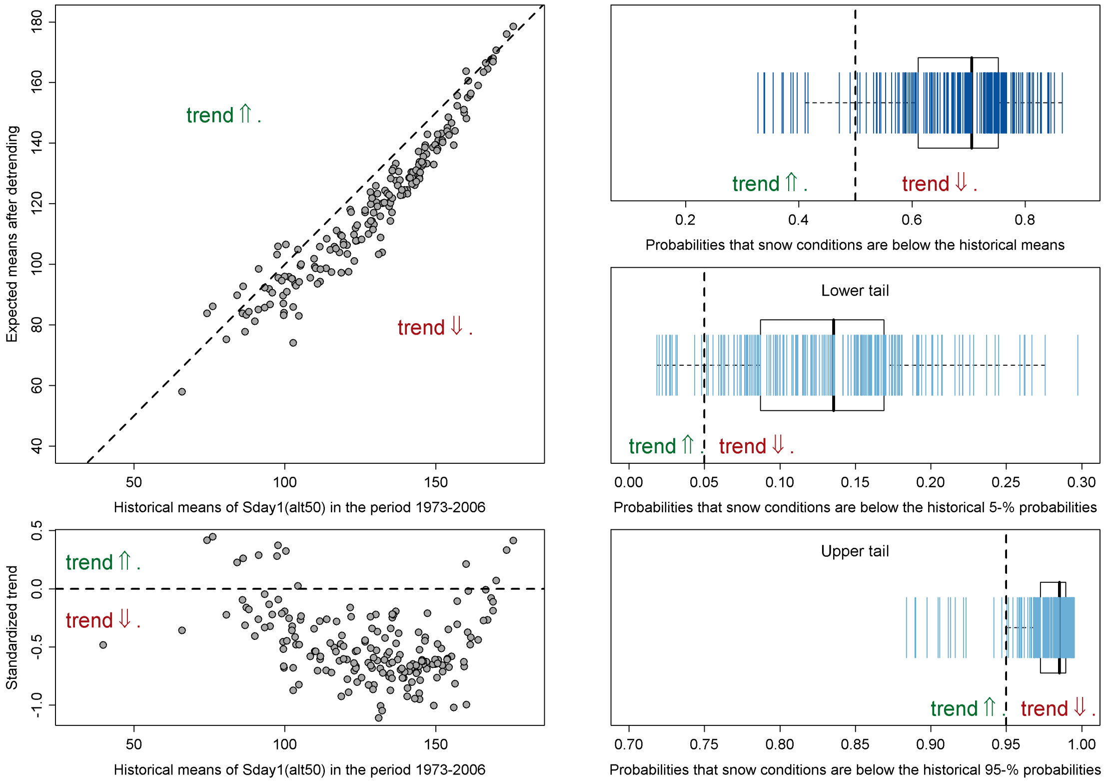


Figure 5.2: Comparison of historical means and expected means after trend inclusion for $Sday_1(alt_{50})$ in ski areas (left plots); Effects of trend inclusion on probabilities that $Sday_1(alt_{50})$ in ski areas are below the historical 5-%, 50-% and 95-% probabilities (right plots)

other model specifications and with other meteorological indices, in this subsection as well as in the sensitivity analysis provided in Subsection 5.1.4. Estimation results for the reference model are given in full detail in Appendix B.[7]

Before presenting the results for all areas, which is necessarily done in a more comprehensive way, it is again shown on the example of Kitzbuehel, how the estimated impact of snow conditions on overnight stays can be interpreted. In principle, the sensitivity parameter β_1 derived from the regression models in Equation 4.9 to Equation 4.14 provide information on this impact. For Kitzbuehel $\beta_1 = 0.0471$, which means that a one σ-change in snow conditions WI_t leads to a 4.71 % change in overnight stays $nights_t$.

[7] Results for other weather indices and model specifications are available on request.

Unlike in the case of univariate regression models[8], it is not possible to directly illustrate the relationship between the dependent variable $nights_t$ and the variable of interest WI_t in a multivariate regression model. However, the impact of WI_t can be visualized by a partial regression plot (added variable plot), which shows the effect of adding an additional variable (WI_t) to a model in which the other explanatory variables are already included. In such a plot the slope of the regression line corresponds to β_1, which is illustrated for Kitzbuehel in Figure 5.3.

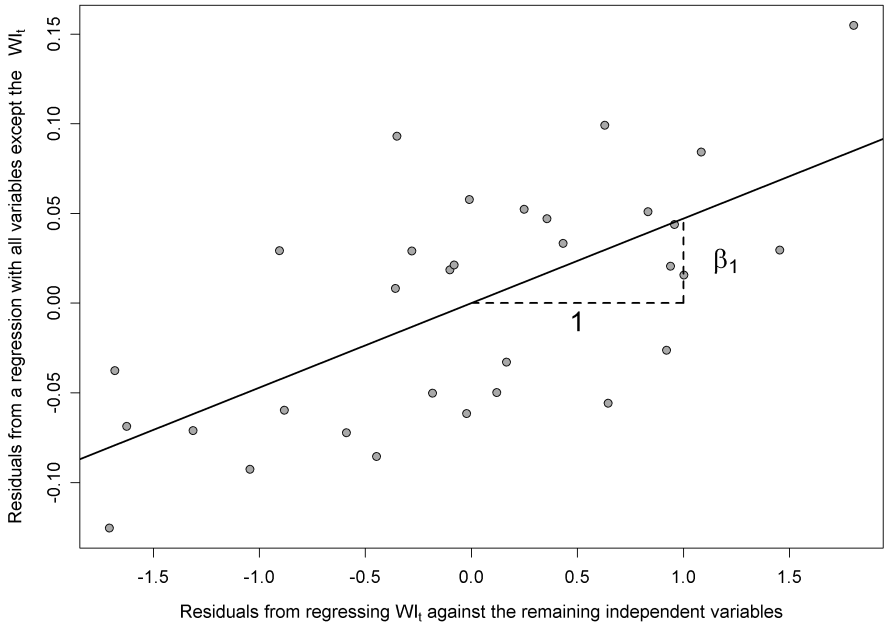


Figure 5.3: Partial regression plot (added variable plot) for Kitzbuehel

Doing calculations for all areas shows that, as expected, snow conditions $Sday_1(alt_{50})$ have a predominantly positive impact on tourism demand in Austrian ski areas. The reference log-lin ADL model, applied to 185 ski areas, reveals 146 positive and 39 negative coefficients (42 positive and 3 negative coefficients are significant at the 10 % level). As pointed out in Table 5.2, this pattern also does not substantially change for log-log or lin-lin specifications, when including additional linear time trends in the model, and for the static model with differenced variables. However, it is noteworthy that these results indicate the exact opposite of what one would expect from the static simple regression model often used for explorative analysis of weather dependencies. In fact, the static simple regression model would wrongly indicate 144 negative and 41 positive

[8] In fact, two models calculated for comparison reasons, namely the model with differenced variables (Equation 4.13) and the static model (Equation 4.14) are univariate, but the other model specifications used for the bulk of analysis are multivariate.

coefficients, presumably resulting from spurious correlations between the mostly positive trending $nights_t$ and negative trending WI_t.

Specification	Formula	+(*)	-(*)	Sign	A:	M:	H:	N:	All
ADL: log-lin	Equation 4.9	146(42)	39(3)	-	17	20	23	9	55
ADL: log-log	Equation 4.10	147(45)	38(3)	178	18	20	26	12	61
ADL: lin-lin	Equation 4.11	144(43)	41(3)	177	12	12	13	12	43
ADL: log-lin$_{trend}$	Equation 4.12	140(44)	45(3)	175	19	27	20	17	59
Static: Δ^2/Δ	Equation 4.13	142(46)	43(8)	157	174	15	7	25	176
Static: log-lin	Equation 4.14	41(7)	144(73)	76	183	7	47	87	184

+(*)/-(*): Number of areas with positive/negative β_1-coefficient (***:** p-value<0.1)
Sign: Number of areas where coefficient signs equal signs with *log-lin* model specification
Violations of the model assumptions (p-value<0.05): **A:** Residual autocorrelation
M: Functional form misspecification; **H:** Heteroscedasticity; **N:** Normal distribution of the residuals; **All:** One out of the tests detects a violation (see Subsection 4.2.3)

Table 5.2: Summary of coefficient signs, significant β_1-coefficients and results of diagnostic testing; Calculations are conducted for 185 ski areas and repeated with different model specifications

From a statistical point of view, the diagnostic tests given in Table 5.2 provide some more evidence on the quality of the different model specifications. For the ADL model specifications, one or several violations of the modelling assumptions occur for a part of the ski areas. This is somewhat expectable when working with *noisy* local scale data without being able to observe individual local-specific effects for each of these areas in more detail[9]. In contrast to that, for the static models diagnostic checking reveals an extremely high level of autocorrelation in the residuals, and in case of the un-differenced model it also detects heteroscedasticity and non-normally distributed residuals relatively frequently. Therefore, although static models exhibit more significant β_1 coefficients, using dynamic models like the ADL model is highly recommendable to avoid violations of the underlying assumptions of regression analysis.

Apart from that, the need for dynamic modelling is also confirmed by the high significance of the lagged dependent variables in the reference model (e. g. 174 out of the 185 $nights_{t-1}$ coefficients are significant at the 10 % level). Interpreting the results in accordance with the tourism demand literature, habit persistence and tourist expectations

[9]Of course, these violations need to be studied in more detail, when the estimated weather dependency of one or several individuals areas are of specific interest. For this, Appendix B provides details which and what kind of violations have been detected for individual areas. For showing more general patterns however, as it is done in the following considerations in this thesis, it should be sufficient to note that some form of bias exists due to model misspecification, without further analysis for individual areas.

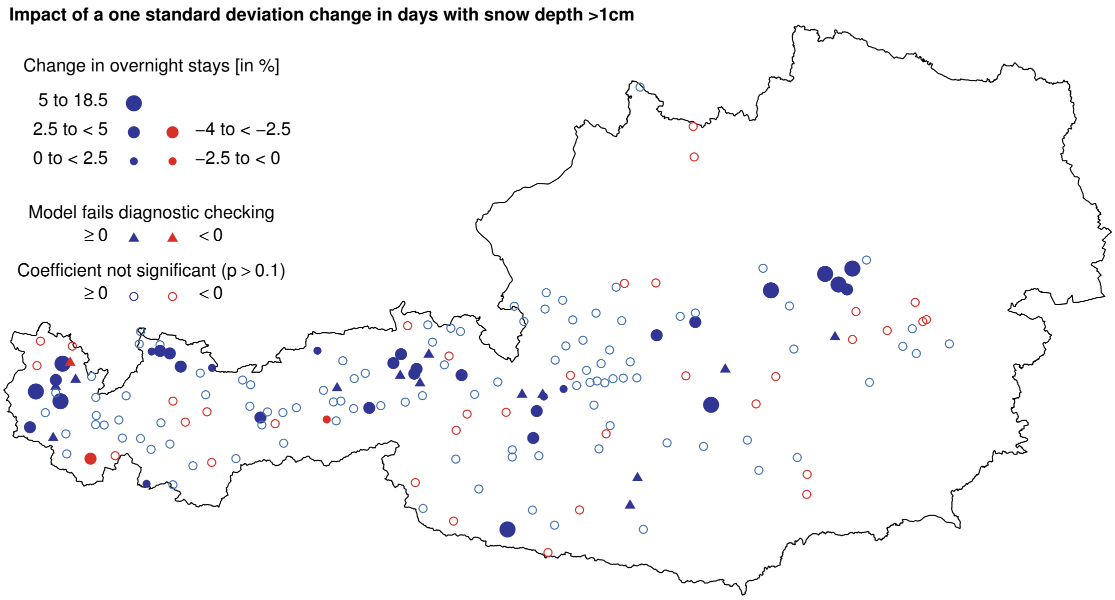


Figure 5.4: Impact of a one σ change in snow conditions on overnight stays

also play an important role on a local scale.[10] As suggested by theory, the coefficient sums of $nights_{t-1}$ and $nights_{t-2}$ are positive, but smaller than one (median ski area: 0.64), with values close to one indicating more stable behaviour patterns.

Turning to the impacts estimated for individual ski areas with the reference model, Figure 5.4 illustrates the impact of a one σ-change in $Sday_1(alt_{50})$ on overnight stays on the spatial scale. The results largely confirm previously described regional demand patterns. On the one hand, β_1 coefficients are significant and positive for a range of areas with a reputation to be particularly dependent on snow conditions. These are rather low lying areas on the north side of the main chain of the Alps, for example in central Vorarlberg, the Tannheimer valley, the region Wilder Kaiser/Kitzbueheler Alps and in Lower Austria. For several other regions, such as the provinces of Salzburg and Carinthia, area specific coefficients are predominantly positive, though not significant in most cases. On the other hand, β_1 coefficients are significant and negative for two Tyrolean areas with particularly good snow conditions, namely Galtuer and Tux/Hintertux, but altogether overnight stays in higher lying areas show comparatively little response to changes in snow conditions.

Redoing analysis with other meteorological indices widely confirms these patterns for $Sday_1(alt_{50})$. Replacing $Sday_1(alt_{50})$ with $Sday_{30}(alt_{50})$, $S_{mean}(alt_{50})$ or the respective indices

[10] As mentioned before, tourism demand studies usually target a more aggregate scale.

for alt_0 does not change these broad patterns, while the estimates for some individual areas differ quite substantially. This is shown in Figure 2 (Appendix D), where estimates and standard errors obtained for these indices are plotted for individual ski areas in descending order of the respective alt_{50}. When using T_{mean}, in most cases the signs of estimated coefficients are reversed compared to those from snow indices. This is only to be expected as temperature is generally negatively related to snow conditions. However, temperature estimates are lower and much less significant compared to the snow indices considered.[11]

Interestingly, the data provides evidence that while higher-lying areas do not really depend on their own snow conditions, they are heavily influenced by snow conditions in other ski areas. For example, a significant negative relationship is found between overnight stays and weighted-average Austrian snow conditions $Sday_{AVG}$ for 6 out of 8 areas with access to glaciers.

The results provide less convincing support for the so-called *backyard hypothesis*[12]. Considering the snow conditions in each of the five major cities (Vienna, Graz, Linz, Salzburg and Innsbruck), rather positive relationships between $Sday_1$ in the respective cities and overnight stays in nearby areas are found. Without further analysis, one could assume that there exist such a *backyard effect* for the respective Austrian ski areas. However, it is supposed that these results can largely be explained by positive correlations between snow conditions in the cities and nearby areas. Especially if correlations are high, it seems uncertain, whether it is really the urban snow conditions or still mountain snow conditions which influence overnight stays. This considerations are illustrated in Figure 3 (Appendix D).[13]

In general, patterns are more unclear for regions with typically small ski areas, most notably in Eastern Austria[14]. Indeed, with the chosen modelling approach, the larger an area is, the more likely is dependence to be significant. This can supposedly be explained by larger modelling uncertainties for smaller areas. The smaller an area, the higher the variability in demand, and the more problematic seems to be the non-inclusion of a range of unknown local non-climatic factors affecting the development of overnight stays. Therefore, it seems to be a good idea to consider impacts also on a more aggregate scale, which is done in Section 5.2.

[11] Where available, snow data should therefore generally be preferred to temperature data in studies of climate change impacts on winter tourism, because as this analysis reveals, studies based on temperature data (e. g. Bigano et al. 2005) are likely to underestimate impacts.

[12] As mentioned in Subsection 2.3.3, Hamilton, Brown and Keim (2007) describe the existence of such an effect for related data on Boston and surrounding US ski areas.

[13] Altogether, one needs to be aware that analysing the backyard effect for individual ski areas in more detail would require to cover urban snow conditions also in other origin countries, to consider the respective shares on total guests, which differ substantially between areas and over time, and to do calculations rather on a daily or monthly level.

[14] Note that several areas in Western Austria account for more overnight stays than all the areas in provinces such as Lower or Upper Austria.

5.1.3 Weather Risk

Weather risk for individual ski areas can be measured based on the impact functions (Equation 4.17), which contain both the distributions of the respective weather indices and the estimated impacts on overnight stays. Before turning to the results obtained for different risk measures and probability levels (α), the basic principle is again illustrated on the example of Kitzbuehel.

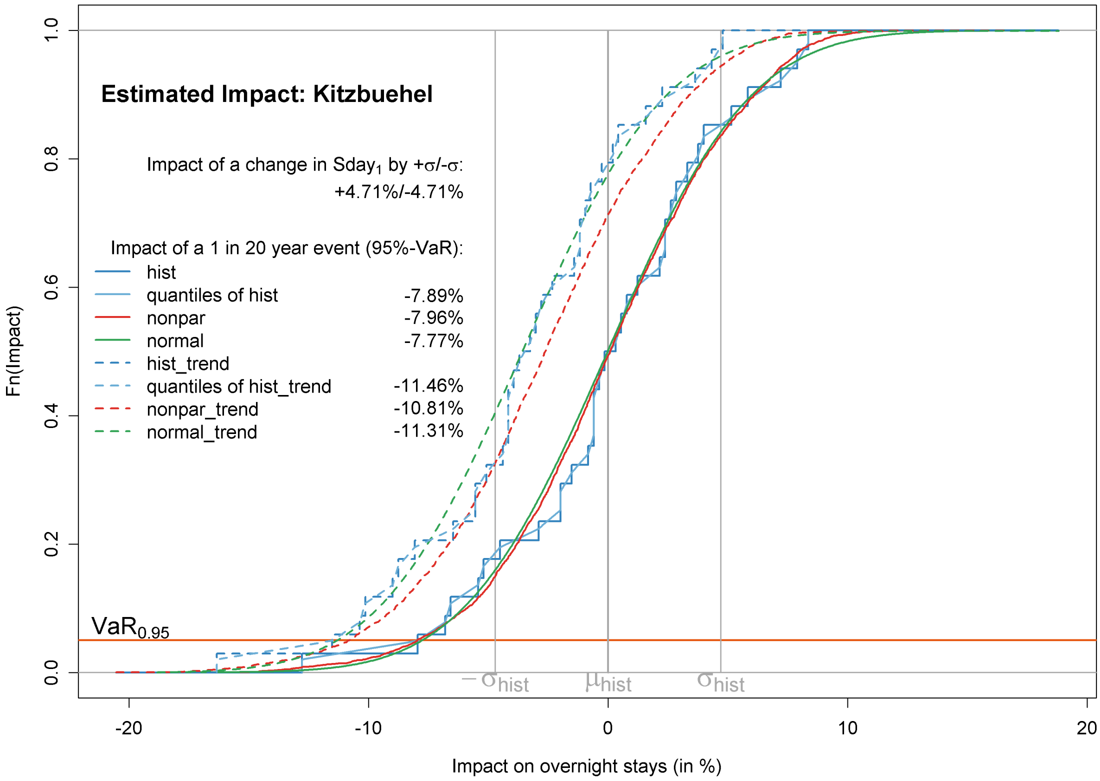


Figure 5.5: Cumulative distribution functions (CDFs) of impacts estimated with different weather index modelling approaches for the example of Kitzbuehel; Alternately, the impact distribution might be illustrated as loss distribution (see Figure 1)

Figure 5.5 provides the cumulative distribution functions (CDFs) of impacts and the corresponding $VaR(weather)_{0.95}$ for Kitzbuehel.[15] It is shown that — as could also be

[15]One might wonder why in Figure 5.5 the $VaR(weather)_{0.95}$ corresponds to the 0.05-quantile of the CDF. Indeed, it is only a matter of taste whether to display the impact function (Equation 4.18) or the loss function (Equation 4.19). When considering the latter, the figure is simply reversed and the $VaR(weather)_{0.95}$ then corresponds to the 0.95-quantile of the CDF, which is illustrated in Figure 1

seen from Figure 5.1 before — using WI_{nonpar} and WI_{normal} delivers similar results, which is in contrast to using WI_{hist}. When incorporating the negative time trend, CDFs move to the left hand side, corresponding to expected higher impacts. As mentioned before, the observed negative trend is more pronounced for Kitzbuehel than for other ski areas and hence the modelled impacts for $WI_{nonpar,trend}$ are generally below WI_{hist_trend} and $WI_{normal,trend}$. Dependent on the weather index modelling approach, the obtained $VaR(weather)_{0.95}$ range from 7.77 % to 11.46 %, with more detailed values being given in the plot itself.

Estimating the $VaR(weather)_{0.95}$ with different weather index modelling approaches for all ski areas basically confirms the pattern described for Kitzbuehel. Although the underlying assumptions of WI_{nonpar} and WI_{normal} differ substantially, the respective risk estimates do not. In contrast, compared to these two approaches, estimates for WI_{hist} exhibit in some cases remarkable deviations in both directions. For the trend adjusted approaches (WI_{trend}) estimates are higher in the vast number of cases. This can be seen in Figure 4 (Appendix D), which provides full details on the estimated $VaR(weather)_{0.95}$ for each individual area (ordered by alt_{50}), and in a more comprehensive way in Figure 5.6, which is described more precisely in the following.

Figure 5.6 systematically compares results obtained when using WI_{hist} with the results obtained with other weather index modelling approaches (WI_{nonpar}, WI_{normal}, $WI_{nonpar,trend}$, $WI_{normal,trend}$). On the one hand, it seems that for areas with a particular high risk, WI_{nonpar} and WI_{normal} give lower $VaR(weather)_{0.95}$ than WI_{hist}. On the other hand, it is noteworthy that incorporating the mostly negative trend in snow conditions only leads to an increase in $VaR(weather)_{0.95}$, if $\beta_1 > 0$. This is not the case if $\beta_1 < 0$, or the other way round, $\beta_1 > 0$, but the trend is positive as well.

Further information on the performance of the different weather index modelling approaches is gained by considering, in addition to the $VaR(weather)_{1-\alpha}$, also the conditional Value at Risk ($cVaR(weather)_{1-\alpha}$), and by changing the probability level from α=0.05 to α=0.1 and α=0.01. It is evident that the modelling of the tails of the distribution becomes more crucial for calculating $cVaR(weather)_{1-\alpha}$, which does not only look at one point of the distribution, and when conducting the analysis for a low α. Results are illustrated in Figure 5.7 and can be summarized as follows:

- When comparing results obtained with different α values, it can be seen that the more the tails of the distribution, or in other words more unlikely events, are of interest, the larger become the differences between modelling approaches.

- The more snow reliable an area is (x-axis), the larger are the differences between modelling approaches. For the approaches using WI_{nonpar} and WI_{hist}, this can be explained by the fact that areas with a high μ also tend to have a left-skewed distribution of the weather index ($\gamma_1 < 0$). Therefore, the results of both of these

(Appendix D).

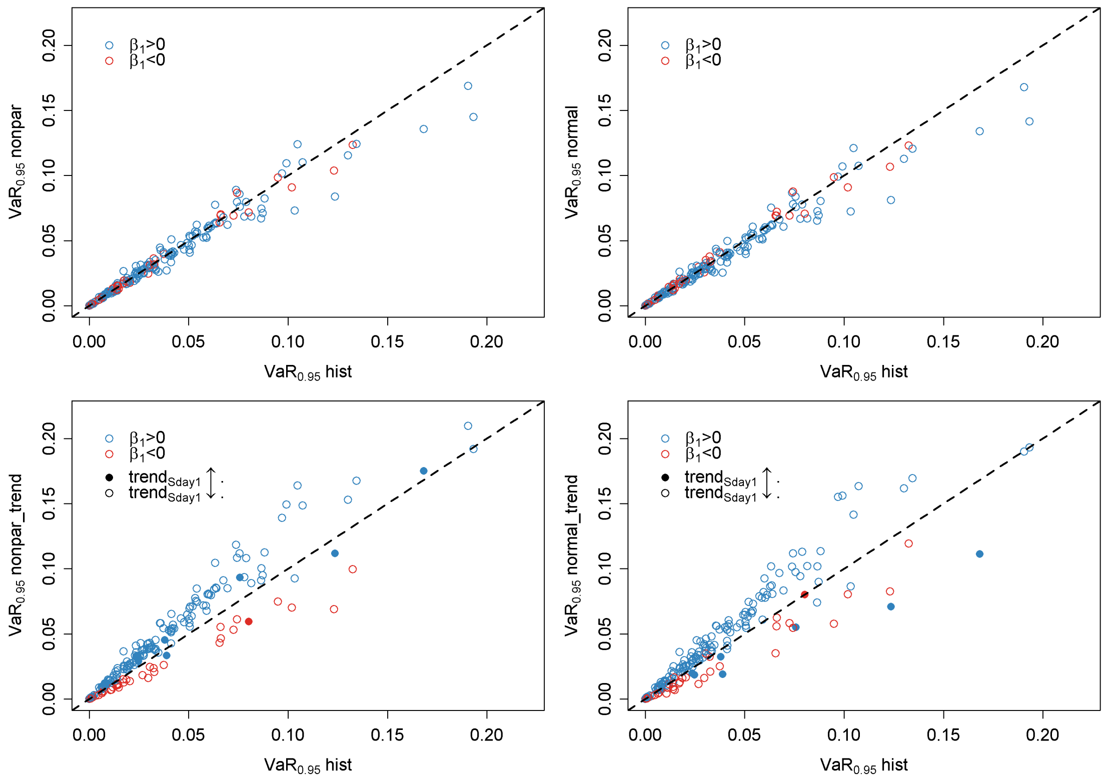


Figure 5.6: Comparison of $VaR(weather)_{0.95}$ for individual ski areas obtained with different weather index modelling approaches; The reference results (x-axis) are obtained using the quantile of the empirical distribution WI_{hist}

approaches depend on whether $\beta_1 > 0$ or $\beta_1 < 0$, while with the assumption of a symmetric normal distribution (WI_{normal}) this is not the case.

- Differences between modelling approaches are more pronounced for $cVaR_{1-\alpha}$ than for $VaR_{1-\alpha}$ (lower plots versus upper plots). As the $cVaR_{1-\alpha}$ is sensitive to the shape of the distribution below a probability level of α, its application reveals one particular weak point of the approach using WI_{hist} and, to a less extent though, of the approach using WI_{nonpar}. For a low α (e. g. 0.01), there is no information available for less likely events, and hence the estimated $cVaR_{1-\alpha}$ equals the $VaR_{1-\alpha}$. As a consequence, for WI_{hist} the $cVaR_{0.90}$ tends to be higher compared to those obtained with WI_{normal} and WI_{nonpar}, while the $cVaR_{0.99}$ is — with a few exceptions — well below those obtained with the other approaches.

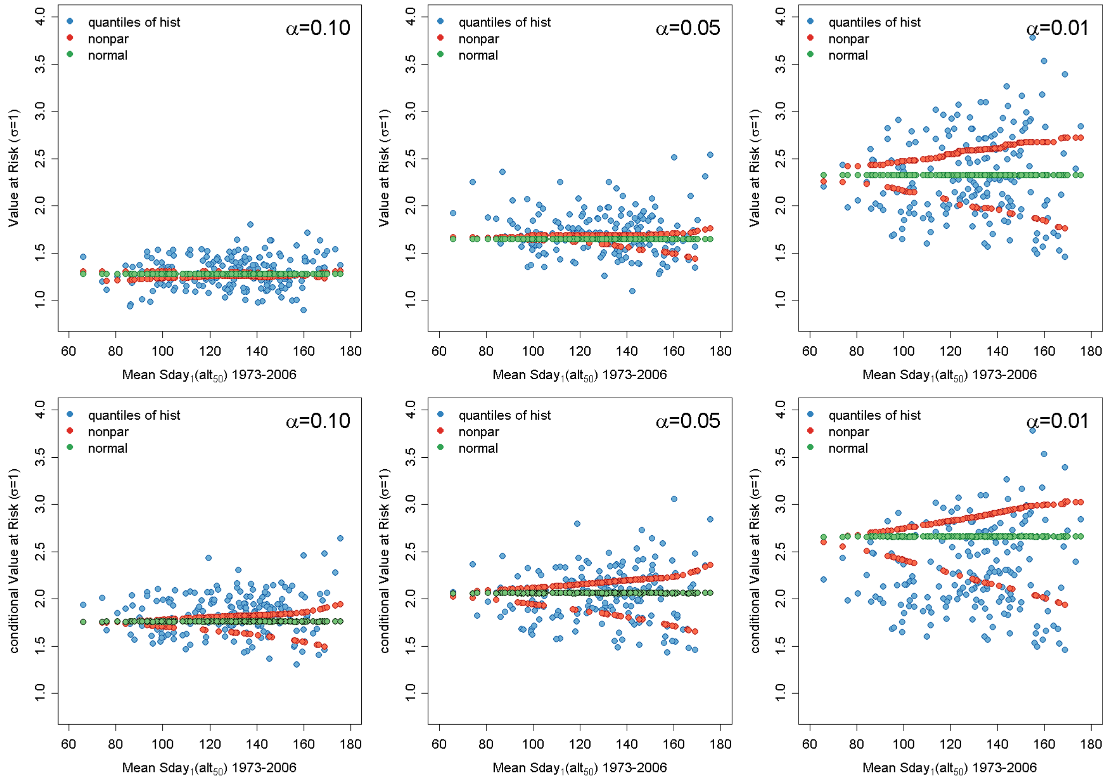


Figure 5.7: Comparison of $VaR(weather)_{1-\alpha}$ and $cVaR(weather)_{1-\alpha}$ estimated with different weather index modelling approaches and for α= 0.10, α= 0.05 and α= 0.01; The estimates are indicated related to a one σ change for comparison reasons.

5.1.4 Sensitivity Analysis

In the preceding subsections, results for individual ski areas have been discussed with regard to different weather indices, different approaches to model these weather indices and different model specifications. In this subsection these considerations are brought together in comparing results systematically. This is done by expressing the sensitivity of results to different assumptions with one single scale, namely the %-change of estimated $VaR_{0.95}(weather)$ compared to the corresponding reference assumption.

Figure 5.8 and Figure 5.9 provide an overview of the results from the sensitivity analysis. In these figures each line represents one ski area and summary statistics are illustrated by the boxplots.

As can be seen in Figure 5.8 (upper plot), the choice of the index crucially determines the estimated impact. Specifically, results for the median area are higher using $Sday_1$

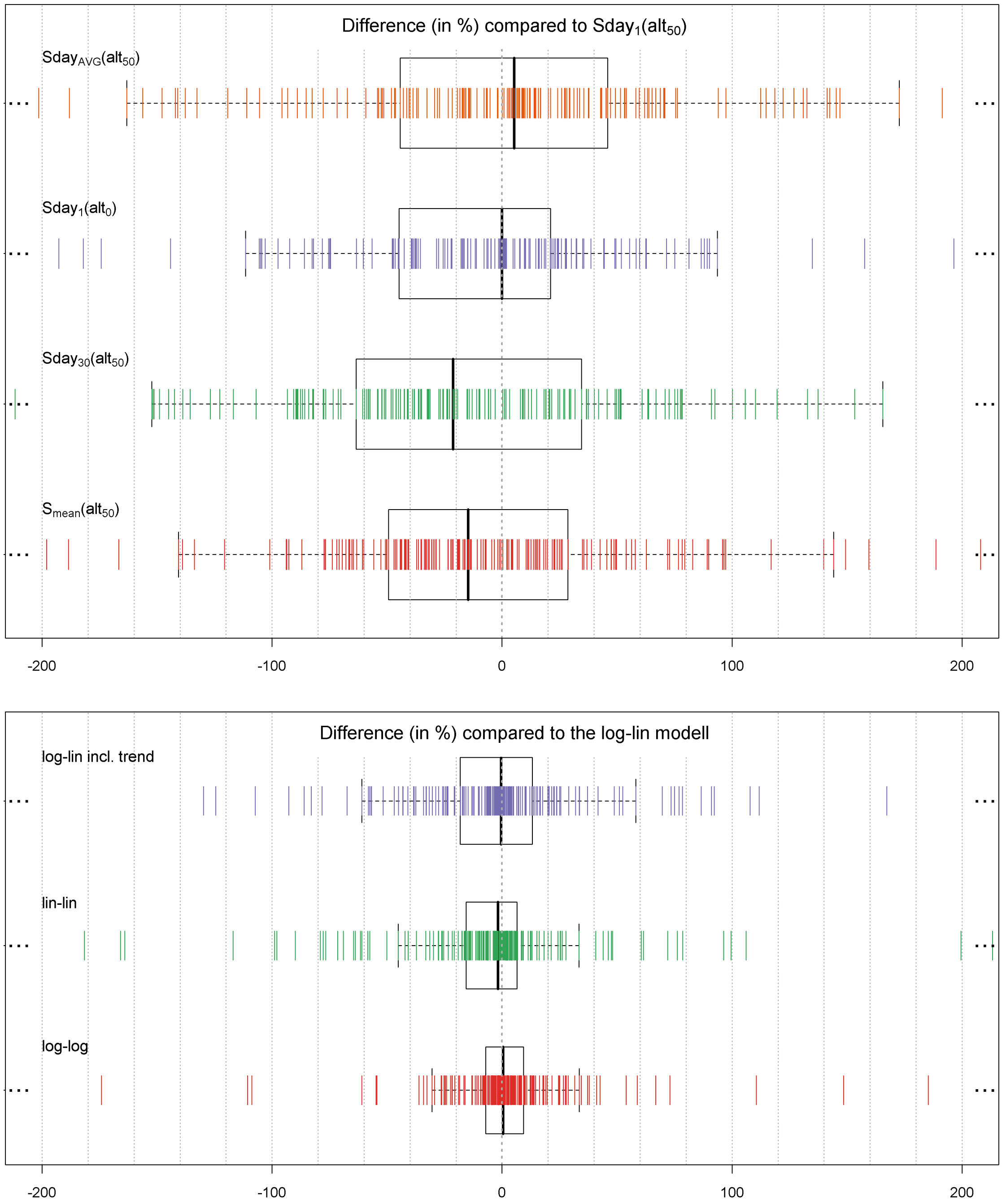


Figure 5.8: Comparison of estimation results for different weather indices (upper plot) and model specifications (lower plot); Each line represents one out of the 185 ski areas and indicates the deviation of results (in %) from the results obtained with the reference weather index or reference model specification respectively

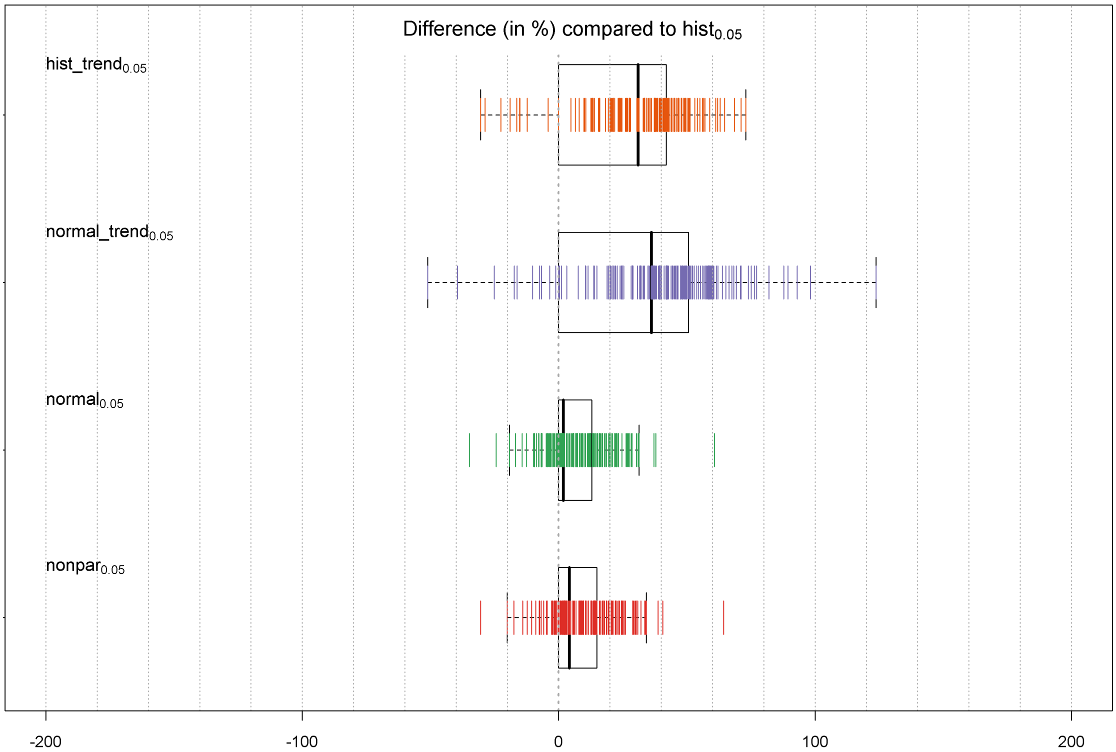


Figure 5.9: Comparison of estimation results for different weather index modelling approaches; Each line represents one out of the 185 ski areas and indicates the deviation of results (in %) from the results obtained when using the quantile of the empirical distribution WI_{hist}

(both for alt_0 and alt_{50}) compared to $Sday_1$ or S_{mean}. Furthermore, for nearly half of the areas estimated impacts are higher when considering $Sday_{AVG}$ rather than area specific snow conditions. Altogether though, the extent and direction of the deviations between results for $Sday_1(alt_{50})$ and those for the other indices vary widely from area to area. The high interquartile ranges (60 to 100 %) provide evidence for this fact and highlight the importance of choosing an appropriate weather index.

Once the weather index is chosen for an area, risk estimations are comparatively less sensitive to other assumptions. Figure 5.9 reveals that all three weather index modelling approaches generate fairly similar results. However, estimates are for all three approaches higher when considering the mostly negative trends in snow conditions. For the median area, trend inclusion increases the $VaR(weather)_{0.95}$ by 30 to 40 %.

In addition, Figure 5.8 (lower plot) indicates that different model specifications have a very modest effect on $VaR(weather)_{0.95}$. For the four illustrated model specifications, estimates do not change for the median area, and interquartile ranges are also comparatively low.[16]

5.2 Aggregate Impacts

In this section I present results for the seven federal provinces with skiing activities, four altitude and three size categories. As explained in Subsection 4.2.4 and Subsection 4.3.3, different approaches can be used to estimate effects on this aggregate level. First, I illustrate results for three approaches where data is aggregated either before or after doing ADL model calculations (option A, B and C). Then, I briefly discuss the results of panel data estimations (Subsection 5.2.2) and finally give a comparison to the results obtained with option A, B and C (Subsection 5.2.3). Note that, like in the previous section, results in this section are always given using the same weather index for all ski areas, provinces, altitude or size categories. This assumption is helpful for doing comparisons, but will be relaxed for providing best estimates of weather risk in Section 5.4, where for each area a different index might be chosen.

5.2.1 ADL Models

To begin with, results are indicated for the approach, where data is accumulated before ADL model estimations. This approach corresponds to option A (Equation 4.20). For each of the provinces, size and altitude categories, calculations are repeated with different weather indices and results are compared by interpreting the obtained β_1 coefficients, which give the impact of a σ change in the respective weather index.

Table 5.3 shows that when grouping all areas on a provincial level, a positive dependency on snow conditions can be found for each of the seven winter sport provinces. Whether and to what extent the relationship is found to be significant or not depends on the chosen weather index, but for each province a significant relationship is revealed for at least two indices.

Impacts are below average in the Western provinces of Tyrol and Vorarlberg, where most of the overnight stays take place in higher-lying areas. In contrast, impacts are by far the highest in the provinces of Carinthia and Lower Austria. At first glance, ski areas in both provinces have not much in common: While areas in Lower Austria are particularly low-lying and exhibit less favourable snow conditions compared to other provinces,

[16] Note that this comparison only bases on different dynamic model specifications. Indeed, differences might be more pronounced, if estimates are e. g. compared to some static specification. However, as the static specifications calculated in this thesis tend to exhibit some form of misspecification (see Table 5.2) such a comparison might be misleading and should not be used for an interpretation of modelling uncertainties.

	$Sday_1$ alt_{50}	S_{mean} alt_{50}	$Sday_{30}$ alt_{50}	$Sday_1$ alt_0	S_{mean} alt_0	$Sday_{30}$ alt_0	$Sday_{AVG}$ alt_{50}	T_{mean} alt_{50}
Total	1.46**	1.43**	1.27**	1.04*	1.22**	1.11*	1.46**	-0.99
	(0.58)	(0.58)	(0.59)	(0.56)	(0.55)	(0.56)	(0.58)	(0.59)
province								
Carinthia	4.01***	4.92***	3.64**	4.65***	3.98***	3.37**	0.68	-4.12***
	(1.31)	(1.39)	(1.36)	(1.10)	(1.29)	(1.30)	(1.44)	(1.15)
Lower Austria	2.17**	2.86***	2.54**	2.44**	3.01***	2.79**	3.39***	-1.60
	(0.99)	(0.99)	(1.06)	(0.96)	(0.99)	(1.02)	(0.90)	(1.05)
Upper Austria	1.23	1.40*	1.73**	1.40	0.99	0.94	2.66***	-0.63
	(0.79)	(0.81)	(0.78)	(0.83)	(0.85)	(0.87)	(0.93)	(0.94)
Salzburg	2.17**	2.07**	1.91**	1.32*	1.88**	1.75**	2.18**	-1.24
e. g.	(0.78)	(0.76)	(0.77)	(0.77)	(0.75)	(0.76)	(0.80)	(0.80)
Styria	0.87*	1.05*	1.18**	0.90*	0.92	0.74	1.04*	-0.56
	(0.48)	(0.54)	(0.52)	(0.49)	(0.58)	(0.55)	(0.54)	(0.55)
Tyrol	1.17*	1.32**	1.07*	0.70	0.97	0.87	1.07	-0.63
	(0.63)	(0.60)	(0.61)	(0.62)	(0.59)	(0.59)	(0.63)	(0.63)
Vorarlberg	1.29**	0.89	0.76	0.91	0.73	0.74	1.55***	-0.57
	(0.55)	(0.55)	(0.58)	(0.54)	(0.54)	(0.54)	(0.54)	(0.61)
altitude (m)								
$alt_{50} < 1200$	1.50**	1.64***	1.61***	1.44**	1.46**	1.34**	1.99***	-0.98
	(0.58)	(0.57)	(0.56)	(0.58)	(0.59)	(0.57)	(0.61)	(0.62)
$1200 \leq alt_{50} < 1500$	2.26***	2.42***	2.33***	1.98**	2.17***	1.96**	2.53***	-1.33
	(0.79)	(0.72)	(0.74)	(0.72)	(0.73)	(0.74)	(0.79)	(0.83)
$1500 \leq alt_{50} < 1800$	2.25***	1.84***	1.73**	1.32**	1.4**	1.39**	2.10***	-1.45**
	(0.62)	(0.65)	(0.64)	(0.64)	(0.62)	(0.63)	(0.63)	(0.64)
$alt_{50} \geq 1800$	-0.35	-0.16	-0.56	-0.47	-0.39	-0.49	-0.68	0.35
	(0.56)	(0.56)	(0.56)	(0.55)	(0.52)	(0.52)	(0.54)	(0.54)
area size $(10^6 Pm/h)$								
$TC < 1.5$	1.60***	1.53***	1.47**	1.63***	1.54***	1.46**	1.81***	-1.48**
	(0.54)	(0.54)	(0.54)	(0.53)	(0.54)	(0.54)	(0.56)	(0.58)
$1.5 \leq TC < 5$	1.18*	1.11*	0.94	1.03	1.12*	0.90	1.37**	-0.86
	(0.63)	(0.62)	(0.64)	(0.61)	(0.62)	(0.62)	(0.64)	(0.65)
$TC \geq 5$	1.57**	1.52**	1.33**	1.01*	1.23**	1.14*	1.48**	-0.99
	(0.59)	(0.59)	(0.60)	(0.58)	(0.56)	(0.57)	(0.59)	(0.60)

p-value: <0.1 * ; <0.05 *; <0.01 ***
Numbers in parentheses beneath the estimates are standard errors.

Table 5.3: Change in overnight stays (in %) for a one σ change in different meteorological indices

areas in Carinthia are generally higher-lying and snow reliable. However, both of these provinces have in common that climate conditions are, compared to other provinces, less related with those in Tyrol and Salzburg, where most of the skiing activities take place (∼70 % market share). Therefore substitution effects between Carinthia and Lower Austria and these core provinces might be one possible explanation for the relatively high coefficients.

All of these results on the provincial level are robust to using different snow indices, except for the weighted-average Austrian snow conditions $Sday_{AVG}$. Especially for the provinces of Lower Austria, Upper Austria and Vorarlberg $Sday_{AVG}$ seem to be much more important than the snow conditions in their ski areas. Supposedly, this again results from the outstanding position of the provinces of Tyrol and Salzburg in market share and concerning the media coverage of winter tourism. If snow conditions are good there, they are believed to be good in Austria in general and thus they positively impact other provinces´ overnight stays. This might not be the case for the Southern province of Carinthia though, for which the estimated impact of $Sday_{AVG}$ is extraordinary low.

Apart from that, aggregating areas according to their mean altitude alt_{50} widely confirms the results for individual ski areas: Areas below 1800 m significantly depend on their own snow conditions, while this is not the case for areas above 1800 m (Table 5.3). When grouping according to the size of ski areas, similar but not that clear-cut results are obtained. Overall, smaller areas (TC$< 1.5 \times 10^6$ Pm/h) exhibit higher impacts, but the difference to medium sized and larger areas depends on the underlying weather index.

In addition, it is interesting to compare these estimates obtained by grouping data before running ADL models to approaches that aggregate estimates for individual ski areas by considerations from portfolio theory (see Subsection 4.3.3), using either option B (Equation 4.21) or option C (Equation 4.22). As mentioned before, option B and C must yield the same estimates under the assumption of WI being normally distributed. In addition to that, option C allows considering other distributions of WI as well as including trends in WI on the level of individual ski areas.

A comparison of estimation results is provided in Table 5.4 for both the impact of a one σ change in $Sday_1(alt_{50})$ and the corresponding $VaR(weather_{agg})_{0.95}$. Results suggest that when adding up estimates for individual areas by option B and C,[17] overall estimates are in most cases slightly (10 %-20 %) lower than for option A. Yet, there are some exceptions: Lower Austria, Styria and areas with $alt_{50} \geq 1800$ m exhibit higher estimates, while Carinthia in particular shows substantially lower estimates.

For Carinthia, the huge differences in estimation results between option A and option B or C are hard to interpret. Dependent on which option is considered, the dependency on

[17] It needs to be emphasized that the level of estimates should not be necessarily a criteria for deciding which of the approaches is more appropriate. From a theoretical point of view, option A is based on the more reliable (less noisy) aggregated data, while option B and C (like the panel approach presented in Subsection 5.2.2) have the advantage that no information is lost due to data aggregation.

	Impact of a one σ-change		VaR$(\text{weather}_{\text{agg}})_{0.95}$		
	option A	option B&C (no div.)	option A	option B&C	option C trend incl.
Total	1.46	1.27 (1.45)	2.41	2.09	2.99
province					
Carinthia	4.01	1.77 (1.98)	6.60	2.92	4.16
Lower Austria	2.17	2.40 (2.60)	3.57	3.96	4.47
Upper Austria	1.23	1.08 (1.22)	2.02	1.79	2.01
Salzburg	2.17	1.73 (1.94)	3.57	2.86	3.96
Styria	0.87	1.11 (1.41)	1.44	1.84	2.45
Tyrol	1.17	1.12 (1.18)	1.92	1.85	2.73
Vorarlberg	1.29	1.17 (1.23)	2.12	1.93	2.80
altitude (m)					
$alt_{50} < 1200$	1.50	1.27 (1.43)	2.47	2.10	2.89
$1200 \leq alt_{50} < 1500$	2.26	2.09 (2.29)	3.71	3.45	4.80
$1500 \leq alt_{50} < 1800$	2.25	1.51 (1.76)	3.71	2.50	3.44
$alt_{50} \geq 1800$	-0.35	0.17 (0.16)	0.57	0.28	0.67
area size $(10^6 Pm/h)$					
$TC < 1.5$	1.60	1.44 (1.80)	2.64	2.37	3.34
$1.5 \leq TC < 5$	1.18	1.18 (1.45)	1.94	1.96	2.81
$TC \geq 5$	1.57	1.29 (1.43)	2.58	2.12	3.03

(no div.): No diversification – Perfect correlation in weather conditions assumed

Table 5.4: Change in overnight stays (in %) when aggregating to the respective category either before (option A) or after ADL model calculations (option B and C)

snow conditions is in comparison to the other provinces really outstanding (as option A suggests) or not. On the one hand, diagnostic testing for the aggregate model (option A) reveals some autocorrelation in the residuals for the model calculated with $Sday_1(alt_{50})$, which might affect the estimation uncertainty. However, estimation results for other weather indices (see Table 5.3) suggest that the particular high estimates for option A are robust and residual autocorrelation does not affect models for most weather indices. On the other hand, except for 3 out of 18 areas coefficients for individual areas are below this aggregate estimate and except for 3 areas they are not significant. Therefore, it is supposed that in the case of Carinthia, calculations with aggregate data could uncover effects which are not seen to a full extent when doing calculations for individual areas and aggregating them by option B or C[18].

In addition, Table 5.4 compares the estimates obtained with option B and C, which take into account correlations and diversification effects by default, to estimates obtained

[18] In a more detailed analysis in Subsection 5.4.2, it is shown that the choice of $Sday_1(alt_{50})$ seems problematic per se for the largest areas in Carinthia, which could be the reason for the comparatively low estimates with option B and C.

without considering diversification effects (in parenthesis). The latter estimates (unrealistically) imply that impacts from weather conditions are perfectly correlated within the respective group of ski areas and total effects can be calculated by adding up estimates for individual areas. As expected from the fact that the majority of ski areas in each of the provinces, size and altitude groups exhibit the same (positive) dependency on snow conditions, the assumption of a perfect correlation results in higher estimates than correcting for diversification effects.[19]

Last but not least, when calculating trend-adjusted $VaR(weather_{agg})_{0.95}$ with option C, higher estimates are obtained than without incorporating trends in WI, as can be seen in Table 5.4. These results are not surprising, given that the same effect of trend inclusion is observed for the vast majority of individual ski areas (see Subsection 5.1.3). Overall, the trend-adjusted $VaR(weather_{agg})_{0.95}$ estimated for all areas is 2.99 %, compared to 2.09 % without considering trends.

5.2.2 Panel Data Models

Beside ADL model calculations, panel estimations have been conducted by Eigner, Toeglhofer and Prettenthaler (2009). The results from these calculations are briefly presented in this subsection and are then compared to the ADL model results in Subsection 5.2.3. Estimation results are given in full detail in Appendix C. Note that, as can be seen in Equation 4.15, panel calculations have been done for a log-log specification and the non-standardized snow index ($snow_{it}$). However, it is easy to transform estimates to a one σ change in snow conditions after calculations, which is done for analyses in this and the subsequent subsection.

All in all, the FE_tw_bc and the SYS_GMM_g model[20] prove to be the most adequate models. Both estimators are systematically unbiased and consistent and deliver reasonable results. One drawback of the SYS_GMM_g probably lies in the inclusion of a relatively large number of instrumental variables, which increases efficiency, but may also enhance finite sample bias. However, this bias does not seem to be pronounced in the specific case, considering the similar values for the sum of the dependent variable coefficients obtained for both models.

Table 10 (Appendix C) compares the general model estimation results with the panel data set. Coefficient signs match expectations and are highly significant for $nights_{it-1}$, $nights_{it-2}$ and $snow_{it}$. For the lagged dependent variables, a value between 0 and 1 was expected and found for all models. This confirms the results from the ADL model and indicates a relatively high level of persistence for overnight stays. The respective

[19] However, if there is a group of areas with both positive and negative β_1 coefficients (for example, this is the case for areas with $alt_{50} \geq 1800$ m), estimates could despite of the assumption of a perfect correlation be lower. This principle of this effect is explained in more detail in Subsection 5.4.1 on the example of urban snow conditions.

[20] For model abbreviations see Subsection 4.2.4.

coefficient for $snow_{it}$ can be interpreted as elasticity and ranges from 0.052 to 0.156, with estimates from the most reliable approaches being in the lower range (0.052 and 0.094). This bandwidth corresponds to a 0.6 % to 1.9 % change in overnight stays for a one σ change in snow conditions.

The variable $beds_{it}$ also turns out to be highly significant (except for one model specification). For the economic variables gdp_{it} and pp_{it} coefficients are less reliable and only significant for some model specifications (most notably for the *FE_tw* and *FE_tw_bc model*). In particular, relative purchasing power pp_{it} does not seem to play a crucial role.[21]

For the variable gdp_{it}, it is interesting to compare the coefficient of adjustment[22] and the income elasticities from these two models with other panel estimations of tourism demand available in the literature (Garín-Munôz and Montero-Martin 2007). A relatively high short-run robustness with respect to external effects is found. The respective model adjustment coefficients of 0.18 and 0.21, show that about 20 % of the adjustment of tourism to changes in the variables takes place within the first two years. The respective long-term income elasticities of 2.18 and 3.01 are in line with other studies (see Garín-Munôz and Montero-Martin 2007; Song, Witt and Li 2009) and reveal that demand in Austrian ski areas is strongly income elastic, as is common for luxury goods.

5.2.3 Comparison of Approaches

In this subsection the estimates from the ADL and panel models are compared on the basis of a one σ change in $Sday_1(alt_{50})$. Note that under the assumption of a normally distributed weather index, these estimates can easily be transformed to $VaR(weather_{agg})_{0.95}$ by multiplying by 1.645. As estimates for panel models are presented for a log-log specification, so are the estimates for the ADL model (options A to C). The difference to log-lin is marginal though.

Figure 5.10 illustrates the estimation results obtained for the ADL and panel models. Blue and light blue shaded areas indicate the standard error and 95-% confidence intervals for the two panel models being perceived to be the two most reliable ones (*FE_tw_bc* and *SYS_GMM_g*). Basically, estimates from all panel data procedures except the *SYS_GMM_v* are within this range. Interestingly, estimates from ADL mod-

[21] As mentioned before, this is probably due to the similarity of price development in Germany, from where most visitors come. Another reason might be that the CPI has been used for constructing this variable instead of some tourism price index. Such an index would ideally include regional accommodation, transport and ski lift prices, but this data cannot be obtained for the given time period and number of observations.

[22] The coefficient of adjustment describes the speed of adjustment resulting from changes in the exogenous variables. It can be obtained by subtracting the total of the lagged dependent variables from 1. Long-term coefficients are then obtained by dividing (short-term) coefficients with the coefficient of adjustment.

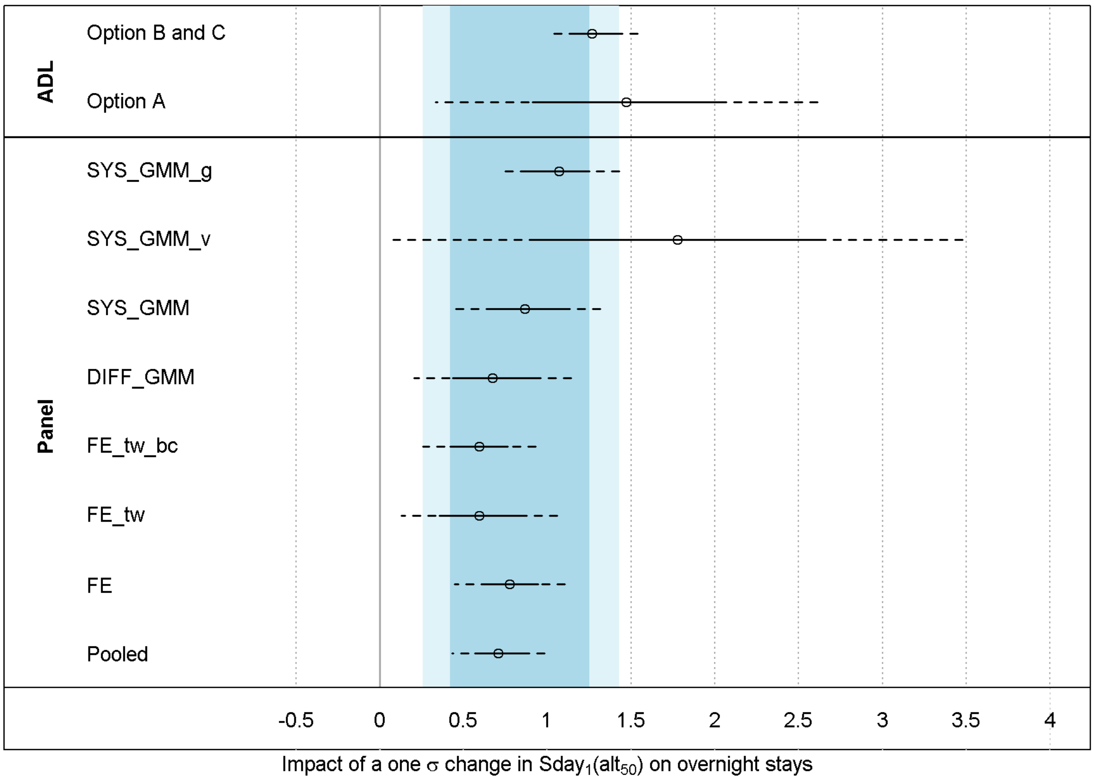


Figure 5.10: Comparison of ADL model results with data aggregation either before (option A) or after model calculations (option B and C) to panel data results
Data source for panel estimations: Eigner, Toeglhofer and Prettenthaler (2009)

els, both for option A as well as option B and C[23], are on the upper end of this range, meaning that these approaches deliver higher estimates than panel procedures.

While it seems evident that for providing estimates on the aggregate level, panel data results are more robust than ADL models, there might be several reasons for the difference in estimates for the analysed data:

1. different procedures to aggregate and weight data;

2. incorporation of additional explanatory variables in panel procedures (collinearity between $snow_t$ and other variables is extremely low, though);

[23] Illustrated confidence intervals for option B and C are estimated based on confidence intervals for individual ski areas and parametric bootstrapping with 1000 permutations.

3. inclusion of time trends in some panel procedures (although Figure 5.8 provides evidence that including trends in the ADL model does not substantially change results);

4. additional differencing for the GMM models.

However, it seems to be difficult to determine which of these potential effects indeed contribute to the lower estimates for panel data.

At any rate, it needs to be pointed out that estimates from all of these approaches are in the same order of magnitude (and therefore provide a consistent picture of the scope of past weather risk), but leave out two important but challenging issues for further understanding ski areas' actual weather risk. These issues, which largely remain outstanding in the current literature, will be covered in the subsequent sections. On the one hand, this involves examining the standard assumption that impacts of snow conditions on overnight stays are constant over time, which might not be the case (Section 5.3). On the other hand, another issue left out is the question of how to estimate aggregate weather risks, if the exposure of each ski area might be of a different nature, as strongly indicated in Section 5.1. This issue will be discussed in Section 5.4, where then estimated weather risks will be expressed in monetary terms and related to other risk factors in the accommodation industry.

5.3 Time Varying Effects

In order to examine the extent to which the sensitivity of tourism demand to adverse weather conditions varies over time, I apply several different approaches outlined in Subsection 4.2.5. I analyse effects by observing changes in overnight stays separately for two extreme seasons, by using moving estimates (ME) from the dynamic regression models and by interpreting changes in the estimates from cross-section regression models as well as from sub-panels. Each of these approaches utilizes data on the level of individual ski areas.

5.3.1 Extreme seasons

Analysing growth rate changes in overnight stays for the two selected warm and relatively snowless winter seasons 1989/90 and 2006/07 provides interesting insights. In order to illustrate growth rate changes, Figure 5.11 uses box plots both for ski areas grouped in altitude categories as well as for other Austrian municipalities. In addition, it provides for each of these categories the mean growth rate change (red line) as well as the total change (dotted line). It should be noted that the median illustrated by box plots (black line) may differ from the mean change in this category (red line), as the performance of areas within a category may be dependent on their size. A lower median than mean simply means that larger areas in the respective category have on average performed better than smaller ones. As can be seen, this effect can be observed for most categories in the winter season 1989/90, but not for 2006/07.

Overall, the results for the two extreme seasons 1989/90 and 2006/07 provide evidence that the impact of winters with poor snow conditions has dramatically decreased. Although meteorological conditions were similar in both seasons, the total change in the growth rate of overnight stays was −8.1 percentage points in 1989/90 and only −2.7 percentage points in 2006/07. Beside that, in both seasons the decrease was more pronounced in lower-lying areas, while no noticeable changes were detected for higher-lying areas ($alt_{50} \geq 1800$ m) or non-skiing areas[24]. For higher-lying areas this goes in line with ADL model results, where no noticeable impacts of own snow conditions are found.

In respect to these results, it should be questioned whether an analogue approach as suggested in the literature and introduced in Subsection 2.3.2 and Subsection 2.6.1 could have come up with results of the same quality. The following considerations are exemplified on the winter season 1989/90.

Dependent on the weather index used, an analogue approach would come up with different seasons to represent a climatologically normal season.[25] Taking $Sday_1$ as a criterion, would mean that the three preceding seasons (1986/87, 1987/88 and 1988/89) as well as the subsequent season (1990/91) could be chosen, although 1988/89 and 1990/91 are less suitable. In contrast, taking T_{mean} would either come up with 1987/88, or one of the three subsequent seasons (1990/91, 1991/92, 1992/93). While T_{mean} is usually considered for finding analogues, results from ADL models for individual ski areas (Subsection 5.1.2) suggest that $Sday_1$ might be more appropriate to use[26].

More importantly, results show the advantage of differencing the data on overnight stays prior to analysis (as done when interpreting growth rate changes) over considering the difference between the analogue and normal season only. Non-differenced overnight stays exhibit a positive trend for most ski areas. Therefore, taking a preceding normal season would result in an underestimation of weather impacts, and vice versa, analysing subsequent seasons would result in an overestimation. The bias is more pronounced the farther away the analogue season is from the normal season. The importance of these considerations can be demonstrated by the fact that taking non-differenced data would, dependent on the choice of the normal season, show an overall impact of +1 % (1986/87)

[24] Based on this analysis, it could be supposed from observing no noticeable change in the season 1989/90 and a slight increase in 2006/07 that there exist hardly any substitution effects between ski areas and non-ski areas. However, a much more detailed framework would be needed (monthly data, spatial patterns) to examine these effects. In addition, it needs to be questioned whether cities, which account for the majority of overnight stays in non-ski areas, rather profit from adverse conditions in ski areas, or from more attractive own weather conditions (e. g. higher temperatures).

[25] For this analysis, a season is simply regarded as a normal season if the weather index does not deviate more than one σ from μ.

[26] However, one methodological constraint is usually that $Sday_1$ are not available from global climate models in order to choose an analogue season.

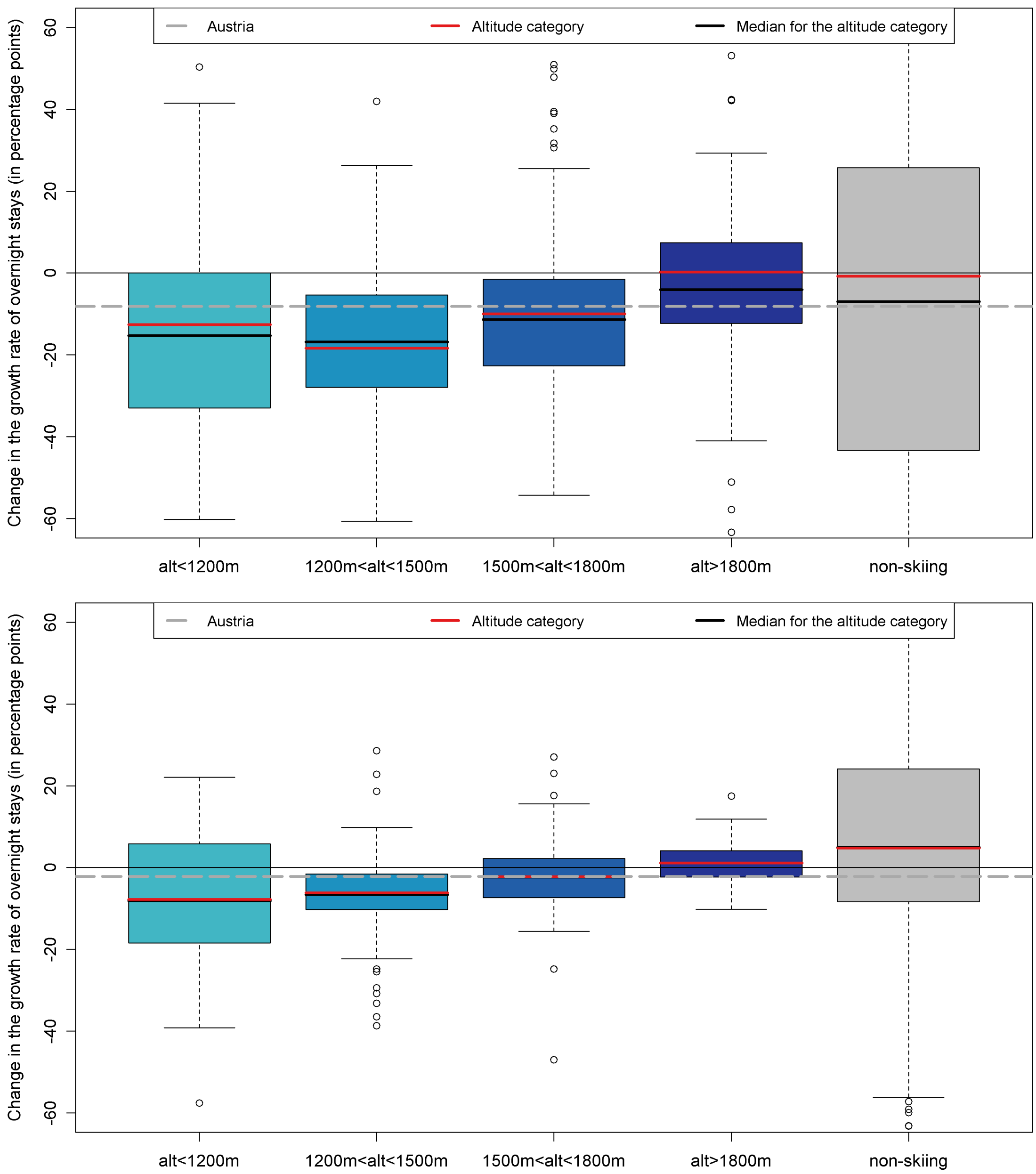


Figure 5.11: Growth rate changes in overnight stays in the extreme seasons 1989/90 (upper plot) and 2006/07 (lower plot) indicated for different altitude categories and non-ski areas

to -12 % (1992/93). In comparison, the growth rate change approach leaves us with a range of -6 to -11 percentage points, with the estimates being much less sensitive to the choice of the normal season[27].

All in all, for conducting analyses with the analogue or similar approaches, it seems to be important to consider variations in the climate as well as in the underlying economic or business data and deal with them accordingly. As the analyses in this thesis suggest, understanding the nature of the latter data is crucial for the quality of results. Of course, applying a growth rate change approach does not help to overcome one major drawback of such a comparison of extreme and normal seasons, namely the non-inclusion of influencing conditions other than weather.

5.3.2 Variable Coefficient Models

In addition to the comparison of extreme seasons, temporal changes in the sensitivity might be detected by several approaches utilizing both the entire cross-sectional and temporal dimension of the data:

1. Moving estimates (ME) from the dynamic regression models indicate a downward shift in the snow coefficient β_1 for the majority of areas. For the median area, estimates for later sub-periods[28] are lower compared to the estimates based on the whole time period. Similarly, the effect of decreasing estimates can be seen when splitting up the estimates for each area into three equal subintervals. Doing so, coefficients for the third subinterval are lower compared to the first and second subinterval for 60 and 66 percent of the areas respectively.

2. Regressing the differenced $nights_t$ and $snow_t$ for each year and the entire cross-section of ski areas, also supports the idea that the sensitivity to snow conditions has declined in recent years. In this approach, β_1 coefficients from Equation 4.16 indicate to what extent changes in overnight stays have been triggered by changes in snow conditions. If $\beta_1 > 0$, ski areas with a stronger increase in $snow_t$ exhibit a stronger growth in $nights_t$, or vice versa, areas with a stronger decrease in $snow_t$ exhibit a stronger decline in $nights_t$. As Figure 5.12 shows, β_1 is positive for most of the time periods, which can be expected from the results from the time series regression models (Subsection 5.1.2). Interestingly though, coefficients seem to be lower from the mid-90s onwards, indicating a less clear relationship between changes in $nights_t$ and $snow_t$.

3. Results for the separate time period panel data models (Eigner, Toeglhofer and Prettenthaler 2009) are listed in Table 11 (Appendix C). While in the *SYS-GMM_g*

[27] Alternatively to comparing growth rates to the previous season, it also might be beneficial to consider the average of several seasons. However, for the analysed data the difference is marginal.

[28] Period 1: 1972/1973–1983/1984 (the lagged dependent variable makes it necessary to dispense with 2 time points); Period 2: 1984/1985–1994/1995; Period 3: 1995/1996–2005/2006.

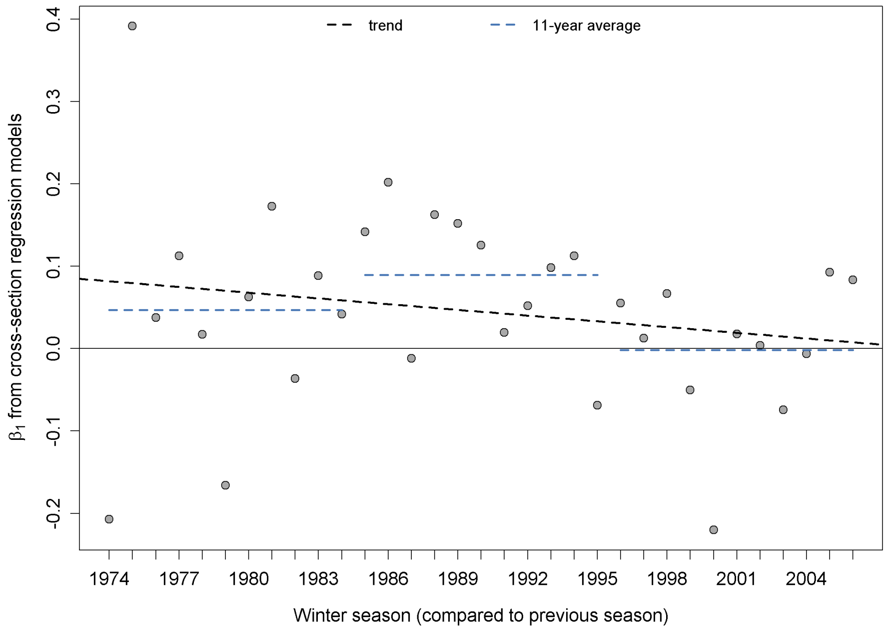


Figure 5.12: β_1-coefficients from the cross-section regression models over time

model the overall trend appears ambiguous for most of the variables, a decline of the $snow_{it}$ coefficient can be observed in the model, from 0.168 in the first period to 0.069 in the third period. The difference is significant at least at the 10 % significance level. However, in the *FE_tw_bc* model this declining trend is only weakly evident, with a decline in the coefficient from 0.087 in the first period to 0.060 in the third period.

Altogether, the results from these analyses as well as the before mentioned comparison of extreme seasons clearly suggest that the sensitivity of overnight stays in ski areas to natural snow conditions has substantially decreased in recent years. Supposedly, this decline can be attributed to the major increase in snowmaking in recent years and a subsequent decline in ski area responsiveness to natural snow cover. Of course, other factors, which will be discussed in more detail in Subsection 6.2.3, might also contribute to this observed trend. However, it is evident that the chosen methodology does not allow to separate between these different influencing factors. Furthermore, uncertainties behind estimation techniques might be too large to understand the exact timing and degree of this decline. At any rate, evaluating effects more closely for individual areas would require additional information, e. g. data on the start of snow making in the respective areas.

5.4 Best Estimates of Weather Risk

Based on the theoretical considerations in Subsection 4.3.4 and the empirical experiences in the preceding sections, I present results from the final step of modelling activities in this section, namely the estimation of best estimates of current weather risk[29] in the accommodation industry in ski areas. I then discuss these results in a broader context (complete winter sport industry, consequences for the Austrian economy etc.) in Chapter 6.

Before presenting best estimates for individual areas and on an aggregate scale, the key assumptions of the modelling approach are summarized and potential sources of bias compared to 'true' weather risk faced in the industry are indicated in the following:

1. **Choice of weather index**

   Weather indices are a product of several complex modelling steps (spatial interpolation, snow cover modelling, assumption of thresholds etc.), leaving high uncertainties on their capability to capture ski areas' weather risk. For each individual ski area, the one[30], out of the 15 available weather indices, indicating the highest $VaR(weather)_{0.95}$ is considered.[31] This use of the highest value can be justified by the theoretical arguments presented in Subsection 4.3.4 and by the evidence provided in Subsection 5.2.1: On the one hand, there exists a potential upwards bias due to this selection procedure from a statistical point of view, as estimates for a certain weather index might simply randomly generate higher estimates. However, on the other hand a substantial downward bias due to the use of imperfect weather indices needs to be considered. For example, using the temperature instead of the best snow index results in a substantially lower estimate (Table 5.3),

[29] The term *current* usually means that a forecast for some future time period is given. The time period $T+1$ would be the season 2007/08 and by the time of writing this thesis it is the season 2010/11 ($T+4$). As the focus of this thesis is not on forecasting, no adjustments based on new data or trend extrapolations of the meteorological and economic data to whatever season are made. Incidentally, the slowdown due to the economic and financial crisis has supposedly helped that overall changes in quantities and prices are comparatively small since T, although patterns might to a large extent differentiate between areas.

[30] Alternatively, it is possible to describe individual ski areas' risk from a bundle of indices. However, as stated before, this approach is not chosen for several reasons. Concerns are mainly about the complex nature of the indices, which are already constructed using a set of underlying assumptions. Furthermore, correlations between most of the indices are high anyway, so that a newly constructed index might not produce considerably better estimation results. Therefore, constructing indices from the existing indices would result in additional complexity but supposedly limited additional information. Beside that, it would be totally against the empirical experiences from the weather risk market, where single indices are used which are kept as simple as possible.

[31] Note that this index usually, but not under any circumstances, corresponds to the index with the most significant impact on overnight stays. For example, even if several indices provide β_1 and t-values in the same order of magnitude, levels of $VaR(weather)_{0.95}$ might be different due to different shapes of the index distribution or trends in the standardized weather indices (WI).

and even the best snow indices supposedly contain altogether a severe geographic, product or local basis risk, which leads to a likely underestimation of weather risk. Uncertainties on both of these biases are high, but the chosen approach seems to counterbalance these biases at least to a certain extent.

Likely magnitude and direction of bias: High uncertainties on both magnitude and total effect.[32]

2. **Distributional assumption**

   The calculated $VaR(weather)_{0.95}$ incorporates for all ski areas trends in the chosen WI, while it is decided on a case to case basis which distribution modelling approach is considered. Trends are included, as analyses show a systematic trend in ski areas' weather conditions and including these trends highly influences weather risk estimates (Subsection 5.1.4). Out of the three WI modelling approaches, the one with the highest estimate is chosen for each area. This is because empirical considerations show that the standard assumption of a normally distributed WI supposedly underestimate events with a low probability of occurrence (Subsection 5.1.1).

   Likely magnitude and direction of bias: Marginal (consideration of both trends and the shape of the distribution).

3. **Model specification**

   Estimations are based on the reference model, the log-lin ADL model. As analyses in Subsection 5.1.4 suggest, estimates do not change substantially for other specifications anyway (log-log, lin-lin, log-lin incl. time trend). Overall, dynamic modelling should reduce potential spurious regression problems. However, using the ADL model for individual ski areas and aggregating them afterwards gives higher estimates than the generally more reliable panel data models (Subsection 5.2.3), which might indicate that they are slightly upwards biased.

   Likely magnitude and direction of bias: Small, possibly upwards.

4. **Stationarity requirement**

   β_1 coefficients from ADL model calculations are taken to describe ski area specific weather risks. They capture the average sensitivity of overnight stays to the respective weather indices in the study period. Overall, analyses show that sensitivity has substantially lowered in recent years (Section 5.3), but different methodological approaches reveal some uncertainty on the magnitude of the effect. Especially for individual ski areas the extent of this change remains unclear. Results from the ME approach indicate a decline for most areas. Differences between areas and estimation uncertainties are high though. Hence, estimated shifts in β_1 from ME are

[32] See Subsection 4.3.4 for a more detailed discussion of these biases.

not considered and the given weather risk estimates need to be interpreted under the assumption of an average historical adaptation level.

Likely magnitude and direction of bias: Upwards, but from ski area to ski area different.

5. **Aggregation of impacts**

   For aggregating individual ski areas‘ $VaR(weather)_{0.95}$, option C (Equation 4.22) is chosen, as it allows to consider different distributional assumptions of the respective WI to calculate $VaR(weather^C_{agg})_{0.95}$. This approach incorporates correlations between weather conditions in ski areas and thus corrects for the effect that due to diversification effects the total weather risk is smaller than the sum of individual ski areas' weather risks.

   Likely magnitude and direction of bias: Marginal.

6. **Cost evaluation**

   The monetary quantification is based on overnight stays in the season 2005/06[33] as well as average sales per overnight stay in the period 2000-2007 (Subsection 3.3.5). Estimates are influenced by quantity and price changes in the respective ski areas since then. In addition, sales in hotels included in the dataset might not be representative for the respective ski area[34], and the spread between winter and summer sales is not incorporated[35].

   Likely magnitude and direction of bias: Downwards (increase in sales over time, summer-winter difference in sales per overnight stay).

Altogether, it needs to be emphasized that the chosen modelling approach helps to overcome a range of potential biases and that remaining biases are likely to effect estimates in both directions. A profound conclusion on which of the effects dominates is not possible, and the overall direction of bias might differ from area to area and from province to province. Indeed, it is conceivable that some of these biases could be removed by introducing additional (simplifying) assumptions, adding additional information (e. g. for the purpose of forecasting) or providing more in-depth studies for individual ski areas.

[33] This is the penultimate season in the data set, as overnight stays in the season 2006/07 have been affected by adverse snow conditions (Subsection 5.3.1).

[34] This might particularly be the case in smaller ski areas with usually a smaller sample of hotels being available or where interpolation had to be chosen.

[35] Overall, guest surveys (T-MONA 2009) indicate a difference of 24 % (135 € vs. 109 €, incl. travel costs), but other sources differ and indeed, the difference among areas might be substantially dependent on the business strategy in ski areas (summer close-downs, pricing strategies etc.)

5.4.1 Type of Exposure

Best estimates of weather risk consider different weather indices for each ski area as well as different approaches to model the distribution of the respective indices. Which weather index and distribution is used as best estimate for each individual area is decided on the basis of $VaR(weather)_{0.95}$. It is assumed that the higher it is, the higher is the sensitivity of the respective ski area to the exposure the index stands for. This subsection discusses which type of exposure is typically identified for which type of ski areas.

Type of exposure	Weather Index	VaR*	Top-1**	Top-3***
Natural snow conditions (mean altitude)	$Sday_1(alt_{50})$	**2.99**	10	51
	$S_{mean}(alt_{50})$	**2.55**	5	35
	$Sday_{30}(alt_{50})$	2.27	17	37
Natural snow conditions (valley station)	$Sday_1(alt_0)$	2.17	14	38
	$S_{mean}(alt_0)$	1.62	3	31
	$Sday_{30}(alt_0)$	1.18	15	26
Artificial snow conditions (mean altitude)	$Sday_{1,art}(alt_{50})$	**2.80**	19	51
	$Sday_{30,art}(alt_{50})$	**2.97**	23	69
Temperature (mean altitude)	$T_{mean}(alt_{50})$	1.85	8	20
Natural snow conditions (urban)	$Sday_1$(Vienna)	0.20	8	23
	$Sday_1$(Linz)	0.11	8	22
	$Sday_1$(Salzburg)	1.11	3	20
	$Sday_1$(Graz)	0.08	7	32
	$Sday_1$(Innsbruck)	1.98	10	29
Natural snow conditions (all areas)	$Sday_1$(average)	**3.66**	35	71

* Relative $VaR(weather_{agg})^C_{0.95}$ calculated for the respective weather index
** Number of ski areas for which the weather index is used as best estimate
*** Number of ski areas for which the weather index is among the top 3 indices

Table 5.5: Aggregate VaR(weather) when using different weather indices for calculations; Number of ski areas for which the respective weather index is used as best estimate or is among the top 3 indices

For a first comparison, Table 5.5 illustrates the aggregate relative risks, more specifically denoted as relative $VaR(weather_{agg})^C_{0.95}$, under the assumption that the same weather index is used for each ski area. Higher estimates (in bold) indicate indices which are most suitable for analysing weather risks in the skiing industry. Quite surprisingly, the weighted-average Austrian snow conditions $Sday_{AVG}$ show the highest estimate in total. This can be interpreted as a clear hint that for the overall development of overnight stays in the period 1973-2006, general snow conditions have been more important than specific snow conditions in ski areas[36]. However, this might have changed in recent years due to the availability of better area specific weather information as well as changes in booking behaviour.

The second highest aggregate estimate is obtained with the chosen reference index $Sday_1(alt_{50})$, but several similar indices which are all based on snow conditions in alt_{50} also produce similar outcomes. Among these indices are snow day indices incorporating information on artificial snowmaking ($Sday_{1,art}$ or $Sday_{30,art}$).[37] Furthermore, indices referring to the lowest altitude of areas alt_0 perform substantially worse than those equivalent for alt_{50}. In particular, the chosen aggregation approach reveals urban snow conditions to have an extremely low explanatory power[38].

In addition, Table 5.5 shows for how many ski areas each of the weather indices is used for obtaining best estimates of weather risk, or is at least under the top 3 indices for a ski area. It needs to be emphasized that while these numbers are dependent on how good a particular index performs, they also depend on the similarity of examined indices. If several indices are highly correlated and are an indicator for the same kind of dependency, each of them is chosen less often compared to other indices. As for example, six natural snow indices but only two artificial snow indices are included in the analysis, each of the latter is included more often, but in total, natural snow indices are used more often for the analysis.

Turning to the question of which kind of index is selected for different regions and altitude levels, Figure 5.13 illustrates the underlying spatial patterns. Indices representing a positive dependency on ski area specific snow conditions are selected for nearly half of all areas (84 out of 185 areas). Indices indicating a stronger positive dependency on general or urban snow conditions than on ski area specific snow conditions are also selected quite often (45 areas), especially for areas on the northern side of the main chain of the Alps. As mentioned, this can be explained in two ways. On the one hand, in many cases snow conditions in these areas highly correlate with average or urban snow conditions and the

[36] Of course, it needs to be emphasized that for calculating this general index, specific snow conditions in ski areas have been used. In other words, using other proxies for general Austrian snow conditions might again result in lower estimates.

[37] This similarity is somewhat expected because of the construction of the indices. Artificial snow indices are an alteration of natural snow indices and the only difference is that in case of cold weather some additional snow depth is added, which increases the number of days where one of the assumed thresholds in snow depth is exceeded (see Subsection 3.2.4).

[38] In the special case of urban snow indices, the particular merits of the variance-covariance approach can be observed. Aggregate estimates close to zero show that urban snow conditions cannot be taken to explain total changes in demand due to snow conditions. Noteworthy, this is the opposite of what one could conclude when using urban snow conditions and simply adding up risks estimated for individual areas. The reason why this approach delivers a zero dependency on urban snow conditions is straightforward: As the same index (e. g. snow conditions in Vienna) is used for all areas, risks are perfectly correlated, either positively (ρ= 1) or negatively (ρ= −1). Therefore, if the number of areas with positive and negative β_1-coefficients is similar (as is the case, except for Innsbruck and Salzburg) area specific effects hedge each other and the aggregate effect is close to zero.

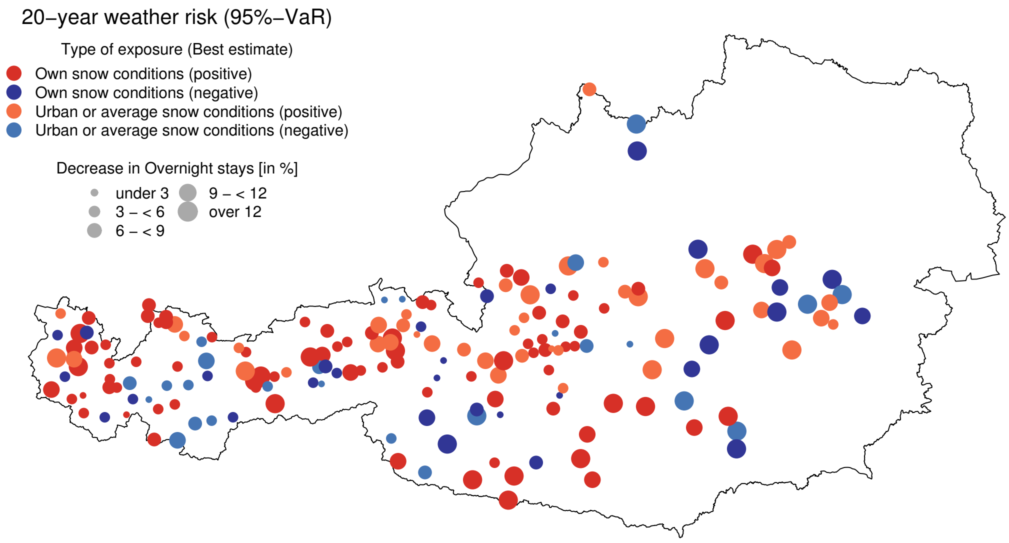


Figure 5.13: Type of exposure considered for best estimates of $VaR(weather)_{0.95}$ for individual ski areas; The size of the points indicates the size of the estimates

latter indices are therefore just a substitute for weather indices representing own snow conditions. On the other hand, these areas, which are usually also closer to important source markets (Vienna, Germany), might indeed benefit from reports on good snow conditions, and less likely, from good urban snow conditions. General Austrian and, to a lesser extent urban snow conditions are also relevant for some areas in North and East Tyrol located on the south of the main chain of the Alps, but for these areas, the estimated dependency is negative. This is in line with the second explanation pattern that areas closer to source markets profit, but remoter and typically more snow reliable areas lose from good snow conditions.

Furthermore, patterns are harder to interpret for Eastern Austria (Lower Austria and Eastern areas of Carinthia and Styria). Best estimates are higher than for most areas in Western Austrian (size of points in Figure 5.13), but the indicated direction of the dependency is seemingly randomly distributed. As stated before, this can supposedly be explained by larger modelling uncertainties for smaller areas. However, for total estimates of ski areas' weather risk these areas do not play a prominent role anyway.

Before finally presenting best estimates of ski areas' weather risk in absolute numbers, Figure 5.14 discusses how results would differ when changing two main assumptions behind best estimates. Firstly, the upper right plot illustrates the effect of only using the assumption of normally distributed weather indices and not considering potential higher estimates from quantile estimations of the historic distribution or the multivariate, non-parametric approach. It can be observed that differences are small but not negligible.

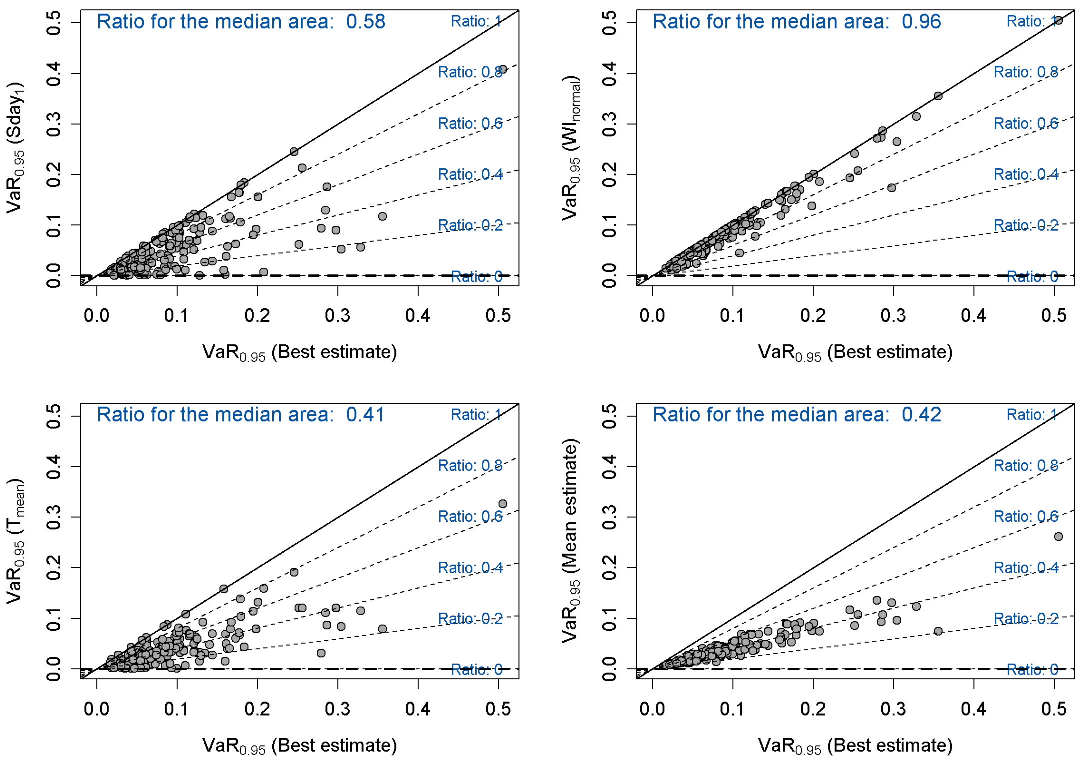


Figure 5.14: Best estimates of weather risk compared to estimates obtained when considering only $Sday_1$, T_{mean} or WI_{norm} as well as to mean estimates from all indices; A ratio of 1 means that estimates are identical

In 77 out of 185 cases the normality assumption is selected anyway for best estimates, and in the other cases, the differences are, with a few exceptions, rather low.

Secondly and more importantly, different assumptions on which weather index to choose result in completely different risk estimates. As indicated in the two left plots, considering only the $Sday_1(alt_{50})$ or the $T_{mean}(alt_{50})$ index instead of selecting from several weather indices results in noticeably lower estimates, but with huge differences between areas. At least for the median area, considering $T_{mean}(alt_{50})$ yields in the same estimate as obtained from taking the mean of VaR estimates from all available weather indices (lower right plot). Compared to that, using $Sday_1(alt_{50})$ results in substantially higher and supposedly more accurate estimates.

To conclude, selecting from a range of potential weather indices (best estimate procedure) overall seems to be the most appropriate strategy, if little is known about the type of the weather exposure, or if it might differ among ski areas. Choosing only one index which is believed, at least for the average area, to be a good indicator ($Sday_1$), is also viable. In contrast, just using an index which is typically easily available, but maybe a less suitable indicator (T_{mean}), results in a substantial underestimation of weather risk, as it is also the case when taking the mean of estimates from a set of indices. In doing so, indices which are, dependent on the area specific type of exposure, potentially less suitable, have the same weight as potentially more suitable indices.

5.4.2 Best Estimates

In this subsection best estimates of ski areas' weather risk are presented, first for individual ski areas and then aggregated to provinces, size and altitude categories. In both cases, relative losses (in %) as well as absolute losses in overnight stays and subsequent sales in the accommodation industry are indicated for $VaR(weather)_{0.95}$.

As illustrated in Figure 5.15 (upper plot), expected relative losses differ widely between ski areas. The expected decrease in overnight stays from adverse weather conditions occurring in 1 out of 20 winter seasons ranges from 1.67 % to 50.54 %, with estimates for the median area being at 7.27 %. A substantial difference in individual ski areas weather risk can be observed between the core ski provinces Salzburg, Tyrol and Vorarlberg and the other provinces. Estimates in these core provinces tend to be lower than in others. However, within the core provinces also some regions can be identified, in which areas' weather risk is higher than in others, e. g. Central Vorarlberg or the region Wilder Kaiser/Kitzbueheler Alps.

Some of these differences between relative estimates can be explained by the effects of altitude, snow reliability and area size[39], which are heavily interrelated. VaR estimates typical decrease with the mean altitude of areas (alt_{50}), mean snow conditions ($Sday_1$), transport capacity (TC) or other similar indicators for area size[40]. Nevertheless, beside size and altitude effects other (unexplained) effects might be important determinants for differences in risk estimates as well. Carinthia seems to be the best example for that: The (weighted) mean altitude of its ski areas corresponds to the Austrian average and (weighted) mean snow conditions are above average. The mean size of areas in Carinthia is below the core provinces Salzburg, Tyrol and Vorarlberg and therefore below Austrian average, but substantially above the other three provinces. Still, estimates for Carinthian areas are in most cases above average and Carinthia is in total the province with the highest risk, as will also be discussed below.

[39] Note however, that some of the size effects might be due to higher estimation uncertainties for smaller areas. For example, the 10 areas with highest relative risk (25 % to 51 %) all exhibit less than 70 000 overnight stays in the mean season, which is below the median area (95 000).

[40] This can for example be demonstrated by regressing $VaR(weather)_{0.95}$ with alt_{50} (or $Sday_1$) and TC (or μ_{nights}).

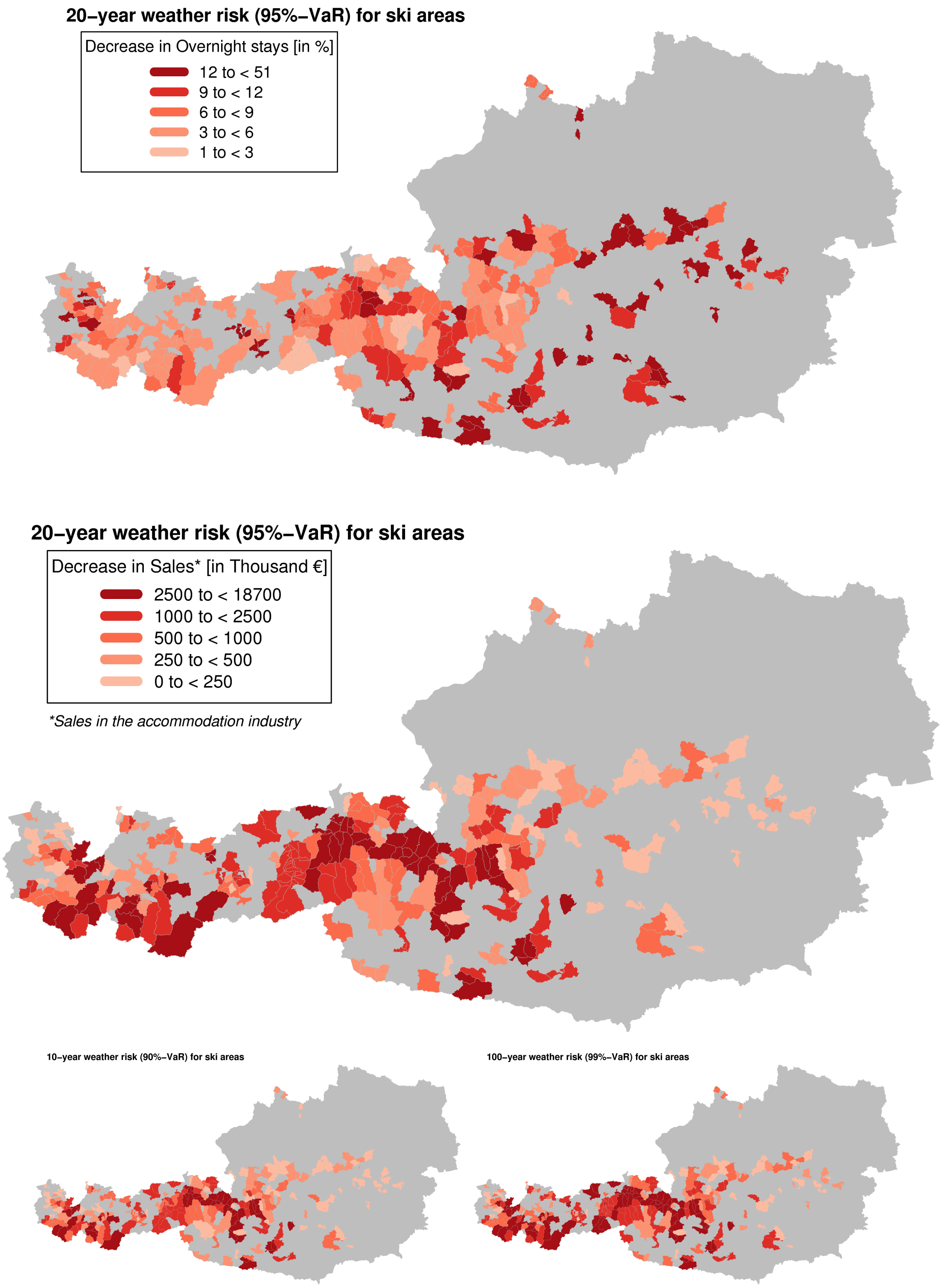


Figure 5.15: Best estimates for ski areas indicated as relative decrease in overnight stays (upper plot) and decrease in sales in the accommodation industry (lower plots)

Compared to relative estimates, considering absolute losses reveals a different picture (Figure 5.15). Although areas in the core ski provinces Salzburg, Tyrol and Vorarlberg in general exhibit lower relative risks, multiplying these estimates by overnight stays and sales reveals a concentration of risks in these provinces, which is little surprising given their importance in the Austrian tourism industry. 43 out of the 50 ski areas with the highest $VaR(weather)_{0.95}$ are located in these core provinces, 6 in Carinthia and 1 in Styria. Out of the top 10, core provinces account for 8 areas and Carinthia for the remaining 2 areas.

All in all, estimated 20-year weather risks in ski areas range from 24 000 € to 18.7 million €, with the median being at 498 000 € and the mean respectively at 1 399 000 €. Alternatively, Figure 5.15 (lower plots) also shows estimates for 10 and 100 year weather risks, which equals a switch in the probability of occurrence from $\alpha = 0.05$ to $\alpha = 0.10$ and $\alpha = 0.01$ respectively[41]. Estimates are in a range from 13 000 € to 15.8 million € for a 1 in 10 year event, and from 28 000 € to 26.9 million € for a 1 in 100 year event. For the median area estimates for $\alpha = 0.10$ are at 434 000 € (13 % lower than for $\alpha = 0.05$), and for $\alpha = 0.01$ at 702 300 € (41 % higher than for $\alpha = 0.05$).

Aggregate risk estimates for provinces, altitude and size categories, which also consider correlations[42] between weather conditions in individual ski areas, are presented in Table 5.6. Best estimates of $VaR(weather)_{0.95}$ are compared to single index estimates for $Sday_1(alt_{50})$, which are calculated with as well as without including time trends in the weather index.

It can be seen that relative risk estimates are the lowest for the province of Tyrol, which has a share of 49 % in overnight stays. This can in particular be explained by a diversification of risks in this province. While some relatively lower lying regions are particularly affected by poor snow conditions, other regions rather seem to profit from them. Among the latter are large areas in the upper land (Oberland) as well as the Ziller valley. In contrast, such an effect can not be observed for Salzburg (share in overnight stays: 26 %), which explains why relative and, despite of the difference in market share, even absolute estimates are slightly above Tyrol. Altogether, these two provinces account for the major share in the expected loss in sales from adverse weather conditions.

Best estimates of relative risk are highest for the province of Carinthia, which does not exactly coincide with the picture presented for $Sday_1(alt_{50})$, where estimates are marginally higher for Lower Austria. Indeed, the ratio between the best estimate and the estimate obtained when using $Sday_1(alt_{50})$ is 1:0.40 for Carinthia, compared to 1:0.60 for Lower Austria and 1:0.72 for Austria. As explained in the previous subsection, lower

[41] Again, it is important to note that uncertainties increase with low α-values, as only a limited number of observations is available to estimate the impacts of such a particularly unusual event. Therefore, estimates for α-levels of 0.05 or 0.10 seem to be more reliable.

[42] The lower the correlation coefficient ρ, the greater is the diversification effect, meaning that the aggregate estimate is lower than the sum of estimates for individual areas.

	Relative loss (in %)			Loss in overnight stays (in thousand)			Loss in sales (in thousand €)		
	Best est.	$Sday_1(alt_{50})$ incl/excl tr.		**Best est.**	$Sday_1(alt_{50})$ incl/excl tr.		**Best est.**	$Sday_1(alt_{50})$ incl/excl tr.	
Total	**4.17**	2.99	2.09	**1 768**	1 245	873	**156 857**	103 517	71 652
province									
Carinthia	**10.49**	4.16	2.92	**278**	99	70	**24 355**	8 104	5 700
Lower Austria	**7.44**	4.47	3.96	**26**	16	14	**1 894**	1 106	1 002
Upper Austria	**4.86**	2.01	1.79	**28**	11	10	**1 923**	764	656
Salzburg	**5.61**	3.96	2.86	**654**	469	338	**57 645**	40 900	29 187
Styria	**3.59**	2.45	1.84	**92**	55	40	**7 645**	4 629	3 396
Tyrol	**3.23**	2.73	1.85	**651**	546	370	**53 223**	40 554	26 862
Vorarlberg	**4.24**	2.80	1.93	**169**	110	76	**23 538**	12 586	8 777
altitude (m)									
$alt_{50} < 1200$	**4.51**	2.89	2.10	**129**	77	56	**9 377**	5 382	3 922
$1200 \leq alt_{50} < 1500$	**6.12**	4.80	3.45	**799**	626	452	**64 505**	49 794	35 855
$1500 \leq alt_{50} < 1800$	**5.14**	3.44	2.50	**741**	470	339	**66 987**	40 829	29 045
$alt_{50} \geq 1800$	**1.69**	0.67	0.28	**243**	99	47	**30 483**	9 971	5 271
area size $(10^6 Pm/h)$									
$TC < 1.5$	**6.06**	3.34	2.37	**111**	58	42	**8 743**	4 525	3 243
$1.5 \leq TC < 5$	**4.13**	2.81	1.96	**320**	216	151	**24 404**	16 593	11 542
$TC \geq 5$	**4.10**	3.03	2.12	**1 357**	977	686	**125 002**	82 923	57 335

Note: Do not add up estimates for provinces, altitude and size categories (diversification effect)!
est. = estimate, incl/excl tr. = inclusion or non-inclusion of trends in $Sday_1(alt_{50})$

Table 5.6: Best estimates of aggregate weather risk (95%-VaR) compared to single index estimates with or without including trends in the weather index

ratios imply that the chosen weather index, in this case $Sday_1(alt_{50})$, is simply not capable to capture the different exposures faced by different ski areas within a province, and in particular for Carinthia the best estimate procedure seems to have its merits[43]. All in all, the high relative best estimate for Carinthia means that also the absolute risk estimate is high compared to its market share (share in overnight stays: 5 %) and the loss in sales is on the same level as for the province of Vorarlberg (share in overnight stays: 11 %).

Furthermore, estimates are, in relative terms, above average for the provinces of Lower and Upper Austria, and marginally below average for Styria. In absolute terms however, risks are comparatively low for these provinces due their minor market share (share in overnight stays: 1 %, 2 % and 6 % respectively). To give one example, expected losses are considerably higher in each of the three areas with the highest weather risk than in the provinces of Lower Austria, Upper Austria and Styria together[44].

[43]The reason for this low ratio in Carinthia can be found when studying its two largest areas, which account for approximately 60 percent of the absolute risk. For these areas best estimates are obtained with $Sday_1(alt_0)$ and are, quite surprisingly, three times higher than estimates for $Sday_1(alt_{50})$. Therefore, choosing only one reference weather index without testing other possibilities would have supposedly underestimated weather risks faced by this province.

[44]Of course, estimates for the three provinces account for diversification effects, while single area estim-

5.4.3 Interaction with other risk factors

In a final step of analysis, it is examined how best estimates of weather risk interact with other risk factors in the accommodation industry. How likely adverse weather conditions may lead to financial troubles also depends on how resilient enterprises in the industry are.

For examining this, three operating figures derived from the balance sheet data for 88 mostly larger ski areas (see Subsection 3.3.5) are compared to weather risk estimates: Average ROI, profit ratio and debt ratio, with the latter being traditionally considered as a weak point in the accommodation industry. For each of these indicators as well as relative $VaR(weather)_{0.95}$, values for individual ski areas are subdivided into two groups representing values below and above the median. Risk is considered to be particularly high, when individual ski areas' weather risk is above the median (>6 %), and, depending on the indicator, average profit ratio is below the median (<0.24), average ROI is below the median (<0.12) or average debt ratio is above the median (>0.98). In contrast, risk is considered to be particularly low, when none of the two conditions is fulfilled.

Figure 5.16 illustrates the interaction between operating figures of hotels and weather risk estimates[45]. Red colours indicate higher risks and green colours lower risks. As in other visualizations before, dark blue colours represent higher lying ski areas, and light blue colours lower lying ski areas. At first sight, light blue colours seem to dominate in the double red regions (high risk), while dark blue colours tend to be stronger represented in double green regions (low risk).

To examine this effect in more detail, the probabilities are calculated that, given the areas altitude or size, they are classified in one of the four groups (low-low, low-high, high-low, high-high). Results are illustrated in form of contingency tables in Table 5.7 to Table 5.12. In these tables, information is available both for each of the indicators separately (row sums: weather risk, column sums: operating figures) and combined (weather risk versus operating figures)[46]. Results of this analysis are striking, though not surprising.

For altitude categories the suspicion that the accommodation industry in lowest lying areas is double exposed to risk is clearly confirmed (Table 5.7, Table 5.9 and Table 5.11). On the one hand, weather risk is substantially above average for the lowest lying and below average for the highest lying areas ($alt_{50} \geq$ 1800 m), with medium altitude categories (1200 m $\leq alt_{50} <$ 1500 m and 1500 m $\leq alt_{50} <$ 1800 m) in general lying in between. On the other hand, debt ratio is above average and profit ratio below average for the lowest lying areas, while the opposite is true for the highest lying areas. Patterns for

ates do not.

[45]Note that for illustrative purposes and in this figure only, one outlier (Kreischberg) with a particular high weather risk estimate (0.35) is removed.

[46]As operating figures of hotels are more likely available for larger and generally higher lying areas, less observations are available for the categories including areas with a particularly low altitude ($alt_{50} <$ 1200 m) or of a particularly small size (TC< 1.5 $10^6 Pm/h$).

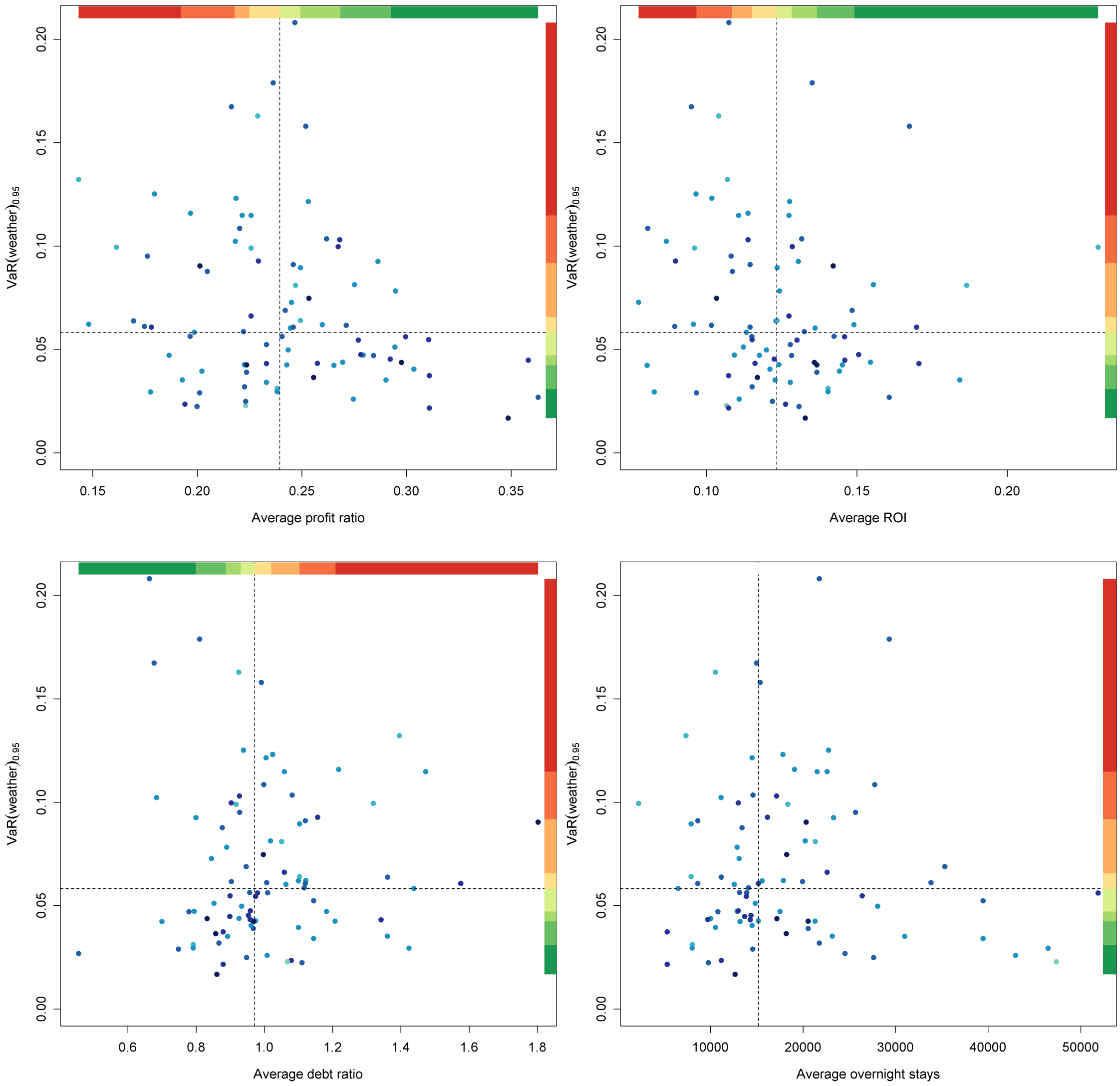


Figure 5.16: Interaction between weather risk and operating figures of hotels in ski areas; Dotted lines represent the median for the respective indicator

ROI are less clear. Putting this information together allows to identify the probability that an area faces both high weather risk and comparatively adverse operating figures. This probability is, dependent on the indicator, approximately two to three times higher for lowest lying compared to highest lying areas.

When considering the size of ski areas, there is clear-cut evidence that hotels in smaller areas are disadvantaged (Table 5.8, Table 5.10 and Table 5.12). To name one example, all six areas of the smallest size category (TC$< 1.5\ 10^6 Pm/h$) exhibit above average weather risk and a below average ROI. Altogether, the probability that an area faces both high weather risk and comparatively adverse operating figures tremendously increases with lower area size.

To sum these considerations up, it is not only the case that lower lying and smaller areas typically face higher weather risk, but they also seem to be more vulnerable, as hotels in these areas not only tend to be less profitable, but also to exhibit higher debt ratios. These results demonstrate that the potential consequences of weather risks faced by ski areas are heavily dependent on the financial resilience of the stakeholders in the industry.

Altitude in m (No. of obs.)		*ROI* LOW	HIGH	
$alt_{50} < 1200$ (8)		37.5	37.5	75.0
$1200 \leq alt_{50} < 1500$ (33)	*Weather risk*	21.2	27.3	48.5
$1500 \leq alt_{50} < 1800$ (25)	HIGH	40.0	20.0	60.0
$alt_{50} \geq 1800$ (22)		13.6	18.2	31.8
TOTAL (88)		**26.1**	**23.9**	**50.0**
$alt_{50} < 1200$ (8)		12.5	12.5	25.0
$1200 \leq alt_{50} < 1500$ (33)	*Weather risk*	30.3	21.2	51.5
$1500 \leq alt_{50} < 1800$ (25)	LOW	16.0	24.0	40.0
$alt_{50} \geq 1800$ (22)		27.3	40.9	68.2
TOTAL (88)		**23.9**	**26.1**	**50.0**
$alt_{50} < 1200$ (8)		50.0	50.0	100.0
$1200 \leq alt_{50} < 1500$ (33)		51.5	48.5	100.0
$1500 \leq alt_{50} < 1800$ (25)		56.0	44.0	100.0
$alt_{50} \geq 1800$ (22)		40.9	59.1	100.0
TOTAL (88)		**50.0**	**50.0**	**100.0**

Table 5.7: Contingency tables for altitude categories: Weather risk versus ROI

Area size in $10^6 Pm/h$ (No. of obs.)		ROI LOW	HIGH	
$TC < 1.5$ (6)	*Weather risk* HIGH	100.0	0.0	100.0
$1.5 \leq TC < 5$ (29)		34.5	37.9	72.4
$TC \geq 5$(53)		13.2	18.9	32.1
TOTAL (88)		**26.1**	**23.9**	**50.0**
$TC < 1.5$ (6)	*Weather risk* LOW	0.0	0.0	0.0
$1.5 \leq TC < 5$ (29)		13.8	13.8	27.6
$TC \geq 5$ (53)		32.1	35.8	67.9
TOTAL (88)		**23.9**	**26.1**	**50.0**
$TC < 1.5$ (6)		100.0	0.0	100.0
$1.5 \leq TC < 5$(29)		48.3	51.7	100.0
$TC \geq 5$ (53)		45.3	54.7	100.0
TOTAL (88)		**50.0**	**50.0**	**100.0**

Table 5.8: Contingency tables for size categories: Weather risk versus ROI

Altitude in m (No. of obs.)		*Profit ratio* LOW	HIGH	
$alt_{50} < 1200$ (8)	*Weather risk* HIGH	50.0	25.0	75.0
$1200 \leq alt_{50} < 1500$ (33)		24.2	24.2	48.4
$1500 \leq alt_{50} < 1800$ (25)		32.0	28.0	60.0
$alt_{50} \geq 1800$ (22)		18.2	13.6	31.8
TOTAL (88)		**27.3**	**22.7**	**50.0**
$alt_{50} < 1200$ (8)	*Weather risk* LOW	25.0	0.0	25.0
$1200 \leq alt_{50} < 1500$ (33)		24.2	27.3	51.5
$1500 \leq alt_{50} < 1800$ (25)		28.0	12.0	40.0
$alt_{50} \geq 1800$ (22)		13.6	54.5	68.1
TOTAL (88)		**22.7**	**27.3**	**50.0**
$alt_{50} < 1200$ (8)		75.0	25.0	100.0
$1200 \leq alt_{50} < 1500$ (33)		48.4	51.5	100.0
$1500 \leq alt_{50} < 1800$ (25)		60.0	40.0	100.0
$alt_{50} \geq 1800$ (22)		31.8	68.1	100.0
TOTAL (88)		**50.0**	**50.0**	**100.0**

Table 5.9: Contingency tables for altitude categories: Weather risk versus profit ratio

Area size in $10^6 Pm/h$ (No. of obs.)		*Profit ratio* LOW	HIGH	
$TC < 1.5$ (6)	*Weather risk*	66.7	33.3	100.0
$1.5 \leq TC < 5$ (29)	HIGH	48.3	24.1	72.4
$TC \geq 5$(53)		11.3	20.8	32.1
TOTAL (88)		**27.3**	**22.7**	**50.0**
$TC < 1.5$ (6)	*Weather risk*	0.0	0.0	0.0
$1.5 \leq TC < 5$ (29)	LOW	20.7	6.9	27.6
$TC \geq 5$ (53)		26.4	41.5	67.9
TOTAL (88)		**22.7**	**27.3**	**50.0**
$TC < 1.5$ (6)		66.7	33.3	100.0
$1.5 \leq TC < 5$(29)		69.0	31.0	100.0
$TC \geq 5$ (53)		37.7	62.3	100.0
TOTAL (88)		**50.0**	**50.0**	**100.0**

Table 5.10: Contingency tables for size categories: Weather risk versus profit ratio

Altitude in m (No. of obs.)		*Debt ratio* LOW	HIGH	
$alt_{50} < 1200$ (8)	*Weather risk*	25.0	50.0	75.0
$1200 \leq alt_{50} < 1500$ (33)	HIGH	18.2	30.3	48.5
$1500 \leq alt_{50} < 1800$ (25)		28.0	32.0	60.0
$alt_{50} \geq 1800$ (22)		9.1	22.7	31.8
TOTAL (88)		**19.3**	**30.7**	**50.0**
$alt_{50} < 1200$ (8)	*Weather risk*	12.5	12.5	25.0
$1200 \leq alt_{50} < 1500$ (33)	LOW	24.2	27.3	51.5
$1500 \leq alt_{50} < 1800$ (25)		28.0	12.0	40.0
$alt_{50} \geq 1800$ (22)		50.0	18.2	68.2
TOTAL (88)		**30.7**	**19.3**	**50.0**
$alt_{50} < 1200$ (8)		37.5	62.5	100.0
$1200 \leq alt_{50} < 1500$ (33)		42.4	57.6	100.0
$1500 \leq alt_{50} < 1800$ (25)		56.0	44.0	100.0
$alt_{50} \geq 1800$ (22)		59.1	40.9	100.0
TOTAL (88)		**50.0**	**50.0**	**100.0**

Table 5.11: Contingency tables for altitude categories: Weather risk versus debt ratio

Area size in $10^6 Pm/h$ (No. of obs.)		*Debt ratio* LOW	HIGH	
$TC < 1.5$ (6)		50.0	50.0	100.0
$1.5 \leq TC < 5$ (29)	*Weather risk*	24.1	48.3	72.4
$TC \geq 5$(53)	HIGH	13.2	18.9	32.1
TOTAL (88)		**19.3**	**30.7**	**50.0**
$TC < 1.5$ (6)		0.0	0.0	0.0
$1.5 \leq TC < 5$ (29)	*Weather risk*	10.3	17.2	27.5
$TC \geq 5$ (53)	LOW	45.3	22.6	67.9
TOTAL (88)		**30.7**	**19.3**	**50.0**
$TC < 1.5$ (6)		50.0	50.0	100.0
$1.5 \leq TC < 5$(29)		34.4	65.5	100.0
$TC \geq 5$ (53)		58.5	41.5	100.0
TOTAL (88)		**50.0**	**50.0**	**100.0**

Table 5.12: Contingency tables for size categories: Weather risk versus debt ratio

6 Discussions

Having identified and quantified weather risks in the accommodation industry in ski areas in the previous chapters, I focus on discussing two more general issues in this chapter. First, I outline the impacts of a relatively snowless and warm winter on the entire winter tourism as well as other industries. Then, I turn to different strategies for mitigating weather risks in winter tourism, including financial, business and technological strategies, and I end this chapter by giving some concluding remarks on these strategies.

6.1 Economic Impacts

6.1.1 Winter Tourism Industry

Discussing the overall economic impacts of adverse snow conditions on winter tourism and more general the Austrian economy, several aspects need to be considered. To begin with, best estimates for the accommodation industry (Subsection 5.4.2) reveal a loss in sales by 157 million € occurring in 1 in 20 winter seasons. This estimation is based on the assumption that enterprises are not able to reduce their costs when facing a reduction in overnight stays. In fact, this assumption seems to be quite reasonable for weather effects. Basically, unfavourable weather conditions occur unexpectedly and affect enterprises on a daily to monthly scale. While hotels face reductions in guests in such a period, they can not completely close down. Therefore they can neither adapt long-term fixed costs (debt services etc.) nor quasi-fixed costs like personal, and variable costs seem to be comparatively irrelevant.

Furthermore, presented losses in sales by 157 million € only account for losses in the accommodation industry. The total effects on the winter tourism industry could be estimated by considering two more factors, namely the share of expenditures in other sectors than accommodation and the respective weather sensitivity of these expenditures.

Firstly, it is difficult to determine the exact share of sales in the accommodation industry on total sales in the winter tourism industry for several reasons (different methodologies and data sources, summer-winter etc.). One possibility is to base analyses on survey data from T-MONA (2009). This data indicates total expenditures of 135 € per night (incl. travel costs) in winter, which would mean that the considered average sales per night of 81 € in the accommodation industry from OHT (2008) account for approximately 60 percent of the total expenditures.[1]

[1]However, several other estimation procedures seem to be possible. Taking an alternative source,

Secondly, it needs to be questioned whether other products and services in the winter tourism industry are more or less responsive to adverse weather conditions than the accommodation industry. Clearly, the cable car industry seems to be more dependent on weather than the accommodation industry, and a stronger variability in visitor numbers provided in other studies (e. g. Bark, Colby and Dominguez 2009; Hamilton, Brown and Keim 2007) point in this direction. In contrast to overnight stays, visitor numbers in ski areas are also dependent on day trippers which can flexibly react to adverse weather conditions. A high variability in visitor numbers do not only affect cable car providers, but also restaurants and bars near slopes. In contrast, restaurants, bars as well as culture and entertainment facility in the valleys might exhibit the same weather dependency as overnight stays, or be altogether even less dependent, as tourists might substitute skiing with other activities in case of unfavourable weather and spend more on these activities.

To sum considerations up, weather and in particular relatively snowless winters have a substantial effect on the Austrian tourism industry. Balancing uncertainties from the weather risk modelling for the accommodation industry as well as considerations for other winter sport products and services in this subsection, the direct weather-related losses from a season occurring in 1 in 20 years are very likely to be in the range between 200 and 400 million €. However, it needs to be emphasized that any change in tourism demand might also have broader implications for the Austrian economy in form of indirect effects. For example, Prettenthaler et al. (2009) examine the impacts of a uniform 10 % decrease in overnight stays in the winter season and show that the overall macroeconomic effect in terms of GDP doubles the initial demand shock to tourism. In addition, their results suggest that the most important negative macroeconomic effects are not to be borne by the tourism intensive provinces such as Tyrol and Salzburg, but by Upper and Lower Austria, with their high share in the food industry and other sectors that deliver to the tourism sector.

6.1.2 Other Industries

Beside these considerations for winter tourism demand, it is important to consider the interaction with weather effects for other industries. This is in particular the case for changes in the demand for energy services, as snowless winters usually go in line with warmer temperatures, and resulting reductions in heating energy demand have substan-

according to Laimer, Ostertag and Smeral (2009) hotels and other types of accommodation account for only 31 % of tourists' expenditures. The remaining amount is spent on restaurants (27 %), transport services (16 %), culture and entertainment (9 %) and other tourism related goods and services (17 %). However, while some of the services not accounted for in the 31 % should be included in sales from OHT (2008), the exact proportion is unknown. Another approach would be, at least for the cable car industry, to conclude from net sales in cable car companies according to Austrian Cable Cars (2009), which amounted to 1.17 billion € in the winter and summer 2008/09. In comparison, estimated sales in ski areas' accommodation industry in the winter season alone account to 4.13 billion €.

tial economic impacts[2]. While this was not the focus of the present thesis, Toeglhofer et al. (2009) show that for the current building stock and energy prices a warming of $\sim$2.2 °C (as indicated by the regional climate scenario reclip:more) would result in an overall decrease in heating costs by approximately 500 million €. For individual buildings, this corresponds to a 20 % to 35 % decrease in heating energy demand, dependent on climate zone, altitude and most importantly building type[3]. Inferring from these figures on the impacts of short-term climate variability, a $\sim$2.2 °C warmer winter incidentally has a probability of occurrence of approximately 5 %[4], which allows to compare the scale of savings in heating energy demand with losses in the winter sport industry.

Concluding from these discussed effects for the energy and tourism industry, the overall effect of unusually warm and snowless winter seasons on the Austrian economy is unclear. The given values provide some evidence that positive effects from a reduction in heating energy costs for Austrian consumers could more than outweigh negative effects from lower revenues in the winter tourism industry.[5] In addition, a complete analysis of impacts would also require to consider other potential positive (e. g. reduced costs for winter services and due to traffic disruptions) and negative effects (e. g. less hydro power production in case of below-average precipitation). Taken altogether, it can be seen that, while for the Austrian economy effects might hedge out, a substantial weather risk remains for particular stakeholders, industries and regions, which they need to deal with accordingly. This is discussed in the following section.

[2] Overall effects of warm winters have been quantified e. g. for the US by Changnon and Hewings (2001), who model the impact of the unusually warm winter season 2001/02. The study concludes that reduced costs for heating are the main economic impact and account for 7.4 billion US Dollar, with great benefits for consumers and businesses, as lower costs provide them with more financial resources for other purposes.

[3] Notably, while the accommodation industry is affected by less visitors due to adverse snow conditions, it also profits from lower heating energy costs. As data from OHT (2008) reveals, on average energy costs equal 5 % of sales, and supposedly a large share of these energy costs are heating costs. Therefore, calculating with a 20 % to 35 % decline in heating costs would result in approximately 40 million € savings in heating costs in the accommodation industry alone.

[4] This estimate is simply calculated inferring from data for Graz-Airport and assuming a normal distribution. Dependent on whether trends in the temperature data are included or not for probability estimations, a one in 20 year event is at 2.8 °C or respectively 1.8 °C.

[5] One could ask why a reduction in tourism demand is unfavourable for the Austrian economy, while the opposite is true for heating energy demand. Tourism in Austria is heavily export-oriented (share of domestic guests in ski areas: 17 %) and a reduction in demand means that foreign guests spend their money abroad. In contrast, a large share of heating fuels is imported. Therefore, the negative effects on domestic energy suppliers owing to reduced heating energy sales are supposedly much smaller than the positive effects from increased consumer spendings on other goods and services.

6.2 Risk Mitigation and Adaptation

As shown in the empirical part of this thesis, stakeholders in the winter tourism industry are severely exposed to weather risks. Having identified and measured these risks, stakeholders need to plan and adopt strategies to deal with them. In principle, beside the strategy of *risk avoidance*, which would mean a complete withdrawal from weather-related activities, stakeholders might adopt either *financial, business or technological strategies.*

6.2.1 Financial Strategies

To begin with, *financial strategies* are most flexible and are regarded to have a considerable potential in the winter tourism industry, particularly in case that *technological strategies* might not be feasible for risk reduction (Scott et al. 2006, p 394). Among financial strategies, *risk retention* is currently presumably the most popular one, meaning that risks are borne by companies themselves. Once being aware of potential weather related losses, companies can either accept risks, or actively manage them by establishing an internal provision for loss. Alternatively, weather risks might be shared with other parties by *risk transfer.* As a rule, companies should only transfer out risks if the cost of risk transfer is lower than the cost of risk retention, unless for certain risks retention is entirely unacceptable, for example if it may lead to financial distress (Lam 2003, p 100).

In the context of the winter tourism industry, two strategies for transferring weather risk are regularly mentioned in the literature (e. g. Scott et al. 2006; Abegg et al. 2007; McGill 2007): *weather insurances* and *weather derivatives* (see Section 2.5). In practice, a differentiation between these two forms of risk transfer may lead to some confusion, as typical derivative products are sometimes labelled weather insurance or weather index insurance. However, in theory, a differentiation is straightforward, namely for derivative based contracts, pay-off is solely based on the underlying weather index and not on actual damage[6]. Most contracts offered in practice have a derivative structure and are not contractualized like a classical insurance[7].

[6] This differentiation between derivative based and insurance products goes along with three important issues, which affect premiums. Firstly, transaction costs differ (cost of meteorological data, contractualization, prove of damage etc.). Secondly, moral hazard is a major problem with insurances, but not with derivatives (except for a potential manipulation of measurement data). Thirdly, offering classical insurance products might lead to an adverse selection of risks, as only enterprises with higher risks would buy weather contracts, while this is not an issue for derivatives.

[7] Note that also the only case where a *weather insurance* has reportedly lead to a pay-off for a skiing company, namely the protection of Vail (Colorado) in the winter season 1999/2000 with a payment of 13.9 million dollar, has supposedly not been a typical insurance product, but was based on a snow index. However, reports about this hedge (e. g. Scott et al. 2006; McGill 2007) have only been taken from an article in the Financial Post Canada in 2004, with no more details being available to me. Another case where weather derivatives have been supposedly used for protection is the case of the French ski lift operator 'Compagnie des Alpes', with some (unconfirmed) statements that they have

Based on the experiences from weather risk analyses in this work, the following implications for the use of risk transfer strategies in the Austrian winter tourism industry can be drawn:

- In principle, with several hundred million € being at risk each season in the winter tourism industry, risk transfer might be an adequate strategy to increase resilience in the industry. For companies, protecting cash flows might reduce risks related to financial distress and lead to more favourable financing conditions. In addition, because of Austria's progressive income tax system, entrepreneurs in the industry may aim for positive tax effects.

- Transaction costs might make the use of weather hedges unattractive for smaller enterprises in the industry. However, there are some arguments in opposition to the argumentation from Scott et al. (2006) who deduce from larger companies' experiences that the current cost is 'sure to exclude the small to medium size enterprises that are at greatest risk'. Firstly, recent years brought up a series of new products, selling platforms and sellers of weather risk products[8]. Secondly, as shown, for individual stakeholders weather risks might indeed be substantial, with e. g. the Value at Risk for the accommodation industry in the the median ski area being at 500 000 €. While in most areas risk is typically borne by several stakeholders, some have also business activities in several areas, making the use of weather products supposedly at least feasible for a range of medium sized and larger enterprises. For other enterprises, some form of coordinated initiatives would be necessary to make a financial transfer of weather risks feasible[9].

- Correlations between weather indices largely differ from area to area and index to index, but unlike stated in Abegg et al. (2007), finding buyers and sellers facing negatively correlated risks to the same weather indices is not a necessary condition for the implementation of weather derivatives. In general, experience shows that especially in less mature fields of the weather market, risks are usually not exchanged by cross-hedging anyway, but rather by the cumulation of risks by professional sellers[10] of derivatives, which then again transfer their risks to larger companies, e. g. reinsurance companies. In addition, empirical data suggests that in some cases cross-hedging might be feasible between higher and lower lying areas,

been used, but also some reports that their use has been considered to be too expansive (Huault and Rainelli 2009, p. 16).

[8]For Mid-Europe e. g. Celsius pro (http://www.celsiuspro.com), a Swiss company, who has reportedly also specialized on solutions for hedging also smaller risks.

[9]To name an example, in 2004 to 2006 some joint protection against low rainfall has been provided for 11 smaller hydro power producers under the lead of the Salzburg AG (for more details see Toeglhofer (2007)).

[10]For these sellers, variability in weather conditions across areas is even advantageous, as they can geographically diversify their risks.

which are exposed to opposite snow risks, or between skiing companies and enterprises with a high heating energy demand[11], as suggested by negative correlations between snow conditions and temperature.

- Analyses in this thesis have highlighted the importance of including trends in weather indices for the quantification of current weather risks. While some authors (Scott et al. 2006; McGill 2007) argue that changes in climate make weather products less attractive due to higher premiums, this should not be the case, when buyers and sellers of such products have the same level of information. In contrast, as weather risk of buyers increase, risk transfer might be more and in any case less attractive for them. In other words, higher premiums might simply reflect higher risks, as is heavily suggested by trend analyses. Then, products seem only less attractive if buyers do not share the perception of increasing risks, e. g. if they base their risk calculation on historic experiences only and do not account for trends. In this case, perceptions on the level of a fair (risk-free) premium would differ[12].

- The most crucial issue for introducing weather products for the Austrian ski industry seems to be the availability of adequate meteorological data. Measurement data with a sufficient record history is available from the Central Institute for Meteorology and Geodynamics (ZAMG) for around 20 out of 185 ski areas, with the data mostly being representative for valley stations. While some form of measurement data seems to be available for most ski areas, quality and data history differs, which certainly affects the risk premium sellers of weather derivatives would add. Using weather stations from larger cities and neighbouring valleys instead would increase basis risk. Alternatively, reconstructing weather indices from snow cover models, which is the chosen approach in this thesis, enables to have weather indices for each individual ski area. However, it is unlikely to be the chosen approach for hedging weather risks, simply because the complexity and uncertainties behind modelling would raise concerns about data reliability and product basis risk, which buyers and sellers of weather products might not be willing to deal with.

Of course, beside these basic conditions for risk transfer in winter tourism, a range of other issues also affects whether financial products may be used in the industry or not. A primary concern is on a general lack of awareness regarding the weather sensitivity of companies as well as the available possibilities for hedging against weather risks.

[11] Unlike consumers of energy, energy supply companies generally do not profit from warm winters, which makes them less suitable for cross-hedging.

[12] However, even with the same perception on risk, sellers might argue that there are higher uncertainties related to climate change and consequently increase the risk premium (surcharge to a fair premium). Especially in the case of non-catastrophic weather risks though, risk predictions should at least be possible on a year-to-year or even shorter basis, the usual time horizons for weather products, and therefore, such an increase in risk premiums would be hard to argue.

According to Wunsch (2008) — and these results also seem applicable for the ski industry — the bulk of Austrian entrepreneurs are not familiar with the concept of weather derivatives. The majority of enterprises either do not see an absolute necessity for hedging their weather risks by means of financial risk management instruments or regard such products as too exotic and complex. Further reasons for not choosing risk transfer as a strategy might be found in the ownership structure of enterprises, business models etc.

6.2.2 Business and Technological Strategies

In comparison to *financial strategies* to deal with weather risks, *business strategies* and in particular *technological strategies* are less flexible, as they typically need more time for implementation and may be irreversible. Beside that, stakeholders in different sectors (e. g. accommodation versus cable car industry) might need different strategies, as not all forms of adaptation are suitable to protect revenues for all types of stakeholders. Furthermore, many of these strategies can not be implemented by single stakeholders in the industry who find their businesses to be particularly dependent, but need some form of cooperation. This is for example the case for timing the season or larger investments in snowmaking facilities.

Amongst *business strategies* to make the winter sport industry less vulnerable to adverse snow conditions, enterprises are able to diversify their risks by implementing new business models or by offering additional non-snow related activities. Beside traditionally rather loose forms of co-operation (e. g. regional associations), businesses might seek to diversify risks by either vertical or horizontal integration. Vertical integration would mean that enterprises engage in several activities, or are organized even as a resort company or destination holding, offering everything from booking to the travel back home. Horizontal integration would mean that companies acquire ski areas or hotels in different regions. (Abegg et al. 2007, p 53)

From a weather risk point of view, horizontal integration seems to be a particularly promising strategy. For North America, Scott et al. (2006) report that several companies have built ski area conglomerates in that they have acquired areas across the continent. In comparison, such a regional diversification in business operations, which goes beyond intra-regional co-operations, is not typically pursued in the Austrian winter sport industry, with a few notable exceptions[13]. As results from this work suggest, substantial diversification effects could also be yielded across the Alps, with areas ideally being located in different regions and on different altitude levels. In this respect, analysis

[13]Take, for example, the case of Cordial hotels and holiday clubs (www.cordial.at), which run locations in four municipalities with skiing activities, but each with a different intensity and with some focus on summer tourism also (Achenkirch, Going am Wilden Kaiser, Reith bei Kitzbuehel, Bad Gastein) as well as in cities (Salzburg, Vienna) and in the Tuscany. Other cases of horizontal strategies include prominent Tyrolean entrepreneurs engaging in Carinthian ski areas etc.

conducted within this thesis, e. g. on the different types of exposure and relative level of weather risk, might provide valuable information for building such conglomerates.

On the other hand, the effect of vertical integration strategies on the level of weather risk faced by enterprises largely depends on the type of weather exposure these enterprises face. For example, a merger of a cable way company and a hotel in a heavily ski-sport oriented region, might not lead to any substantial reduction in weather risk, as both companies face the same exposure, but, for the reasons mentioned before, with some difference in the sensitivity they exhibit. In other cases, where the type of business activities and their weather exposure is considerably different, some diversification of weather risk could be achieved. Anyhow, for all kinds of vertical and horizontal integration strategies, a lot of motives and factors other than seeking to reduce weather risks seem to be dominant. Therefore, whether such a strategy should be chosen or not needs to be decided dependent on weighing all potential synergies and problems, with considerations going beyond the focus of this work.

As described in more detail in Abegg et al. (2007), other strategies to diversify business activities and make enterprises less dependent on snow conditions involve:

- changes in the way ski areas manage the running and timing of the season towards periods with more snow-reliability;
- investments to attract the growing share of non-skiers, offering diversified tourism products including spas, health clubs, indoor sports, concerts, festivals, exhibitions and a variety of bars, restaurants and retail stores;
- an engagement in year-round tourism to reduce the heavy reliance on winter sport in some municipalities, including offers for the summer and shoulder seasons, but also weather independent offers such as congress or health tourism.

Altogether, the authors conclude that 'non-snow related offers play an important role, as they add to the variety of offers available and they support the winter business. However, they are not able to carry the winter industry. For the time being, there is no activity available that could substitute the revenue-generating power of traditional winter sports, in particular skiing (Abegg et al. 2007, p 55).'

Last but not least, ski area operators are able to reduce their weather risk as well as resulting risks for related businesses by different *technological strategies* for adaptation. In fact, technological adaptations are perceived to be the main type of adaptation strategies implemented in the winter tourism industry and include measures for: landscaping and slope development (reducing the snow depth required for ski operation), snow management measures ('snow farming', shading ski runs etc.), concentration of ski operations in higher lying locations and north-facing slopes, extensions of ski areas to glaciers and the utilization of snow making (Abegg et al. 2007). Altogether, *technological strategies* have in common that they require long-term investment decisions and are often considered problematic from an environmental point of view (resource use for snow making, fragility of high mountain ecosystems etc.)[14].

In Austria, all of these adaptation strategies have been used in the past. For example, data analysis in this work reveals that the majority of areas have more capacities in higher lying regions than close to the valley station (Subsection 3.3.1). Furthermore, the eight areas that have access to glaciers typically exhibit a low sensitivity to own weather conditions in winter. These areas currently account for 11 % of overnight stays in ski areas and there are some ongoing debates about further capacity extensions. Most notably, the use of snow making technology is more widespread in Austria than in Switzerland or the French Alps. It has increased tremendously, from 6 % of ski runs being equipped with snow making technology in the season 1992/93 (Breiling, Charamza and Feilmayer 2008) to 66 % in the season 2008/09 (Austrian Cable Cars 2009). With investments of 163 million € on new and upgraded snow making infrastructure (Austrian Cable Cars 2009) it is by far the economically most important adaptation strategy.

6.2.3 Concluding Remarks

With regard to weather risk mitigation strategies and snow making investments in particular, several questions remain open which will be briefly discussed in the following:

1. *Are these strategies implemented to mitigate weather risk or/and to adapt to climate change?*

   All of these strategies are discussed in context of an adaptation to long-term climate change, while simultaneously having effects on short-term weather risks faced by the industry. An exact determination what factors trigger the implementation of these strategies is difficult, but there is some evidence that attention needs to focus on weather risk as one of several risk factors influencing economic decisions in the industry.

   For example for the strategy of snowmaking, Steiger and Mayer (2008, p 292) find for the province of Tyrol that there does not appear to be any link between a ski area's altitude and the degree of snowmaking coverage. Their results are confirmed by qualitative interviews with ski area operators as well as manufacturers of snowmaking and ski lift technology, making clear that the continuing diffusion process of snowmaking is driven by a complex bundle of factors. Among them are, beside an increased affordability of the technology, pressures from increased competition as well as trends in winter tourism, such as the relevance of resort opening in late

[14] More detailed discussions on the economic, ecological and technological dimension and possible future development of these strategies can be found in a series of studies, including Steiger and Mayer (2008); Abegg et al. (2007); Breiling, Charamza and Feilmayer (2008); Teich et al. (2007); Gonseth (2008).

autumn according to schedule as well as the promise of a 'snow guarantee'. Therefore, the author's conclude that 'the one dimensional perspective—climate change is responsible for the diffusion of snowmaking— would be too simple to capture the complexity of the phenomenon. [...] Climate change is one reason, but surely not the main reason for the diffusion of snowmaking facilities.'

In fact, decisions by stakeholders seem to be driven by competitive economic pressures to secure revenues, which demand strategies to deal with current weather risk. Changes in long-term climate affect weather risks and hence the need for and design of these strategies. This is also the idea behind the approach chosen in this thesis, and including past trends in weather is a first step in the direction of providing probabilistic estimates of current weather risk to support risk management in the industry.

2. *Which of these strategies has led to the observed decrease in the sensitivity of overnight stays to snow conditions?*

   One key result of the present study is that the tourism-stifling effect of a snow-poor winter almost disappeared in recent years. Of course, one explanation for this decrease is the major increase in snowmaking, which presumably is the most popular weather risk mitigation strategy, and a subsequent decline in ski area dependency on natural snow conditions. However, some of this observed decline in sensitivity might also be explained by other factors such as quality improvements or an increased supply of tourist activities less sensitive to weather conditions. In contrast, some other factors such as a more spontaneous booking behaviour (destination choice, last-minute bookings) possibly counteract this effect.

3. *Does a reduction in weather risk always go in line with a reduction in total risk?*

   No. In general, implementing strategies to mitigate weather risks need some initial investments, especially when technological strategies are chosen, and might therefore put enterprises at risk for other financial reasons. To name one example, snowmaking investments are heavily capital intensive. Therefore, even if they pay off after several years, as stated by the industry, they may require to acquire additional loan capital and the debt ratio increases for the first few years. If adverse weather conditions occur in this period, they will have less of a negative impact on revenues than before, but altogether business indicators such as the debt ratio might still be worse than without investments. Of course, reducing analysis on balance sheet figures might be too restrictive, given the current credit policies in the industry and manifold other interventions, such as the role of the public sector in supporting the industry.

4. *How is weather risk related to other risk factors for the tourism industry, such as economic conditions, terms of financing or socio-demographic changes?*

   Basically, economic and meteorological risks are uncorrelated, which means that the occurrence of poor economic conditions and the occurrence of adverse weather conditions are independent. However, these risk may add up at certain times. For example, the impacts of the world recession and economic crisis, such as a decline in sales or a tougher bank credit policy, challenge the tourism industry. This could increase the industry exposure to additional risk factors, other than adverse weather conditions, putting the industry also more at risk from weather-related events. Thus, while other risk factors do not affect the likelihood that adverse weather conditions occur, they might decrease the resilience towards weather and require all the more protection against weather-related losses.

7 Conclusions

The objective of the present thesis was to develop a methodological framework for assessing non-catastrophic weather risks and to apply it on the winter tourism industry in Austria. While risk is basically a combination of the probability of an event and its potential impact, empirical examinations usually focus on one of these two aspects or both aspects of risk separately. The approach presented in this thesis considers both aspects together. Modelling the distribution of the weather index as well as its relationship with the respective economic indicator allows to provide a probabilistic risk measure to indicate the impact from adverse weather conditions.

To demonstrate this approach, impacts of snow conditions on tourism demand are estimated for 185 Austrian ski areas. For doing so, data is made available for individual ski areas by determining their altitude, size and exact location and in matching municipalities with skiing activities to these areas. This allows a combined analysis of meteorological data which is provided on a grid basis from a snow cover model by ZAMG, and data on overnight stays in municipalities which is available for the winter seasons 1972/73 to 2006/07 from Statistics Austria. Furthermore, several other economic datasets are considered, such as data on business indicators for the accommodation industry.

Modelling employs a three-step approach. First, snow indices (days with snow depth >1 cm and >30 cm respectively, mean snow cover) are, in addition to the empirical distribution, modelled by a multivariate non-parametric approach as well as a normal distribution. Modelling is repeated by accounting for time trends in the respective indices. Second, the dependency of overnight stays on snow conditions is estimated with an Autoregressive Distributed Lag model, using several different model specifications. Then, in order to provide indicators of weather risk, information from these modelling steps is combined. The resulting risk is expressed as Value at Risk (VaR), corresponding to the maximum loss from weather which is not exceeded with a given level of confidence over a given period of time. In addition, several approaches are outlined on how to add up risks from individual ski areas.

Results strongly emphasize the importance of considering both the probability of an event and its potential impact for estimating weather risks. Trend analyses provide evidence that the probability of seasons with adverse natural snow conditions substantially increases. They reveal a decline in snow conditions for most areas, e. g. with a −0.45 % per year change in days with snow depth >1 cm for the median area. At the same time, impact analyses show a predominantly positive, but declining dependence of overnight stays on snow conditions. Especially for lower lying areas a positive relationship is found, while higher lying areas typically show no dependency on their own snow conditions. Instead, some of them negatively depend on average Austrian snow conditions. Importantly, temporal analyses (moving estimates, comparison of extreme seasons etc.) reveal that impacts have decreased in recent years. A possible explanation for this decrease is the major increase in snowmaking and a subsequent decline in dependency on natural snow conditions. Of course, other factors such as an increased supply of tourist activities less sensitive to weather conditions might also be the reason for this observed trend.

Overall, estimates of the 95%-VaR from adverse snow conditions (corresponding to a 1 in 20 year event) range from a 1.7 % to 50.5 % loss in overnight stays in ski areas, with a 7.2 % loss for the median ski area. This corresponds to a loss in sales of up to 19 million Euro, with a 500 000 Euro loss for the median ski area. Aggregating individual ski areas losses yields a total 95%-VaR of 157 million Euro for the accommodation industry. Potential biases in these estimates are discussed, most notably a likely underestimation due to uncertainties in the meteorological data and a likely overestimation as estimates are based on the average adaptation level in the study period. Considering these uncertainties and effects for other winter sport products and services, the direct economic effect of a one in 20 year event is likely to be in the range between 200 and 400 million Euro. In a final step, linking weather risk estimates to financial ratios for hotels like the profit ratio, the return on investment or the debt ratio, clearly reveals that lower lying and smaller areas are more vulnerable, as they typically do not only face higher weather risk, but also tend to be less profitable and exhibit higher debt ratios.

The research that has been undertaken for this thesis has highlighted a number of topics on which further research would be beneficial. First of all, it needs to be highlighted that in principle, the developed methodological framework and modelling approach for estimating weather risks is easily extendible to other data than overnight stays, for the tourism as well as other industries. Of course, modelling might need some adaptations, dependent on the nature of the meteorological and economic data used and in particular when doing analysis with a different temporal resolution (e. g. daily or monthly). For the specific case of the winter tourism industry, it might be interesting to further study interactions with price effects, as weather supposedly not only lowers capacity utilization, but probably also leads to a price erosion. It is also conceivable to investigate weather effects for tourists from different origin countries, testing the hypothesis that tourists with longer travelling distances are less sensitive to short-term weather conditions. Other topics include the effects of quality (e. g. hotel stars) on weather sensitivity, or the sensitivity of other tourism products and services, most interestingly the cable car industry.

Furthermore, related to each of the three modelling steps presented in this thesis, particular attention should be paid to the following topics:

Step 1: Statistical Modelling of the Weather Index In this thesis, linear time trends in weather indices are calculated using OLS and the inclusion of trends highly affects weather risk estimates. As trend estimates are sensitive to the method used and the time period considered, other procedures for dealing with trends in meteorological data might prove to be effective with regard to this modelling step. In addition, probabilities of occurrence can be estimated by a range of other approaches than the three discussed in this work. Which of them might be appropriate is highly dependent on the weather index which is of interest.

Step 2: Modelling of the Impact Function A primary objective in climate impact research should be to further develop methodological tools to understand the impacts of weather variability on economic activities. As results from the econometric modelling show, one step in this direction is to apply dynamic time series regression methods or panel data methods. Overall, results from these approaches in general seem to be more robust than those found in supply side studies or studies covering single years only, as they allow to compare sensitivities for different regions and in particular to observe sensitivities over time. Regarding this step, a major issue which also deserves attention is the inclusion of potential non-linearities in the impact function.

Step 3: Risk Measurement In discussing several aggregation methods, this thesis creates the basis for systematically adding up typically local scale weather risks. In this respect, more detailed considerations might be needed related to the use of correlation matrices, especially in case of non-linear dependencies between weather indices. Beside the aggregation of risks for different stakeholders, regions or industries, another topic is the aggregation of risk estimates for different periods and time horizons. Especially the latter might be important to achieve an integration of weather risk in corporate risk management to aggregate risk across an enterprise. Of course, this includes considering potential pitfalls of using VaR as a risk measure.

For studying the economic long-run effects from climate change, valuable lessons can be learned from the analysis of potential sources of bias in this thesis. It has been shown that even when estimating short-run weather risks for the tourism industry, results crucially depend on the choice of the weather indices, the econometric modelling approach and the period under research (presumably dependent on adaptation levels). For estimating long run effects, uncertainties are likely to be more pronounced, and results should therefore not be used automatically to predict impacts for future time periods without further analysis.

In this respect, before drawing far reaching conclusions, a range of other questions need to be addressed and a closer look at interactions with economic processes is needed. Take, for example, the case of snowmaking as an adaptation strategy. Its increased utilization reduces the exposure of ski areas towards natural snow conditions, but this positive effect could in the longer term be offset by a negative impact of price elasticity of demand. An evaluation of this counter effect requires a better understanding of how price changes influence ski tourism as well as an analysis of the extent to which the costs of snowmaking investments have been directly passed on to consumers (or taxpayers, since some regions were subsidizing this kind of investment) rather than being covered by revenues from additional demand. From an economic point of view, further research should go into this direction, particularly as recent work indicates that, while even at lower altitudes snow making might climatically still be possible under a 2 °C warming scenario, its intensified application will lead to significantly higher operation costs (Steiger & Mayer 2008).

Beside the topic of snowmaking, many more related questions on the economics of adaptation to long term change in snow conditions need to be considered. For example, while this thesis has covered patterns for Austria at the local scale, climate-related demand shifts to or from other international winter sport destinations as well as countries with mild winter temperatures also need to be taken into account.

All in all, the future of the winter tourism industry in the Alps depends on how good strategies for dealing with short-term weather variability are, an issue that is becoming more crucial in the context of climate change. However, in the long term other factors than climate may prevail and the industry's fate appears tied to its ability to deal with mega trends in tourism, e. g. the rise of environmentally and socially conscious and responsible tourism.

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Appendix A

Table 1 to Table 6 list all ski areas and the corresponding municipalities which either have direct access to the respective areas (*Municipalities*) or which are considered to be directly affected because of the close distance to the areas (*Other municipalities*). Areas marked by an asterisk ($*$) are excluded from model calculations for missing values in the overnight stay data. The two areas marked by a star ($\star$) are both attributed to Carinthia, although they are both in the border region between Styria and Carinthia and are likely to influence overnight stays in both provinces.

ID		Ski area	Municipalities	Other municipalities
Carinthia				
2001	⋆	Turracher Höhe	Reichenau Predlitz-Turrach	
2002		Spittal	Baldramsdorf Spittal an der Drau Seeboden	
2003		Katschberg Aineck	Rennweg am Katschberg Sankt Michael im Lungau Sankt Margarethen im Lungau	
2004		Mölltaler Gletscher/Flattach	Flattach	Obervellach
2005		Nassfeld/Hermagor	Hermagor-Pressegger See	Gitschtal
2006		Bad Kleinkirchheim	Bad Kleinkirchheim	Radenthein Feld am See
2007	∗	Innerkrems	Krems in Kärnten	
2008		Ankogel Mallnitz	Mallnitz	
2009		Kötschach-Mauthen	Kötschach-Mauthen	
2010		Weißensee	Weißensee	
2011	∗	Flattnitz	Glödnitz	
2012	∗	Hochrindl	Albeck	
2013	∗	Simonhöhe	St. Urban	
2014		Gerlitzen	Treffen am Ossiacher See Steindorf am Ossiacher See Feldkirchen in Kärnten	
2015	∗	Verditz	Afritz am See	
2016	∗	Dreiländereck	Arnoldstein	
2017	∗	Petzen	Feistritz ob Bleiburg	
2018		Klippitzthörl & Koralpe	Wolfsberg Bad St. Leonhard im Lavanttal	
2019	⋆	Hebalm	Preitenegg	
2020		Emberger Alm	Berg im Drautal	
2021		Heiligenblut	Heiligenblut	
Lower Austria				
3001		Hochkar	Göstling an der Ybbs	
3002		Lackenhof am scher	Gaming	
3003		Hirschenkogel	Semmering	
3004		Mönichkirchen-Mariensee	Aspangberg-St. Peter Mönichkirchen	
3005		Gemeindealpe/Josefsberg	Mitterbach am Erlaufsee	
3006		Annaberg	Annaberg	
3007	∗	Sankt Corona am Wechsel	St. Corona am Wechsel	
3008		Türnitz	Türnitz	
3009		Königsberg - Hollenstein	Hollenstein an der Ybbs	
3010	∗	Puchenstuben	Puchenstuben	
3011		Reichenau an der Rax	Reichenau an der Rax	
3012	∗	Puchberg am Schneeberg	Puchberg am Schneeberg	
3013		Maria Schutz	Schottwien	
continued				

Table 1: List of ski areas and municipalities (1)

ID	Ski area	Municipalities	Other municipalities
Upper Austria			
4001	Hinterstoder	Hinterstoder	Klaus an der Pyhrnbahn
4002	Kasberg - Grünau	Grünau im Almtal	
4003	Wurzeralm	Spital am Pyhrn	Edlbach
4004	Feuerkogel	Ebensee	
4005	Gmunden	Gmunden	
4006	Hochficht	Klaffer am Hochficht Schwarzenberg am Böhmerwald Aigen im Mühlkreis	Schlägl
4007	Krippenstein/Obertraun	Obertraun	
4008	Katrinalm	Bad Ischl	
4009	Forsteralm	Gaflenz	Weyer Land
4010	Vorderstoder	Vorderstoder	Edlbach Windischgarsten
4011	Sternstein Lifte	Bad Leonfelden	
4012	Kirchschlag bei Linz	Kirchschlag bei Linz	
Salzburg			
5001	Gosau - Russbach - Annaberg (Dachstein West - Teil)	Gosau Rußbach am Paß Gschütt Annaberg-Lungötz	
5002	Gaißau Hintersee	Krispl Hintersee	
5003	Hallein Dürrnberg	Hallein	
5004	Abtenau im Lammertal	Abtenau	
5005	Zwölferhorn St. Gilgen	Sankt Gilgen	
5006	Postalm Strobl	Strobl	
5007	Untersberg/Groedig	Grödig	
5008	Faistenau	Faistenau	
5009	Skiwelt Amade - Flachau Flachauwinkl	Flachau	
5010	Skiwelt Amade - Wagrein Kleinarl	Wagrain Kleinarl	
5011	Skiwelt Amade - Filzmoos	Filzmoos	
5012	Skiwelt Amade - Altenmarkt Radstadt	Zauchensee	Altenmarkt im Pongau Radstadt
5013	Skiwelt Amade - Eben	Eben im Pongau	Hüttau
5014	Schischaukel Dorfgastein Großarltal	Großarl Dorfgastein Lend	
5015	Schischaukel Bad Gastein Bad Hofgastein Sportgastein	Bad Gastein Bad Hofgastein	
5016	Obertauern	Untertauern Tweng	
5017	Fageralm Forstau	Forstau	
5018	Werfenweng	Werfenweng	
5019	Goldegg	Goldegg	
5020	Sankt Johann im Pongau	Sankt Johann im Pongau	
continued			

Table 2: List of ski areas and municipalities (2)

ID		Ski area	Municipalities	Other municipalities
5022		Grosseck Speiereck	Mauterndorf	
5023		Fanningberg Mariapfarr	Mariapfarr Weißpriach	Göriach Sankt Andrä im Lungau
5024		Rauris	Rauris	
5025		Kaprun Kitzsteinhorn und Maiskogel	Kaprun	Piesendorf Niedernsill
5026		Weißsee	Uttendorf	
5027		Hochkönig	Mühlbach am Hochkönig Dienten am Hochkönig Maria Alm am Steinernen Meer Saalfelden am Steinernen Meer	Taxenbach
5028		Saalbach-Hinterglemm-Leogang	Saalbach-Hinterglemm Leogang	Maishofen Viehhofen
5029		Zell am See	Zell am See	Bruck an der Großglocknerstraße
5030		Loferer Almbahnen	Lofer Unken Sankt Martin am Tennengebirge	Sankt Martin bei Lofer
5031		Skiarena Wildkogel	Neukirchen am Großvenediger Bramberg am Wildkogel	
5032		Kitzbüheler Alpen - Mittersill Hollersbach	Mittersill Hollersbach im Pinzgau	
5033		Zillertalarena - Wald/Krimml	Wald im Pinzgau Krimml	
Styria				
6001		Stuhleck	Spital am Semmering	
6002		Weinebene	Trahütten	
6003	*	Veitsch	Veitsch	
6004		Niederalpl	Mürzsteg	
6005		Lammeralm	Langenwang	
6006		Kreischberg	Sankt Georgen ob Murau	
6007		Schladming	Schladming	
6008		Hochwurzen	Rohrmoos-Untertal	
6009		Reiteralm	Pichl-Preunegg	
6010		Haus im Ennstal	Haus	
6011		Skiregion Ramsau/Dachstein	Ramsau am Dachstein	
6012		Tauplitz	Tauplitz Bad Mitterndorf	
6013		Loser	Altaussee	
6014		Präbichl	Vordernberg	
6015	*	Riesneralm	Donnersbachwald	
6016		Planneralm	Donnersbach	
6017		Hirschegg und Salzstiegl	Hirschegg Pack	
6018		Lachtal	Schönberg-Lachtal	
6019		Aflenzer Bürgeralpe	Aflenz Kurort	
6020		Rieseralm	Obdach	
6021		Galsterbergalm	Pruggern	Michaelerberg
6022		Mariazeller Bürgeralpe	Mariazell	
6023		Turnau	Turnau	

continued

Table 3: List of ski areas and municipalities (3)

ID		Ski area	Municipalities	Other municipalities
6024		Grebenzen St. Lambrecht	Zeutschach Sankt Lambrecht	
6025		Hohentauern	Hohentauern	
6026		Teichalm	Fladnitz an der Teichalm	
6027		Hauereck	St. Kathrein am Hauenstein	
6028		Gaaler Lifte	Gaal	
6029		Elfenberg Mautern	Mautern in Steiermark	
6030	*	Alpl	Krieglach	
6031		Stoderzinken	Gröbming	
6032		Sankt Jakob im Walde	Sankt Jakob im Walde	
Tyrol				
7001		Lienz	Gaimberg Lienz Nußdorf-Debant	
7002		Kals Matrei	Matrei in Osttirol Kals am Großglockner	
7003		Sankt Jakob in Defereggen	St. Jakob in Defereggen	
7004		Sillian Hochpustertal	Sillian	Kartitsch Heinfels
7005		Obertilliach	Obertilliach	
7006		Kitzbüheler Alpen - Jochberg	Jochberg	
7007		Kitzbüheler Alpen - Kitzbühel	Kitzbühel Reith bei Kitzbühel	Aurach bei Kitzbühel
7008		Kitzbüheler Alpen - Kirchberg Aschau	Kirchberg in Tirol	
7009		Skiwelt Wilder Kaiser/Brixental - Brixen im Thale Westendorf	Brixen im Thale Westendorf	
7010		Skiwelt Wilder Kaiser/Brixental - Hopfgarten Itter Söll	Hopfgarten im Brixental Itter Söll Thiersee Wörgl	Angath
7011		Skiwelt Wilder Kaiser/Brixental - Scheffau/Ellmau/Going	Ellmau Scheffau am Wilden Kaiser Going am Wilden Kaiser	
7012		Sankt Johann in Tirol	St. Johann in Tirol Oberndorf in Tirol	
7013		Fieberbrunn	Fieberbrunn	
7014		Hündle Thalkirchdorf	Kirchdorf in Tirol	
7015		Waidring Steinplatte	Waidring	
7016		Kössen	Kössen	Schwendt
7017		Pillerseetall	St. Ulrich am Pillersee	
7018		Wildschönau	Wildschönau	
7019		Alpbachtal	Alpbach Reith im Alpbachtal	
7020		Kramsach	Kramsach	
7021		Zahmer Kaiser/Walchsee	Walchsee	
7022		Zillertal 3000 - Tux: Hintertux und Eggalm	Tux	
7023		Zillertalarena - Gerlos	Gerlos	

continued

Table 4: List of ski areas and municipalities (4)

ID		Ski area	Municipalities	Other municipalities
7024		Zillertarena - Zell am Ziller	Zell am Ziller Hainzenberg Gerlosberg Rohrberg	Hippach Ramsau im Zillertal Zellberg
7025		Zillertal: Ahorn Penken Rastkogel Horberg	Mayrhofen Schwendau Finkenberg	
7026		Spieljoch	Fügen	
7027		Hochfügen	Fügenberg	Bruck am Ziller Schlitters Hart im Zillertal
7028		Hochzillertal - Kaltenbach	Kaltenbach Aschau im Zillertal Stummerberg	Ried im Zillertal Stumm Uderns Strass im Zillertal
7029		Achensee	Achenkirch Eben am Achensee	
7030		Kellerjoch- Schwaz Pill	Pill	Schwaz
7031		Stubaitaler Gletscher	Neustift im Stubaital	
7032		Seefeld - Rosshütte und Gschwandtkopf	Seefeld in Tirol Reith bei Seefeld	
7033		Axamer Lizum	Axams	Kematen in Tirol Götzens
7034		Mutterer Alm	Mutters	
7035		Patscherkofel und Nordpark	Innsbruck Patsch	Aldrans Ellbögen Lans
7036		Oberperfuss - Ranger Köpfl	Oberperfuss	
7037		Schlick 2000	Fulpmes Telfes im Stubai	Schönberg im Stubaital
7038		Glungezer	Tulfes	
7039		Bergeralm - Steinach am Brenner	Steinach am Brenner	Matrei am Brenner Mühlbachl Pfons
7040		Serlesbahnen Mieders	Mieders	
7041		Leutasch	Leutasch	
7042		Ehrwald - Zugspitzbahn Wetterstein und Almbahn	Ehrwald	
7043		Grubigsteinbahnen Lermoos	Lermoos	
7044	*	Marienbergbahnen Biberwier	Biberwier	
7045		Berwang	Berwang Bichlbach	
7046		Reuttener Seilbahnen Höfener Alm	Höfen	Lechaschau Wängle
7047		Tannheim	Tannheim	
7048		Jungholz	Jungholz	
7049		Füssener Jöchle - Grän	Grän	
7050		Schattwald	Schattwald	
7051		Nesselwängle	Nesselwängle	
7052		Jöchelspitze - Bach	Bach	
7053		Sölden Obergurgl und Hochgurgl	Sölden	Sautens Umhausen Wenns
7054		Pitztaler Gletscher	St. Leonhard im Pitztal	Arzl im Pitztal
7055		Oetz/Hochoetz	Oetz	
7056		Hochzeiger - Jerzens	Jerzens	Roppen

continued

Table 5: List of ski areas and municipalities (5)

ID		Ski area	Municipalities	Other municipalities
7057	*	Kühtai	Silz	
7058		Imster Bergbahnen	Imst	Karrösten
7059		Grünberg Obsteig	Obsteig	
7060		Nauders	Nauders	
7061		Ischgl (Silvretta Arena ohne Samnaun CH)	Ischgl	
7062		Kappl	Kappl	
7063		Kaunertaler Gletscher	Kaunertal	
7064		Galtür	Galtür	
7065		Serfaus-Fiss-Ladis	Serfaus Fiss Ladis	Pfunds Tösens
7066		Landeck - Zams - Fließ	Zams Fließ Landeck	
7067		See	See	
7068		Fendels-Ried- Prutz	Fendels Prutz Ried im Oberinntal	Kauns
7069		Pettneu am Arlberg	Pettneu am Arlberg	
7070		Arlberg - Sankt Anton/Sankt Christoph	St. Anton am Arlberg	Flirsch
Vorarlberg				
8001		Arlberg - Lech am Arlberg und Zürs	Lech	Steeg Holzgau
8002		Stuben am Arlberg und Klösterle (Sonnenkopf)	Klösterle	Dalaas
8003		Mittelberg - Wamendinger-horn/Ifen/Fellhorn	Mittelberg	
8004		Warth- Schröcken	Warth Schröcken	Au
8005		Silvretta Montafon - Nova und Gargellen	St. Gallenkirch Gaschurn	
8006		Silvretta Montafon - Hochjoch Silbertal	Schruns Silbertal	Bartholomäberg
8007		Brandnertal	Brand Bürserberg Bürs	Bürs
8008		Damüls	Damüls	
8009		Mellau	Mellau	
8010		Diedamskopf	Schoppernau	
8011		Laterns - Gapfohl	Laterns	
8012		Sonntag	Sonntag	
8013		Fontanella/Faschina	Fontanella	
8014	*	Böderle - Schwarzenberg	Schwarzenberg	
8015		Alpenarena Hochhäderich - Hittisau	Hittisau	
8016		Andelsbuch	Andelsbuch Bizau	Schnepfau
8017		Golm im Montafon	Tschagguns Vandans	
8018	*	Alberschwende	Alberschwende	
8019		Schetteregg	Egg	
8020		Pfänderbahn - Bregenz	Bregenz	
8021		Muttersberg - Bludenz	Bludenz	
8022		Dornbirn	Dornbirn	

Table 6: List of ski areas and municipalities (6)

Appendix B

Table 7 to Table 9 give the results from the ADL model for $Sday_1(alt_{50})$. Numbers in parentheses beneath the estimates are standard errors. All estimates and their standard errors are multiplied by 100 for the purpose that snow coefficients are easier to read as a the %-change in $nights_t$ with a σ-change in the snow index. $nights_{t-1}$ and $nights_{t-2}$ indicate the degree of adjustment in %. P-values are denoted as: $< 0.1 : *$; $< 0.05 : **$; $< 0.01 : ***$.

The column *Tests* detects violation of the model assumptions by the following tests:
A : Residual autocorrelation (Breusch 1978; Godfrey 1978)
H : Heteroscedasticity (Breusch and Pagan 1979)
N : Normal distribution of the residuals (Jarque and Bera 1980; Lilliefors 1969)
M : Functional form misspecification (Ramsey 1969)

ID	*intercept*	$nights_{t-1}$	$nights_{t-2}$	$snow_t$	$snow_{t-1}$	Tests
Carinthia						
2001	7.74(80.68)	92.47(19.25)***	5.28(20.34)	2.72(1.47)*	-0.68(1.54)	A
2002	146.91(163.43)	71.15(18.18)***	15.80(18.45)	-1.81(2.31)	1.57(2.28)	A
2003	55.95(42.89)	80.58(17.23)***	12.57(15.73)	1.70(1.08)	3.42(1.11)***	
2004	62.41(94.32)	98.95(19.50)***	-1.36(20.01)	2.37(4.17)	-4.15(3.93)	
2005	202.49(83.56)**	119.32(18.06)***	-25.25(17.76)	-0.47(2.39)	-6.05(2.23)**	
2006	213.81(104.29)*	76.34(17.05)***	6.79(18.13)	4.04(1.87)**	-2.86(1.93)	A
2008	554.33(202.46)**	75.70(18.55)***	-23.29(18.63)	0.51(1.51)	-0.79(1.54)	
2009	634.60(197.74)***	38.07(19.06)*	-3.51(17.18)	8.58(3.00)***	0.07(3.29)	
2010	-42.35(56.61)	114.46(19.48)***	-11.76(19.58)	2.26(2.31)	1.96(2.33)	
2014	122.04(131.48)	94.14(19.34)***	-5.58(20.51)	2.54(2.66)	-0.01(2.86)	
2018	235.05(123.34)*	63.28(21.42)***	14.34(21.40)	4.56(2.77)	-3.17(2.37)	
2019	410.83(160.04)**	32.99(16.89)*	34.17(16.42)**	-4.22(17.17)	-36.24(18)*	N
2020	189.14(94.92)*	71.49(17.26)***	3.85(12.33)	1.68(1.80)	3.06(1.68)*	
2021	469.09(153.21)***	55.03(17.50)***	6.40(16.90)	-0.2(1.77)	-2.86(1.82)	
Lower Austria						
3001	225.38(131.88)*	54.01(15.90)***	24.45(10.53)**	3.10(1.85)	-1.76(1.82)	
3002	962.09(215.12)***	18.65(18.96)	-7.97(13.80)	5.26(1.42)***	-0.59(1.88)	
3003	509.82(147.50)***	67.51(19.04)***	-13.88(17.15)	-0.79(1.38)	0.94(1.40)	N
3004	78.42(53.14)	68.57(17.47)***	24.09(17.33)	0.52(2.47)	-3.70(2.58)	M
3005	73.35(49)	74.29(18.63)***	12.10(17.62)	7.33(2.75)**	2.79(3.14)	
3006	427.21(125.65)***	19.36(15.46)	35.15(14.42)**	5.08(2.50)*	3.81(2.92)	
3008	-60.88(58.62)	86.87(20.22)***	18.22(21.88)	1.87(3.34)	-1.37(3.34)	
3009	89.27(83.33)	75.76(19.15)***	6.18(18.05)	18.92(4.74)***	-6.77(5.87)	
3011	119.61(126.80)	80.39(25.12)***	8.32(26.34)	-0.02(3.90)	-0.89(3.86)	H
3013	547.80(196.04)***	62.48(20.13)***	-30.14(20.17)	-7.50(7.97)	5.66(8.46)	
Upper Austria						
4001	287.72(98.68)***	81.05(17.82)***	-4.97(15)	1.56(1.46)	-3.07(1.53)*	
4002	184.09(74.89)**	74.68(19.30)***	8.98(17.03)	-0.71(1.83)	-0.70(1.85)	H
4003	204.53(97.08)**	49.21(18.29)**	32.19(16.74)*	3.68(2.17)	-3.46(2.14)	
4004	20.73(90.51)	44.25(17.54)**	45.82(17.82)**	4.92(3.00)	2.94(3.09)	
4005	238(129.74)*	44.25(18.06)**	35.19(17)**	-2.3(2.36)	-1.70(2.44)	
4006	53.31(92.91)	73.21(17.29)***	23.54(18.34)	1.72(2.07)	-4.57(2.28)*	
4007	465.58(185.48)**	45.55(18.71)**	7.81(19.31)	1.13(1.92)	1.34(1.81)	
4008	65.65(143.05)	83.14(19.18)***	11.04(20.08)	1.05(1.18)	-0.63(1.24)	
4009	132.46(80.33)	64.56(17.92)***	3.89(16.36)	4.59(8.20)	20.59(9.66)**	
4010	627.57(192.30)***	28.77(19.61)	16.80(17.14)	1.51(1.49)	-2(1.59)	
4011	158.53(150.51)	40.38(18.43)**	43.97(21.03)**	-4.22(3.21)	2.86(3.05)	A/N
4012	141.50(78.90)*	63.17(19.03)***	23.50(18.55)	-5.54(7.37)	-1.44(7.91)	
Salzburg						
5001	325.39(76.37)***	40.50(17.53)**	32.09(14.34)**	1.21(1.74)	-0.51(1.75)	H/M
5002	161.02(58.35)**	66.45(18.54)***	15.59(16.83)	1.49(2.43)	1.86(2.64)	
5003	-74.13(123.78)	66.69(16.51)***	41.33(17.67)**	3.09(2.31)	-5.54(2.48)**	
5004	219.46(134.90)	83.08(18.02)***	-3.14(15.62)	1.61(1.12)	0.39(1.16)	
5005	197.46(128.89)	70.06(18.28)***	8.39(18.03)	2.42(2.59)	3.32(2.76)	A
5006	323.09(106.66)***	60.20(17.94)***	11.26(13.75)	1.25(3.47)	-4.20(3.59)	
5007	263.39(64.93)***	58.01(16.14)***	15.10(14.55)	0.06(2.33)	0.07(2.48)	
5008	250.41(101.71)**	36.29(19.04)*	39.12(17.69)**	1.81(2.81)	-1.37(2.97)	
5009	110.05(52.48)**	81.01(18.44)***	9.60(17.06)	2.56(1.09)**	-0.73(1.18)	
5010	99.47(63.62)	75.92(19.06)***	15.62(18.68)	2.33(1.22)*	-1.01(1.27)	
5011	485.03(126.41)***	35.86(18)*	24.89(14.36)*	0.72(1.16)	-0.72(1.16)	
5012	285.08(84.69)***	59.77(18.79)***	17.87(15.53)	1.09(1)	0.14(0.97)	
5013	478.99(102.57)***	45.74(18.14)**	13.50(14.59)	-0.11(1.56)	-0.83(1.53)	
5014	115.53(58.24)*	77.66(18.24)***	11.76(16.49)	3.73(1.28)***	-0.69(1.43)	
5015	114.83(89.91)	55.41(18.89)***	34.34(18.52)*	3.96(0.72)***	0.73(0.93)	
5016	23.98(57.01)	74.81(19.31)***	22.05(18.71)	1.13(0.78)	0.38(0.81)	
5017	71.26(55.10)	99.80(19.37)***	-8.04(17.90)	2.75(1.84)	-0.76(1.91)	A/M
5018	361.18(105.22)***	65.43(16.52)***	3.02(15.62)	0.95(1.23)	-0.52(1.28)	
5019	364.77(100.67)***	79.02(17.45)***	-15.26(15.56)	2.46(1.99)	4.12(2.08)*	H
5020	37.11(69.81)	62.21(17.47)***	30.56(17.24)*	4.87(2.08)**	1.95(2.24)	
5022	193.94(76.75)**	98.27(17.19)***	-15.28(14.89)	-1.25(0.94)	2.50(0.94)**	
5023	425.17(84.65)***	39.26(17.16)**	23.20(12.76)*	0.61(0.90)	1.92(0.89)**	
5024	371.27(90.44)***	64.63(19.41)***	4.72(13.93)	-0.44(1.42)	0.50(1.45)	
5025	354.47(96.02)***	49.38(18.84)**	24.07(15.64)	-0.66(1.33)	0.16(1.25)	
5026	147.21(86.30)	82.49(17.25)***	4.74(16.68)	0.34(2.50)	-0.98(2.55)	

continued

Table 7: Estimation results for $Sday_1(alt_{50})$ (1)

ID	*intercept*	$nights_{t-1}$	$nights_{t-2}$	$snow_t$	$snow_{t-1}$	Tests
5027	195.62(85.53)**	73.89(19.13)***	10.45(16.71)	1.68(1.22)	0.48(1.24)	H
5028	242.89(185.54)	87.62(19.62)***	-6.19(18.11)	3.11(1.47)**	-0.20(1.52)	
5029	185.96(80.40)**	90.51(18.83)***	-4.67(15.35)	0.38(0.95)	0.46(0.91)	
5030	349.67(91.69)***	59.22(18.99)***	12.08(15.06)	0.99(0.97)	0.51(0.99)	
5031	122.14(66.38)*	66.94(18.08)***	22.38(17.21)	1.58(1.26)	0.24(1.33)	
5032	172.91(60.31)***	80.36(19.67)***	4.46(17.29)	1.72(1.09)	0.06(1.14)	
5033	142.73(52.34)**	55.69(16.30)***	32.38(15.47)**	1.79(1.44)	-0.66(1.50)	A
Styria						
6001	61.26(96.74)	70(21.82)***	23.55(23.81)	0.79(2.32)	0.34(2.38)	M
6002	231.10(117.77)*	79.71(19.48)***	-3.44(20.54)	-2.51(4.63)	-2.86(4.77)	
6004	380.75(111.65)***	31.05(17.22)*	36.10(14.12)**	-6.50(4.91)	-1.71(5.28)	H
6005	588.34(153.90)***	34.14(19.53)*	-1.44(14.99)	-4.40(5.19)	-1.73(5.02)	
6006	170.73(71.22)**	69.53(18.63)***	15.40(16.71)	4.05(3.68)	-2.95(3.71)	M
6007	235.81(72.38)***	73.88(19.21)***	7.40(15.98)	0.82(1.01)	-1.15(1.03)	
6008	242.75(90.09)**	77.31(19.23)***	2.97(16.52)	1.28(1.06)	-0.81(1.09)	
6009	369.95(85.41)***	60.09(19.42)***	7.79(14.87)	1.10(0.88)	-0.34(0.90)	H
6010	220.56(82.92)**	61.90(18.67)***	19.44(16.26)	0.52(1.01)	-0.04(1.04)	H
6011	292.01(128.08)**	93.06(20.62)***	-16.96(17.18)	0.67(0.99)	0.48(0.97)	
6012	460.07(153.47)***	81.62(17.69)***	-18.66(15.68)	2.52(0.96)**	-2.61(1.05)**	
6013	357.50(72.24)***	58.40(17.85)***	8.42(14.04)	1.20(1.78)	-3.57(1.85)*	
6014	159.34(99.81)	93.40(18.40)***	-10.90(18.75)	1.64(4.04)	-1.62(4.09)	H
6016	189.63(102.28)*	93.99(19.81)***	-11.75(19.18)	0.01(1.10)	1.13(1.16)	
6017	74.83(89.85)	56.44(17.53)***	36.21(17.68)*	4.38(5.35)	-6.21(5.57)	
6018	175.72(135.18)	78.25(18.93)***	2.50(18.98)	6.01(2.76)**	-3.27(2.95)	
6019	8.42(97.78)	74.81(18.74)***	23.33(20.07)	3.37(1.68)*	-1.86(1.71)	N
6020	334.79(191.55)*	28.47(17.26)	32.20(18.84)*	3.51(4.01)	-6.02(3.74)	
6021	73.55(54.31)	81.09(19.18)***	11.59(18.01)	0.37(1.88)	0.84(1.96)	M
6022	145.41(62.08)**	70.15(17.86)***	15.43(16.76)	3.01(1.67)*	-1.04(1.88)	
6023	40.15(108.34)	71.3(19.03)***	25.39(19.47)	-0.09(4.82)	-2.54(4.96)	
6024	46.26(82.63)	99.54(15.70)***	-3.58(15.35)	1.55(2.99)	-2.53(2.86)	H
6025	161.69(114.66)	38.60(17.99)**	42.75(17.76)**	8.12(3.06)**	-2.06(3.02)	
6026	463.06(189.12)**	34.79(18.51)*	16.71(18.14)	4.20(3.30)	-0.53(3.40)	N
6027	355.72(164.50)**	42.29(18.53)**	18.81(18.80)	0.56(3.19)	-3.15(3.21)	M
6028	323.60(147.24)**	47.21(16.81)***	16.91(17.19)	-5.35(5.51)	-2.83(5.65)	
6029	157.52(97.73)	40.66(17.37)**	41.76(17.72)**	-4.3(5.96)	-4.95(6.17)	H
6031	375.72(153.61)**	74.83(18.84)***	-12.59(19)	1.23(2.35)	0.60(2.29)	
6032	143.62(91.06)	99.14(17.30)***	-13.33(17.07)	1.37(1.53)	-3.84(1.56)**	
Tyrol						
7001	645.31(192.94)***	67.96(17.83)***	-20.33(17.65)	0.45(2.91)	-4.27(2.88)	
7002	289.60(139.47)**	45.85(17.48)**	27.29(17.49)	1.99(2.31)	-1.80(2.31)	A/M
7003	528.08(124.25)***	26.16(17.23)	31.44(14.26)**	-1.56(1.60)	-0.46(1.61)	
7004	119.67(85.28)	85.78(17.84)***	5.03(18.18)	2.35(2.57)	-3.68(2.59)	
7005	339.55(111.39)***	83.42(17.51)***	-2.63(15.84)	-1.21(2.37)	-5.84(2.37)**	H/M
7006	72.83(84.50)	85.35(19.56)***	3.33(18.88)	6.47(1.51)***	0.74(1.95)	H
7007	136.80(120.77)	61.48(18.54)***	24.93(18.06)	4.71(1.04)***	2.09(1.39)	
7008	113.67(136.90)	87.91(19.40)***	1.32(19.89)	4.72(1.25)***	-0.32(1.60)	
7009	203.93(118.50)*	95.51(18.57)***	-13.14(17.29)	3.52(1.35)**	0.71(1.57)	
7010	176.71(77.75)**	72.33(18.92)***	12.79(16.93)	2.86(1.21)**	1.72(1.38)	
7011	87.71(61.26)	97.96(19.67)***	-5.76(18.47)	3.77(1.18)***	-0.27(1.50)	
7012	287(105.42)**	82.21(19.47)***	-5.68(17.17)	3.18(1.03)***	0.06(1.28)	A
7013	399.57(125.36)***	44.11(18.49)**	23.20(16.25)	0.53(1.36)	0.40(1.39)	
7014	306.63(61.12)***	69.56(16.42)***	4.54(14.36)	0.42(1.15)	1.12(1.19)	
7015	341.36(76.44)***	56.05(18.84)***	13.86(15.24)	1.86(1.97)	0.24(2.01)	
7016	164.91(72.36)**	90.65(18.99)***	-4.07(15.86)	0.29(1.17)	0.03(1.18)	
7017	479.56(81.60)***	58.17(15.25)***	0.87(12.78)	-0.81(1.15)	0.40(1.16)	H
7018	285.98(133.51)**	91.41(18.30)***	-14.36(15.81)	1.47(0.92)	0.60(0.97)	
7019	307.69(126.30)**	56.3(17.07)***	18.72(16.99)	1.41(1.35)	-0.51(1.36)	
7020	490.14(79.21)***	53.09(13.18)***	2.37(11.62)	1.78(2.09)	0.55(2.22)	
7021	150.05(66.10)**	121.11(15.86)***	-34.11(12.07)***	-1.14(1.19)	2.22(1.23)*	A
7022	108.74(36.48)***	117.48(18.46)***	-24.71(17.02)	-2.13(0.61)***	1.39(0.66)**	
7023	84.71(90.86)	95.83(20.50)***	-4.57(21.10)	3.25(1.48)**	0.25(1.61)	
7024	130.28(49.49)**	83.11(19.56)***	6.75(18.51)	1.44(1.50)	-0.66(1.52)	
7025	131.48(39.37)***	44.07(15.02)***	46.03(14.30)***	0.66(1.02)	0.79(1.06)	H
continued						

Table 8: Estimation results for $Sday_1(alt_{50})$ (2)

ID	*intercept*	$nights_{t-1}$	$nights_{t-2}$	$snow_t$	$snow_{t-1}$	Tests
7026	207.73(73.72)***	96.45(18.66)***	-13.88(14.67)	3.18(1.68)*	-2(1.84)	A/M
7027	133.76(71.76)*	87.56(19.66)***	0.73(17.50)	0.99(2.57)	-0.10(2.43)	
7028	103.99(42.73)**	76.93(21.81)***	14.69(20.59)	0.64(1.79)	0.93(1.58)	
7029	156.23(65.25)**	83.01(18.29)***	3.81(15.69)	1.86(0.94)*	1.32(1.01)	
7030	353.55(94.38)***	70.3(15.51)***	-8.51(13.82)	3.71(2.41)	5.50(2.54)**	H/M
7031	184.72(46.72)***	66.12(16.91)***	20.32(14.67)	0.37(1.32)	-0.54(1.22)	
7032	647.81(197.25)***	40.72(20.27)*	10.37(16.15)	1.43(1)	-0.03(1.03)	
7033	146.91(86.65)	74.07(17.23)***	8.19(16.63)	3.67(1.81)*	5.27(1.97)**	
7034	201.77(146.32)	72.24(19.18)***	6.75(19.65)	2.74(2.52)	0.84(2.55)	
7035	751.45(286.47)**	31.63(18.46)*	9.97(19.04)	1.02(1.83)	1.71(1.88)	M
7036	740.84(147.02)***	45.28(14.77)***	-20.97(14.23)	3.64(2.65)	-0.17(2.80)	A
7037	529.73(118.46)***	71.85(18.37)***	-13.83(12.62)	1.50(1.47)	-1.99(1.44)	A
7038	311.27(125.78)**	49.65(16.36)***	19.54(15.47)	0.39(2.08)	1.11(2.08)	
7039	314.35(251.41)	47.11(18.92)**	20.29(20.24)	7.31(4.59)	-1.24(4.34)	N/M
7040	330.86(93.23)***	61.57(18.62)***	6.92(15.13)	0.07(2.20)	1.90(2.17)	A/M
7041	429.43(88.08)***	59.57(19.85)***	6.59(15.29)	0.15(1.05)	0.54(1.13)	A
7042	526.50(78.10)***	24.33(14.54)	30.87(11.80)**	1.75(0.90)*	2.75(0.96)***	
7043	181.86(84.96)**	66.19(18.24)***	18.92(18.02)	0.43(1.32)	0.18(1.39)	
7045	370.61(98.98)***	40.59(18.57)**	28.12(15.33)*	2.43(1.07)**	-0.27(1.22)	
7046	172.31(118.08)	45.44(18.51)**	36.95(18.37)*	3.34(1.94)*	0.99(1.84)	
7047	253.55(76.03)***	48.06(20.17)**	29.17(17.96)	1.85(1.06)*	1.03(0.97)	
7048	646(240.29)**	17.20(21.94)	21.36(18.03)	2.08(1.26)	2.06(1.53)	N
7049	112.85(68.04)	73.47(19.46)***	16.24(18.93)	1.02(1.54)	0.57(1.54)	A
7050	145.04(67.78)**	71.52(19.90)***	11.42(17.66)	3.14(2.04)	2.64(2.08)	H
7051	201.28(68.57)***	62.81(18.94)***	16.87(15.95)	3.59(1.26)***	0.51(1.39)	
7052	265.70(93.70)***	22.04(15.19)	50.97(13.67)***	0.91(2.18)	3.21(2.22)	
7053	128.20(53.64)**	100.26(23.01)***	-8.76(21.50)	-1.02(1.25)	0.62(1.04)	N
7054	60.45(40.98)	106.66(16.85)***	-11(15.67)	0.09(1.27)	-0.20(1.26)	M
7055	268.54(80.69)***	82.35(17.20)***	-4.69(15.57)	-2.07(2.20)	1.11(2.18)	
7056	159.82(52.49)***	56.86(17.98)***	31.65(16.62)*	-0.87(1.32)	-1.29(1.34)	
7058	282.35(72.18)***	63.62(16.44)***	11.03(14.06)	-0.27(1.64)	1.26(1.76)	
7059	240.08(87.03)**	80.22(19.68)***	-3.10(16.56)	2.64(2.61)	0.57(2.82)	
7060	230.55(63.87)***	48.60(11.64)***	27.11(10.64)**	2.06(1.15)*	1.48(1.16)	M
7061	70.00(45.81)	84.69(18.63)***	9.87(17.62)	-0.43(1.06)	1.16(1.06)	
7062	139.91(60.56)**	78.42(19.55)***	10.24(18.01)	-0.04(1.89)	1.07(1.77)	
7063	6.49(61.21)	69.30(17.37)***	21.87(16.55)	1.53(1.85)	2.23(1.91)	M
7064	352.08(116.97)***	63.67(16.68)***	11.71(11.81)	-4.22(1.33)***	0.01(1.56)	
7065	44.16(40.35)	102.82(18.90)***	-7.10(18.04)	1.44(0.89)	0.56(0.96)	
7066	202.06(78.18)**	79.31(17.98)***	3.28(16.49)	0.52(1.75)	-0.14(1.86)	A
7067	276.19(51.07)***	42.70(17.41)**	33.80(14.90)**	-0.02(1.45)	-0.59(1.43)	
7068	217.61(36.18)***	51.78(15.65)***	30.84(14.15)**	-0.07(1.70)	-1.27(1.77)	H
7069	95.79(112.43)	57.92(18.11)***	32.96(16.80)*	1.16(2.76)	1.50(2.86)	
7070	91.60(61.65)	86.45(17.19)***	6.84(16.82)	0.51(1.03)	-0.35(1.05)	
Vorarlberg						
8001	432.77(142.93)***	66.12(19.03)***	2.26(16.05)	0.62(0.69)	-0.58(0.69)	
8002	272.29(76.91)***	52.79(18.60)***	23.69(15.85)	0.05(1.53)	-1.13(1.48)	
8003	586.96(144.43)***	51.23(19.42)**	5.36(15.59)	1.13(0.75)	-0.17(0.75)	
8004	108.04(66.80)	81.66(16.46)***	8.85(16.64)	1.61(1.08)	-0.17(1.15)	H/M
8005	145.43(73.07)*	77.93(18.32)***	11.10(16.50)	0.71(1.07)	-0.52(0.99)	
8006	254.97(95.39)**	65.46(18.57)***	14.24(15.67)	0.62(0.93)	-0.62(0.86)	
8007	230.76(124.83)*	57.53(18.39)***	21.69(16.05)	4.41(1.06)***	-0.81(1.36)	
8008	60.40(87.08)	72.39(17.83)***	21.78(18.51)	2.29(1.09)**	-1.01(1.20)	H
8009	144.67(87.69)	85.12(18.20)***	0.80(13.69)	4.01(1.39)***	-1.12(1.53)	
8010	132.12(61.44)**	86.61(19.16)***	1.19(17.57)	2.41(1.06)**	-1.05(1.17)	H/M
8011	262.36(72.43)***	53.14(17.43)***	18.53(15)	6.51(3.02)**	-3.22(3.10)	
8012	334.25(95.30)***	118.63(16.05)***	-55.36(14.81)***	10.16(2.62)***	-8.81(2.75)***	
8013	453.25(212.28)**	25.28(18.04)	30.02(17.30)*	2.47(3.12)	0.97(2.89)	
8015	327.04(113.09)***	55.47(18.28)***	12.58(16.77)	-0.93(2.73)	2.28(2.71)	
8016	283.56(144.34)*	64.83(23.08)***	6.43(16.33)	6.83(1.85)***	-1.79(2.69)	
8017	279.72(68.45)***	57.52(18.56)***	19.50(15.69)	1.49(1.10)	-0.45(1.13)	H
8019	395.93(146.96)**	74.87(17.41)***	-13.21(16.45)	-6.01(2.77)**	7.24(2.91)**	
8020	-64.60(80.63)	56.06(15.59)***	49.91(15.41)***	-1.03(1.67)	2.71(1.79)	
8021	396.01(144.62)**	42.17(20.76)*	18.85(18.32)	2(1.73)	-0.27(1.79)	
8022	45.54(64.10)	79.58(20.16)***	16.78(19.04)	-0.74(1.35)	-0.40(1.47)	

Table 9: Estimation results for $Sday_1(alt_{50})$ (3)

Appendix C

Table 10 and Table 11 give results from the panel data estimations described in Subsection 5.2.2 and Subsection 5.3.2 respectively.

Variable/Test	Pooled	FE	FE_tw	FE_tw _bc	DIFF _GMM	SYS _GMM	SYS _GMM$_v$	SYS _GMM$_g$
$ln\ nights_{it-1}$	0.718***	0.610***	0.597***	0.637***	0.475***	0.638***	0.599***	0.639***
	(11.97)	(10.46)	(10.57)	(67.17)	(6.43)	(11.96)	(4.76)	(11.48)
$ln\ nights_{it-2}$	0.214***	0.173***	0.186***	0.160***	0.166***	0.164***	0.270***	0.183***
	(3.87)	(3.76)	(4.32)	-(16.63)	(5.32)	(3.92)	-(3.88)	(3.72)
$ln\ snow_{it}$	0.062***	0.068***	0.052**	0.052***	0.059***	0.076***	0.156**	0.094***
	(5.03)	(4.61)	(2.50)	(3.46)	(2.81)	(3.78)	(2.05)	(5.90)
$ln\ beds_{it}$	0.085***	0.112***	0.131***	0.117***	0.200***	0.200***	0.139	0.218***
	(7.39)	(5.47)	(5.76)	(10.20)	(4.47)	(6.32)	(1.36)	(7.41)
$ln\ gdp_{it}$	0.036	0.011	0.410***	0.439***	0.985	0.683	0.361	0.553***
	(0.68)	(1.26)	(3.26)	(5.87)	(1.45)	(1.50)	(0.93)	(2.61)
$ln\ pp_{it}$	-0.041***	-0.036***	-0.029**	-0.028**	-0.021	-0.011	-0.035	0.008
	(-3.35)	(-2.83)	(-2.24)	(-2.30)	(-0.32)	(-0.17)	(-0.61)	(-0.28)
R^2 within	-	0.776	0.784	-	-	-	-	-
corr(μ_i, Xb)	-	0.955	0.926	-	-	-	-	-
rho[1]	-	0.639	0.604	-	-	-	-	-
AR(1)	-	75.4	3	-	-	-	-	-
(p-value)	-	(<0.001)	(.005)	-	-	-	-	-
F-statistics	14741	1114	362	-	113	35732	288600	253398
diff AR(2)	-	-	-	-	0.203	0.88	0.175	0.728
Sargan test	-	-	-	-	<0.001	<0.001	<0.001	<0.001
Hansen test	-	-	-	-	1.000	1.000	0.143	1.000

p-value: <0.1 * ; <0.05 **; <0.01 ***
All regressions except FE include time dummies, which are not displayed for space reasons
Numbers in parentheses beneath the estimates are t-statistics
-Pooled based on the Eicker/Huber/White/sandwich variance estimator
-FE, FE_tw based on non-parametric bootstrapping with 100 permutations
-FE_tw_bias_cor based on parametric bootstrapping with 50 permutations
-GMM models based on Arellano-Bond robust VCE

[1]fraction of variance due to fixed effects μ_i

Table 10: General model estimation results with the complete panel data set
Source: Eigner, Toeglhofer and Prettenthaler (2009)

Variable/Test	FE_tw_bc[1] Period 1	Period 2	Period 3	SYSTEM_GMM$_g$[2] Period 1	Period 2	Period 3
$ln\ nights_{it-1}$	0.653***	0.592***	0.730***	0.595***	0.557***	0.698***
	(24.83)	(19.96)	(26.73)	(10.53)	(5.73)	(17.31)
$ln\ nights_{it-2}$	0.084***	-0.003	-0.031	0.209**	0.152**	0.122***
	(3.53)	(-0.15)	(-1.31)	(2.45)	(2.21)	(3.37)
$ln\ gdp_{it}$	0.875	-0.005	0.515	1.383***	0.071	0.188
	(0.95)	(-0.03)	(0.70)	(3.32)	(0.29)	(1.29)
$ln\ snow_{it}$	0.087*	0.058**	0.060***	0.168***	0.092***	0.069***
	(1.90)	(2.37)	(3.04)	(5.22)	(3.36)	(2.96)
$ln\ beds_{it}$	0.100**	0.255***	0.245***	0.232**	0.360**	0.219***
	(2.24)	(5.78)	(7.06)	(2.39)	(2.10)	(3.32)
$ln\ pp_{it}$	-0.050***	0.002	-0.274	-0.004	-0.049	-0.144
	(-2.80)	(0.04)	(-1.28)	(-0.10)	(-1.18)	(-1.17)
R^2 within	0.62	0.34	0.50	-	-	-
F-Test	202.23	36.93	69.60	-	-	-
(k,n)	(15,184)	(16,184)	(16,184)	-	-	-
corr(μ_i, Xb)	0.95	0.96	0.94	-	-	-
rho[3]	0.80	0.92	0.90	-	-	-
Pesaran AR(1)	0.73	8.11	1.78	-	-	-
(p-value)	(0.47)	(<0.01)	(0.08)	-	-	-
wald chi^2 (15)	-	-	-	19929	38312.7	89758.4
diff AR(2)	-	-	-	0.228	0.128	0.83
Sargan test	-	-	-	<0.001	<0.001	<0.001
Hansen test	-	-	-	0.093	0.987	0.993
Diff$_{(GMM)}$	-	-	-	0.899	1.000	1.000
Diff$_{(IV)}$	-	-	-	0.358	1.000	1.000
No. of instruments	0	0	0	136	244	249
No. of observations	1850	2035	2035	1850	2035	2035
No. of groups	185	185	185	185	185	185
Observations per group	10	11	11	10	11	11

p-value: <0.1 * ; <0.05 **; <0.01 ***
All regressions include time dummies, which are not displayed for space reasons
Numbers in parentheses under the estimates are t-statistics:
- Bias corrected two-way FE model based on parametric bootstrapping with 50 permutations
- GMM models based on Arellano-Bond robust VCE

[1] corr(μ_i, Xb), R^2, 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 μ_i
Period 1: 1972/1973-1983/1984
Period 2: 1984/1985-1994/1995
Period 3: 1995/1996-2005/2006

Table 11: Panel data estimation results for the separate time period models
Source: Eigner, Toeglhofer and Prettenthaler (2009)

Appendix D

Figure 1 to Figure 4 show several additional, mostly larger graphical illustrations to support empirical considerations in Subsection 5.1.2 and Subsection 5.1.3 respectively. Note that Figure 2 and Figure 4 are optimized for the web version (pdf), while, for that effects are shown for all individual ski areas, they appear small in print.

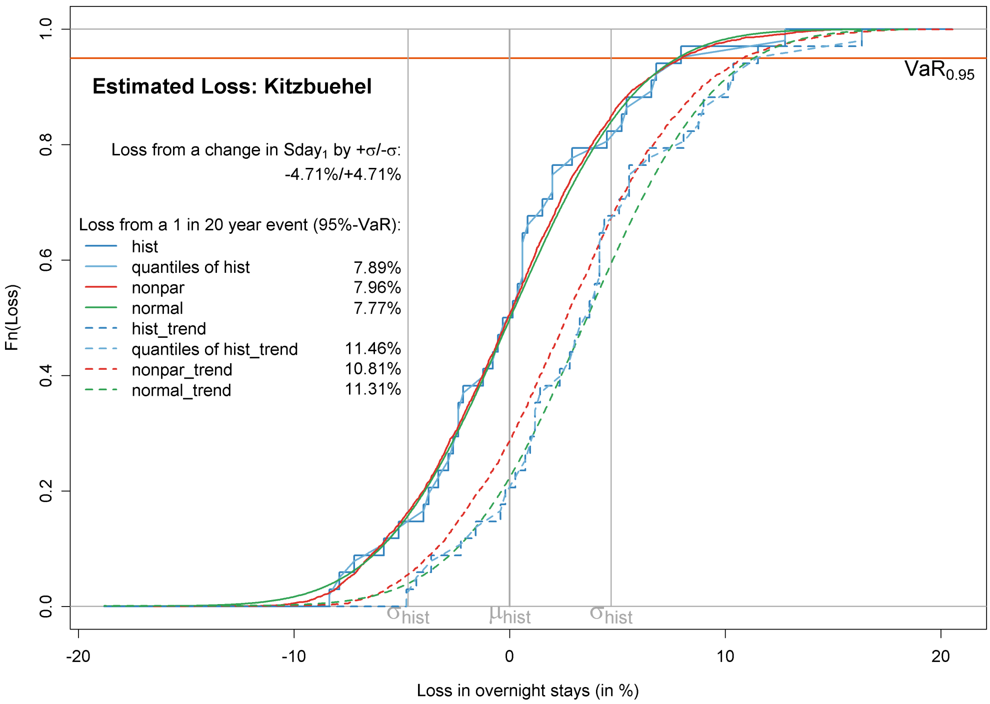

Figure 1: Cumulative distribution functions (CDFs) of losses estimated with different weather index modelling approaches for the example of Kitzbuehel

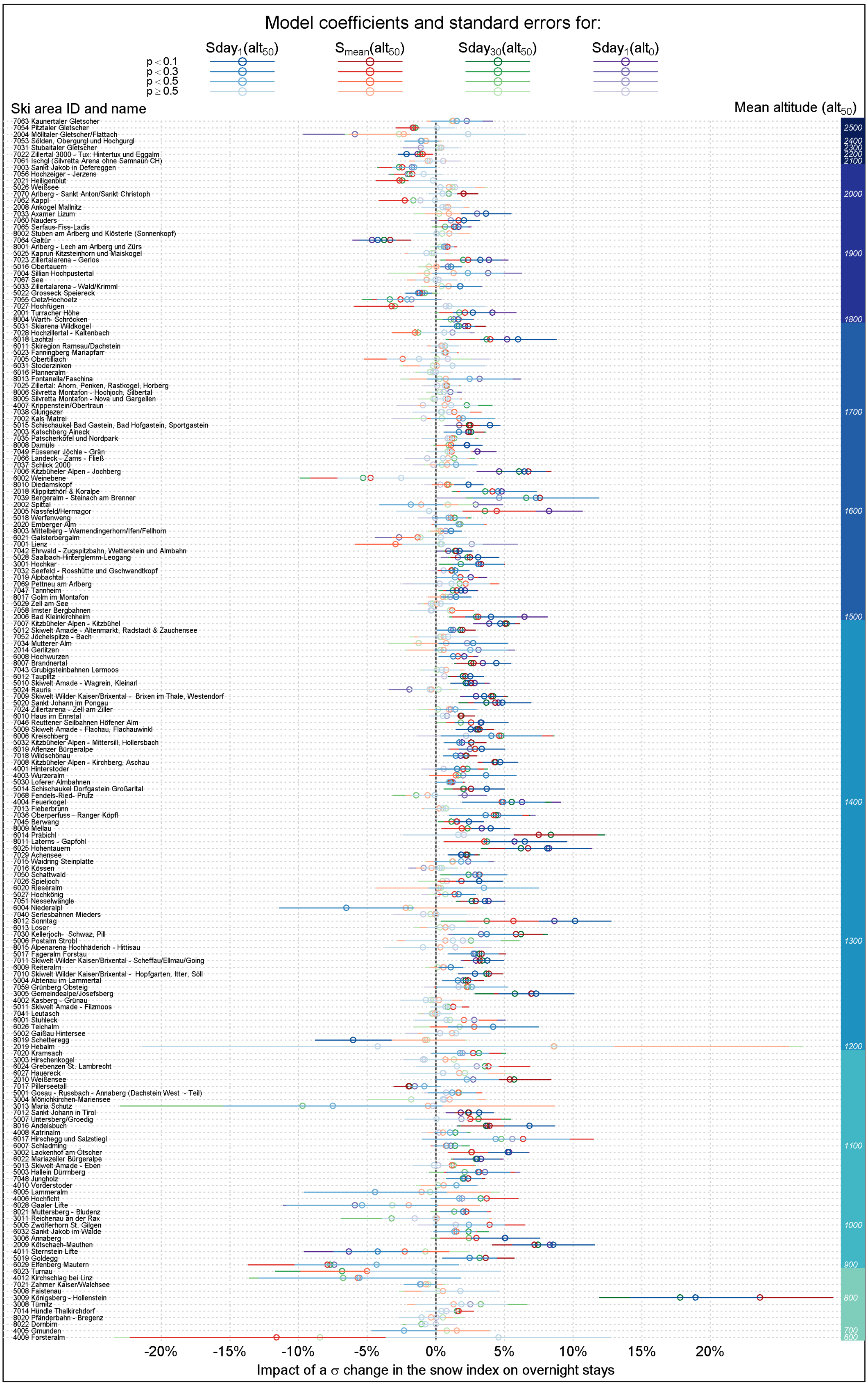

Figure 2: Estimation results for different weather indices

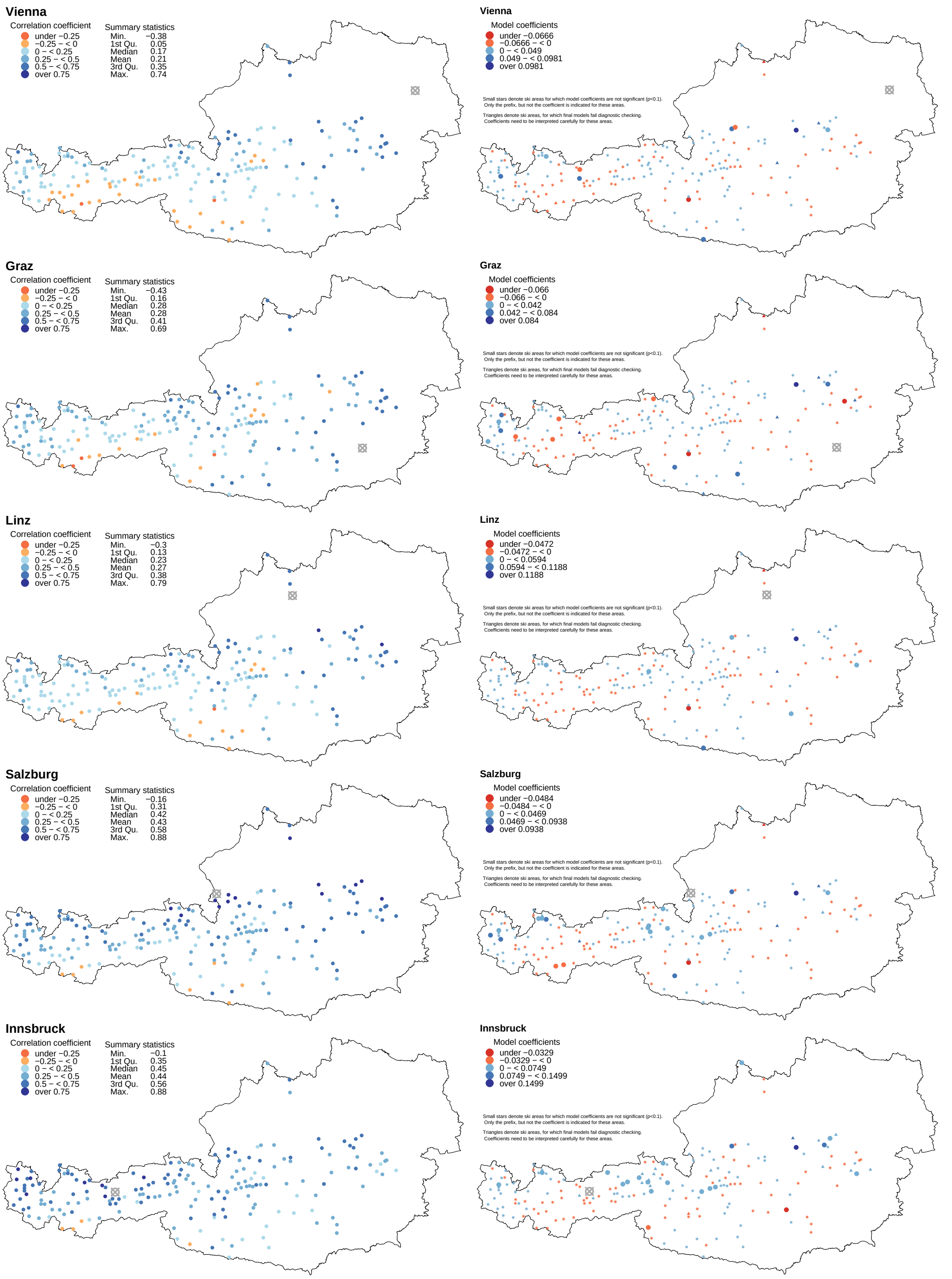

Figure 3: Testing for the *backyard effect*; Left: Correlations between urban and ski area snow conditions; Right: Model coefficients for the respective cities

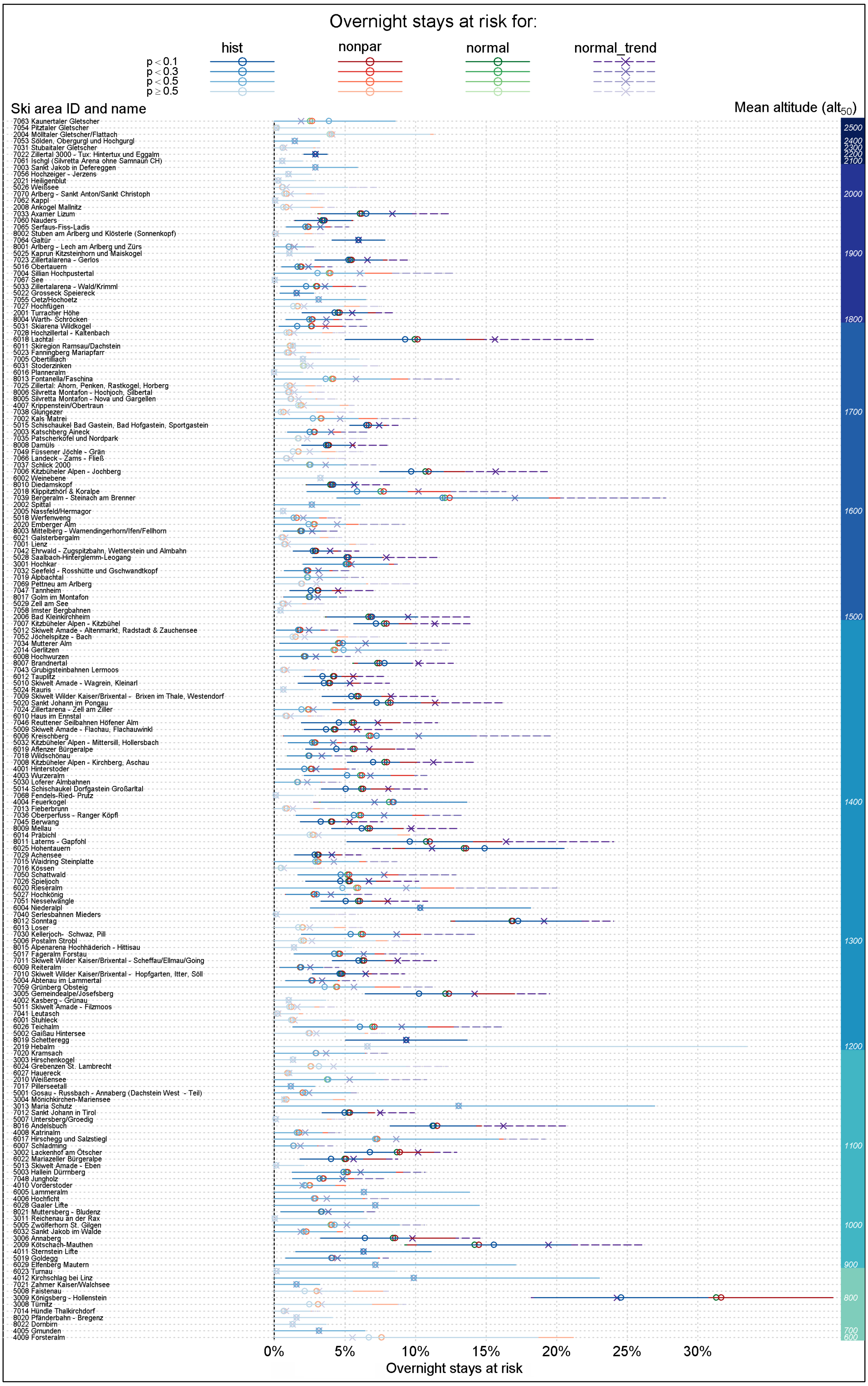

Figure 4: $VaR(weather)_{0.95}$ for different weather index modelling approaches