b
UNIVERSITÄT
BERN

CRED
CENTER FOR REGIONAL
ECONOMIC DEVELOPMENT

The Impact of Weather Forecasts on Ski Demand

CRED Research Paper No. 43

Pascal Troxler
University of Bern,
CRED

April 2023

Abstract

In the wake of stagnating demand across Alpine ski areas, new pricing regimes and recent advances in the availability of precise local weather forecasts, the relation of weather forecasts to ski demand gains new relevance. I use an activity choice framework in which agents evaluate the utility of skiing relative to alternative opportunities. Thereby, agents decide early based on forecasts or spontaneously based on observed weather outcomes. By matching the demand data of three Swiss ski areas to local forecast and weather data, I show that forecast errors affect skiing demand above the variation through weather alone. Furthermore, I find suggestive evidence that reactions to pessimistic forecast errors exceed those to optimistic errors when agents are more risk averse, less enthusiastic towards skiing or the ski area is located further into the Alps.

Key words: activity choice, skiing demand, weather, weather forecasts, forecast errors

JEL classification: Z21, Z31

CRED
Universität Bern
Schanzeneckstrasse 1
Postfach
CH-3001 Bern

Tel. +41 31 684 37 11
info@cred.unibe.ch
www.cred.unibe.ch

1 Introduction

It is well established in the literature that weather and snow conditions significantly impact skiing demand (Malasevska & Haugom, 2018; Malasevska et al., 2017b; Shih et al., 2009). However, most people will likely base their decision on weather forecasts rather than the actual weather. Weather forecasts provide information about possible skiing conditions and shape the expectation of potential skiers. This helps an agent in planning the activity. As conditions in an unstable weather environment only become visible at the site, the value attached to the activity is determined after bearing the transaction costs of packing and driving to the area entrance. Therefore, switching to another activity is more expensive the more planning is involved and the higher the opportunity costs. The ability to assess the conditions at the site and make a decision close to the entrance in time and space is more viable for those already close by. Consequently, weather forecasts might explain demand fluctuations better than the weather itself and more so when the forecasts deviate from the actual weather and when agents face high switching costs.

I study the impact of weather forecasts on skiing demand by (i) providing a theory about individual behavior using an activity choice model, (ii) using novel weather forecast data with a detailed spatial and temporal resolution, (iii) recovering causal estimates of optimistic and pessimistic weather forecasts in the aggregate and for subgroups regarding age and pass validity types and (iv) derive under what circumstances asymmetric reactions occur due to these forecasts. Thereby, I link and contribute to two strands of literature.

The first considers skiing demand and its relation to weather outcomes and dynamic pricing. In the light of climate change that endangers snow-reliability in ski area operations (Elsasser & Bürki, 2002; Gonseth, 2013; Gössling et al., 2012; Koenig & Abegg, 1997; Scott & Gössling, 2022; Steiger & Abegg, 2017, 2018) and is considered a critical factor in stagnating skiing demand within the Alps (Plaz & Schmid, 2015), operators react by implementing disruptive price strategies while making costly mitigation investments (Falk, 2015; Falk & Scaglione, 2018; Lütolf et al., 2020; Malasevska et al., 2020; Wallimann, 2019). Thus, accurate predictions of demand serve ski area operators in at least two aspects: It helps to plan staff and keep daily operation costs in check[1], and it increases pricing efficiency for those areas implementing dynamic pricing[2]. So far, none of these papers empirically incorporate

[1]For example, by deciding which slopes to groom, which lifts to open at what speed and which restaurants and other facilities to run.

[2]Ski area operators across Switzerland increasingly base ticket prices on expected demand to extract the willingness to pay of skiers conditional on the season day and the weather (Lütolf et al., 2020; Malasevska et al., 2020). Such a pricing strategy might be efficient as daily operations have very low variable costs. Mainly, operators offer early bookers a substantial discount to shift the weather risk from the area to the

the effect of local weather forecasts on skiing demand.[3]

The second strand of literature uses weather forecasts or other meteorological information to study decisions in the agricultural sector. In an early work, Katz et al. (1982) use minimum temperature forecasts to identify the value of forecast information to protect orchards from destructive frost periods. More recently, Cerdá Tena and Quiroga Gómez (2011) make a similar exercise but include risk aversion and evaluate how it affects optimal decisions by farmers to protect their crops. A summary of different methods for quantifying the economic value of weather and climate forecasts is provided by Katz and Lazo (2012). The present work is closely related to the approach of Jewson et al. (2021). They build a decision framework based on the Cost-Loss Model (Murphy, 1969; Winkler et al., 1983) and run an algorithm to evaluate whether a decision about an event should be made on the current forecast or postponed to the next period, where a more accurate forecast is available. The difference to the present work is that their algorithm is only tested on theoretical utility levels. In my context, this would instruct a potential skier how she should optimally decide based on forecasts, but would neither tell us anything on how that affects demand in the aggregate nor whether the theory is an accurate model of reality. In contrast, I provide all of that: How decisions are formed, how that translates to the aggregate and whether these reactions coincide with empirical behavior.

In a two-period activity choice model, I argue that potential skiers might react to weather forecasts in two ways: They make a plan and commit themselves early on to engage in skiing or they make no plan and make the final decision when they actually observe the weather. Having all information in the second period, agents decide to either ski, remain home or engage in an alternative outdoor activity. Further, I distinguish agents in their costs across two dimensions.

First, switching costs are heterogeneous. For some agents (Type A) switching costs away from and to skiing are both high. In the former case, the gear organization, the ski pass or the journey to the ski area are sunk costs. In the latter case, these preparations for a skiing day are not feasible because the ski area is too far away and the weather is only observed once the ski area has opened already. These high switching costs force type A agents to commit to an early decision as skiing in the second period becomes too expensive. For the others, the type B agents, switching costs are low as they, for instance, stay in proximity to the ski

skier.

[3] Scaglione and Doctor, 2008 wrote a paper with a similar focus but was never published. The forecast data in their work is outdated (based on TV forecasts) as advances in information technology made weather forecasts in recent years broader available in time (via mobile phone apps or internet browsers) and space (tailored to ZIP codes, municipality names or specific locations like mountains).

area and own a season pass. They have no incentive to make early plans because a decision in the second period eliminates uncertainty by observing the actual weather. Therefore, by waiting, their choice becomes deterministic and their demand varies, accordingly, only to changes in the observed weather.

Second, preferences over the activities are heterogeneous. All agents have idiosyncratic costs of the alternative activity relative to skiing. Thus, depending on the forecast information, type A agents trade-off the commitment for skiing in the first period against the alternative activity in the second period. The alternative activity includes every possible opportunity except skiing. Accordingly, heterogeneous preferences are modelled as different levels of opportunity costs. That is, the cost to engage in the alternative activity. Generally, those with relatively large opportunity costs tend to favor skiing and those with low opportunity costs require a relatively better forecast (or weather outcome for type B agents) to decide and commit in favor of skiing.

From these individual choices, it appears that optimistic forecasts increase and pessimistic forecasts decrease aggregate skiing demand. Under certain circumstances, the effect of pessimistic forecast errors is larger than those of optimistic errors and vice versa, i.e., the reactions are asymmetric. A first channel that leads to asymmetries is that the forecast provider has more difficulty accurately predicting the weather in typically precipitation-prone large-scale weather situations such as west-wind or so-called Foehn-situations[4]. Hence, the probability of a forecast error is higher in bad large-scale situations than in typical good weather situations. Such a forecasting asymmetry translates, in theory, directly into an asymmetric reaction toward pessimistic forecasts. Moreover, two additional channels lead to an asymmetric reaction: Risk aversion and a skewed opportunity cost distribution among heterogeneous type A agents. The latter channel is of particular concern for ski area operators where mild winters and fewer fog days in the lowlands enhance the attractiveness of alternative outdoor activities relative to skiing (Plaz & Schmid, 2015).

Exploiting panel data of daily ski demand across ten seasons from three large ski areas paired with local weather and weather forecast data allows me to investigate upon these decision patterns. Using a one-dimensional weather index that combines skiing preferences from sunshine duration, precipitation and minimum temperature data of the national weather service, I find that a one standard deviation change in the weather affects demand up to 63% in the aggregate. This gross weather effect is a non-linear combination of the net weather

[4]A Foehn is a wind phenomenon that occurs typically at mountain ranges and is associated with strong winds. In the Alps the Foehn crosses either from south or north and leads to warm, dry downward winds on the lee side and to precipitation and thick clouds on the windward side of the mountains (MeteoSchweiz, 2015; Steinacker, 2006).

effect - the effect a weather change has on type B agents only - and the forecast error effect - the effect of a forecast deviating from the actual weather and inducing more or fewer type A agents to engage in skiing.

The net weather effect, amounting to an average change of up to 48% in demand, is across most groups larger than the forecast error effect, which changes demand on average up to 14%. These differences in effect sizes suggest that in all three areas most of the weather-sensitive changes can be attributed to spontaneous type B agents. In fact, using the relative changes of both types enables me to estimate the share of type A agents among all weather-sensitive one-day pass owners. This share is estimated to be 55% in area 2 and 25% in area 3. Type A agents consist typically of families and day-trippers, who both are expected to have high switching costs. The former have high switching costs due to the long travel distance and the latter due to the time-consuming effort of bringing children onto the slopes.

As the share of type A agents is identified by forecast errors alone, the estimates represent a lower bound of the true share. The reason is that in stable large-scale weather situations potential skiers can make almost risk-free early decisions while, at the same time, weather data is going to reflect early decisions in equal measure to forecast data because of the ease to forecast precisely. These early decisions are then disguised by variation in weather data and, through that, assigned to the share of type B instead of type A agents.

Finally, I find suggestive evidence of stronger pessimistic reactions relative to optimistic reactions due to one of the three possible channels stated in the theoretical part. Further research is necessary to evaluate empirically for which type of agents an asymmetric reaction could be confirmed regarding their enthusiasm, risk aversion or other personal characteristics.

Section 2 covers the activity choice model and the propositions that follow from it. Section 3 presents the data used for the empirical part. Section 4 derives the empirical strategy to evaluate the propositions and Section 5 covers the results before concluding in Section 7.

2 Theory

2.1 Framework

Agents have utility $u(x, l, w) = v(x, w) - c(x, l)$ where v indicates the value of activity x at weather w and c the cost of activity x at plan l. Activities $x \in \{s, h, a\}$ are mutually exclusive and involve s = skiing, h = remaining at home and a = following an alternative outdoor activity. Plans $l \in \{1, 0\}$ are mutually exclusive and involve the plan to ski $l = 1$ and the plan to not ski $l = 0$ (i.e. either home or alternative).

There are two time periods $t = 0$ and $t = 1$ and two weather outcomes $w \in \{g, b\}$ for good and bad conditions, respectively. At $t = 0$ the agent makes a plan l based on a forecast $\mathrm{f} \in \{g, m, b\}$ that signals good, mixed or bad conditions. At period $t = 1$, when the agents make their decision x, the weather outcome is observed. The decision tree is depicted in Figure 1.

Figure 1: Decision nodes faced by the agents

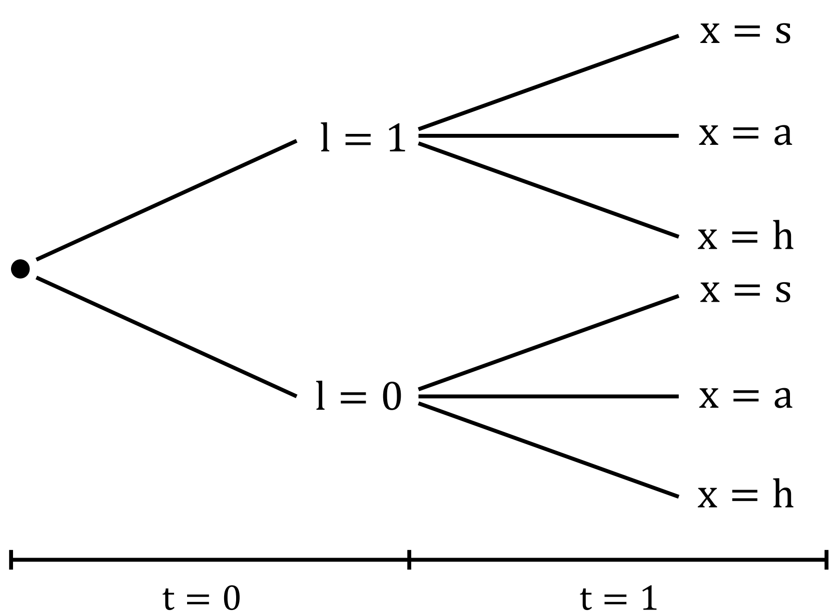

Figure Notes: The first decision node represents the plan $l \in \{1, 0\}$ whether to ski or not to ski and the choice $x \in \{s, h, a\}$ whether to ski, remain home or engage in an alternative outdoor activity. Forecasts are available at period $t = 0$ and the weather at $t = 1$.

The weather and forecast states are materialized with the following probabilities:

f \ w	g	b
g	p_g	$1 - p_g$
m	p_m	$1 - p_m$
b	p_b	$1 - p_b$

The probabilities are ranked such that $p_g > p_m > p_b$ implying that a good forecast leads to a good weather outcome with probability $p_g \approx 1$ (close to 1) a mixed forecast to good weather with probability $p_m \approx 1/2$ and a bad forecast leads to good weather with $p_b \approx 0$ (close to 0).

I impose the following relative valuation of direct consumption utility and related costs: $v(s,g) > v(a,g) > v(h,g) > v(h,b) > v(a,b) > v(s,b)$ and $c(h) < c(a) < c(s,1) \leq c(s,0)$. Skiing in good weather is the most valued outcome, skiing in bad weather is the least valued outcome and skiing is (for most individuals) cheaper when skiing is planned ($l = 1$) than when it is not planned ($l = 0$). Following the alternative outdoor activity is better than remaining at home in good weather but worse in bad weather. Conversely, its value remains below skiing in good weather but above skiing in bad weather. Remaining home is the most valued outcome in case of bad weather but below the valuation of the alternative when the weather turns out good.

Agents are risk averse. Thus, their consumption utility is $U(x,l,w) = u\big(v(x,w) - c(x,l)\big)$ where $u(x)$ is a concave function of values and costs satisfying $\partial u(x)/\partial x > 0$ and $\partial^2 u(x)/\partial^2 x \leq 0$.

The agent's optimization problem at $t = 0$ is

$$\max_l E\big[U(x,l,w)|\mathrm{f}\big] = l\Big[p_{\mathrm{f}}\big(\max_x U(x,1,g)\big) + (1-p_{\mathrm{f}})\big(\max_x U(x,1,b)\big)\Big]$$
$$+(1-l)\Big[p_{\mathrm{f}}\big(\max_x U(x,0,g)\big) + (1-p_{\mathrm{f}})\big(\max_x U(x,0,b)\big)\Big].$$

for $\mathrm{f} \in \{g, m, b\}$.

Using backward induction starting at $t = 1$, the agent evaluates the best choice given the weather, i.e. whether $u\big(v(x,g)-c(x,l)\big) > u\big(v(x,b)-c(x,l)\big)$. For example, when the weather turns out good, skiing is always optimal when skiing was planned because $v(1,g) - c(1,1) > v(0,g) - c(0,1)$. On the contrary, when the weather turns out bad, not skiing is always optimal when not skiing was planned because $v(0,b) > v(1,b) - c(1,0)$. The remaining two maximization problems at $t = 1$ are not straightforward, it depends on the agent's preferences and costs.

Suppose there are two types of skiers, type A and type B. Type A faces large costs to switch plans and ski spontaneously at $t = 1$. For them $c(s,1) < c(s,0)$ because, for instance, they have to travel large distances. Type B, on the contrary, faces $c(s,0) = c(s,1)$ and as such have no change in cost over time.

Switching costs are higher than sticking to the plan for some agents because it involves costs such as setting the alarm clock, organizing gear, packing the car, buying a ski pass or foregoing alternative opportunities. For someone switching away from skiing these are sunk costs and for someone switching to skiing these are not yet borne. On the contrary, switching to skiing for someone staying right next to the ski area entrance is like switching between remaining home and following cheap outdoor activities: It leads to no additional cost because it can be done directly from the agent's doorstep.

We assume type A agents rank their preferences to $v(s,g) - c(s,1) > v(a,g) - c(a,0) > v(s,g) - c(s,0) > v(h,g) - c(h,0)$. The first inequality follows directly from the fact that some individuals choose to ski at all. The second inequality is due to the large switching costs, that is a large difference between $c(s,0)$ and $c(s,1)$ and the last imposes that skiing in good weather is generally preferred to staying home. Then type A plans to ski ($l = 1$) whenever the expected utility of skiing exceeds the expected utility of the alternative(s). That is whenever

$$\begin{aligned} & p_{\mathrm{f}} \cdot u\big(v(s,g) - c(s,1)\big) + (1 - p_{\mathrm{f}}) \cdot u\big(v(s,b) - c(s,1)\big) \\ \geq\ & p_{\mathrm{f}} \cdot \underbrace{u\big(v(a,g) - c(a,0)\big)}_{\text{good weather outcomes}} + (1 - p_{\mathrm{f}}) \cdot \underbrace{u\big(v(h,b) - c(h,0)\big)}_{\text{bad weather outcomes}} \end{aligned} \tag{1}$$

for $\mathrm{f} \in \{g, m, b\}$. Further, we define $V_g = u\big(v(s,g) - c(s,1)\big) - u\big(v(a,g) - c(a,0)\big) > 0$ as the value-difference between good-weather outcomes and $V_b = u\big(v(h,b) - c(h,0)\big) - u\big(v(s,b) - c(s,1)\big) > 0$ as the value-difference between bad-weather outcomes. Ultimately, type A agents stick always to the plan at $t = 0$ because switching is too expensive.

On the opposite, type B agents switch always at $t = 1$ depending on the weather as $c(s,0) = c(s,1)$. Their preferences are, accordingly, $v(s,g) - c(s,1) \geq v(s,g) - c(s,0) > v(a,g) - c(a,0) > v(h,g) - c(h,0)$. Because of having low skiing cost even if it was not planned ($l = 0$), the type B, being typically a local resident or overnight guest, will favor then skiing over the alternative. Therefore, in good weather conditions, these types decide to ski no matter what the forecast signalled. The type B plans to ski ($l = 1$) whenever

$$\begin{aligned} & p_{\mathrm{f}} \cdot u\big(v(s,g) - c(s,1)\big) + (1 - p_{\mathrm{f}}) \cdot u\big(v(s,b) - c(s,1)\big) \\ \geq\ & p_{\mathrm{f}} \cdot \underbrace{u\big(v(s,g) - c(s,0)\big)}_{\text{good weather outcomes}} + (1 - p_{\mathrm{f}}) \cdot \underbrace{u\big(v(h,b) - c(h,0)\big)}_{\text{bad weather outcomes}} \end{aligned} \tag{2}$$

for $\mathrm{f} \in \{g, m, b\}$. As (2) is never satisfied for $c(s,1) = c(s,0)$, type B never plans to ski ($l = 0$) and decides at period $t = 1$ to ski whenever the weather is good (as it is her best choice then) and not to ski whenever the weather is bad (as remaining at home is her best choice then). Notice that in the empirical application, the weather is not either good or bad but rather a continuous variable with all sorts of outcomes between those extremes. Therefore, the decision of type B agents solely hinges on the acceptance of a certain weather outcome to their preferences.

In the following subsection, the two types are modeled by relaxing the strict ranking of preferences by implementing heterogeneity for the two types[5]. Starting at the more straightforward case of type B.

2.2 Heterogeneity in opportunity costs

2.2.1 Type B

The type B agent always chooses $l = 0$. Therefore, her final consumption hinges only on the weather outcome at $t = 1$. She is indifferent between skiing and the alternative[6] at $t = 1$ when

$$u\big(v(s,w) - c(s)\big) = u\big(v(a,w) - c(a)\big). \tag{3}$$

Among the type B agents the cost of the alternative $c_i(a)$ are heterogeneous between boundaries

$$\{c_i(a) : \underline{c} \leq c_i(a) < \bar{c}\} \tag{4}$$

where $\underline{c}$ is the lowest possible cost of the alternative a and $\bar{c} = c(s)$. From (3) I define implicit cost thresholds c^w that satisfy

$$u\big(v(s,w) - c(s)\big) = u\big(v(a,w) - c^w\big) \tag{5}$$

for the two weather outcomes $w \in \{g, b\}$ which are the decision switching points of type B agents. Observe that $c^b > c^g$ capturing the fact that more agents go skiing when the weather is good. Any type B with $c_i(a) > c^w$ decides to ski at $t = 1$. In the model this is everyone if $w = g$ and no one if $w = b$. Furthermore, as the decision for type B agents is deterministic, the degree of risk aversion plays no role. Notice that in the empirical application in Section 4 the weather is continuous and so are the implicit cost thresholds there.

2.2.2 Type A

For the type A agents the forecast has decision value and, thus, the decision at $t = 0$ is stochastic. From the preferences $v(a,g) - c(a,0) > v(s,g) - c(s,0)$. Therefore, the optimal choice at $t = 0$ hinges on the cost-differential of deciding to ski when it is planned $(l = 1)$

[5]Instead, one could think of a model with two types of preferences, ski enthusiasts and non-enthusiasts, and continuous switching costs. Such a model leads to the same predictions regarding the impact of forecasts in the aggregate.

[6]For simplicity, the alternative consists here of any activity except of skiing.

and engaging in the alternative when skiing is not planned ($l = 0$) at $t = 0$. From (1) it follows that the type A is indifferent between skiing and waiting at $t = 0$ when

$$u\big(v(s,g) - c(s,1)\big) = u\big(v(a,g) - c(a,0)\big) + \frac{(1-p_{\mathrm{f}})V_b}{p_{\mathrm{f}}} \tag{6}$$

for the three forecast probabilities $\mathrm{f} \in \{g, m, b\}$. Among the type A agents the cost of the alternative $c_i(a,0)$ are heterogeneous between boundaries

$$\{c_i(a,0) : \underline{c} \leq c_i(a,0) < \overline{c}\} \tag{7}$$

where $\underline{c}$ is the lowest possible cost of the alternative a and $\overline{c} = c(s,1)$.

From (6) I define three implicit cost thresholds $c^{\mathrm{f}} \in \{c^g, c^m, c^b\}$ that satisfy

$$u\big(v(s,g) - c(s,1)\big) = u\big(v(a,g) - c^{\mathrm{f}}\big) + \frac{(1-p_{\mathrm{f}})V_b}{p_{\mathrm{f}}}. \tag{8}$$

These cost thresholds correspond to the decision switching points of type A agents between planning to ski and not planning to ski at $t = 0$. Note that $c^b > c^m > c^g$ capturing the fact that more agents go skiing the better the forecast is. If the forecast entails no uncertainty ($p_g = 1$, $p_b = 0$ and $p_m \in \varnothing$), the three thresholds become irrelevant. With good forecasts everyone would ski and with bad forecasts no one would ski. If and only if $c^g < c(s,1)$ and $c^b > \underline{c}$ type A agents decide upon forecasts at all.

Figure 2 depicts four typical counterfactual situations. An optimistic forecast increases demand by all individuals with cost $c_i(a,0) \in [c^m, c^b)$. On the opposite, a pessimistic forecast decreases demand by all individuals with cost $c_i(a,0) \in [c^g, c^m)$. I compare mixed forecasts to correct forecasts because these are typical situations that individuals encounter regularly. Confident forecasts in either direction are wrong in very rare instances (at the forecast horizons we consider here). From this follows

Proposition 1 *Mixed forecasts reduce demand for skiing when the weather turns out good and increase demand for skiing when the weather turns out bad relative to a correct forecast.*

On top of that, from the derivation of cost thresholds for both types, it follows that skiing demand at a certain day consists always of two types of skiers. Those reacting to forecasts and committing at $t = 0$ to skiing and those waiting to observe the weather and deciding spontaneously at $t = 1$. Thus,

Proposition 2 *Skiing demand is more volatile to forecast errors the higher its share of potential type A agents.*

Proposition 2 means that when demand consists to a larger extent of groups that are typically associated with large switching costs, as e.g. day-trippers or families, then I would expect a larger volatility of their demand to forecast errors.

Figure 2: Cost heterogeneity and related outcomes under different scenarios

(a) Optimistic error **(b) Pessimistic error**

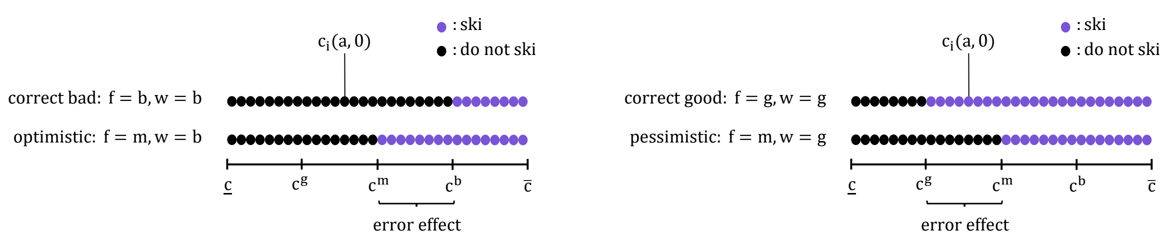

Figure Notes: Both panels indicate two counterfactual situations where the weather turns out bad (in panel a) or good (in panel b) and how type A agents (depicted as dots) decide according to their preferences as idiosyncratic costs of the alternative. On the top line the forecast is correct and all agents with $c_i(a, 0)$ above c^b (in panel a) or above c^g (in panel b) plan to ski and end up doing so ($l = 1$ and $x = s$) while the remaining agents plan not to ski and choose to remain home ($l = 0$ and $x = h$ in panel a) or engage in the alternative ($l = 0$ and $x = a$ in panel b) in the second period. On the bottom line, the forecast is optimistic (in panel a) or pessimistic (in panel b) and all agents above c^m decide to ski. The difference between the two lines is the positive (in panel a) or negative (in panel b) forecast error effect on aggregate skiing demand.

2.3 Asymmetric Effects

Proposition 1 and 2 make no statement on the relative effect size of optimistic and pessimistic forecast errors. The effects are symmetric when the distance between threshold c^g and c^m is the same as the distance between threshold c^m and c^b and the distribution of agent's opportunity cost $c_i(a, 0)$ is uniform across $[\underline{c}, \bar{c})$. The symmetry of the effects hinge on (i) the opportunity cost distribution across agents, (ii) the degree of risk aversion and (iii) the actual probabilities p_{f}.

The first channel that leads to asymmetric effects exists when the opportunity cost distribution of the alternative among type A agents is not uniform (not as drawn in Figure 2). The cost of the alternative hinges to a large extent on the guest structure of the ski area and its available opportunities. For example, day-trippers from urban areas might have fewer alternative outdoor activities than those from rural areas. An area with many urban guests facing high opportunity costs would lead to a left-skewed distribution. In such a setting optimistic error effects might exceed pessimistic error effects. Notice that preferences towards skiing, marginal utilities of repeated skiing, and longer and warmer days towards spring could all affect this distribution.

The second channel works through risk aversion. It makes planning to ski at $t = 0$ for mixed forecasts less attractive due to the fact that the outcome is less predictable (around 50-50 after a mixed forecast) than after receiving a good or bad forecast. The gamble of waiting or skiing after a mixed forecast is second-order stochastically dominated by the other two forecasts and, hence, c^m shifts closer to c^b because it is associated with a higher risk of making the wrong choice. A formal derivation of this result is in Appendix B.1.

Lastly, the third channel inducing asymmetric effects is related to the ability of the forecaster to predict the weather accurately in different large-scale weather situations. In particular, it is easier for the forecaster to predict good weather than bad weather. Typical bad-weather situations such as west-wind and north- or south-Foehn situations exacerbate the prediction in inner-alpine regions because it is *ex ante* uncertain how far the clouds and storms reach into the alps. The complex topography of the mountains makes it almost impossible to predict precisely when clouds appear and where some mountains might protect certain municipalities from these unfortunate weather outcomes. On the contrary, in typical good weather situations such as high pressure and Bise[7] situations the weather is relatively easy to predict accurately as unexpected storms are almost impossible to hit certain inner-alpine areas. Relating absolute forecast errors with weather percentiles in Figure 3 for the three areas reveals precisely this pattern: Forecasts at lower weather percentiles are in all three areas more prone to errors than at higher weather percentiles.

Interestingly, area 1 lies furthest in the mountains and is at the same time exposed to larger discrepancies in forecast errors across weather percentiles. This is in line with the intuition that it becomes more challenging to predict bad weather outcomes the further a place lies in the alps. In fact, using the same forecast and weather data for two-hundred major ski areas reveals precisely this pattern. See Appendix C.2 for a further discussion on this.

In consequence, the probability p_g is in reality rather close to 1 whereas p_b is close to 1/2 instead of being close to 0. This empirical asymmetry translates directly into the inequality in (26). The distance $c^m - c^g$ is no longer clearly smaller than $c^b - c^m$ and, thus, even under risk neutrality the demand shifts due to forecast errors are not necessarily asymmetric in favor of optimistic forecasts. In combination with risk-averse agents, I would argue, the shift

[7] A typical Swiss weather situation when winds blow from northeast to southwest and are channeled by the Jurassian and Alpine mountain ranges. Often it comes with a high fog layer that overcast the Swiss midlands and an inversion (temperatures are higher above the fog than below)(MeteoSchweiz, 2015).

Figure 3: Local polynomial smoothing of absolute forecast errors on weather percentiles

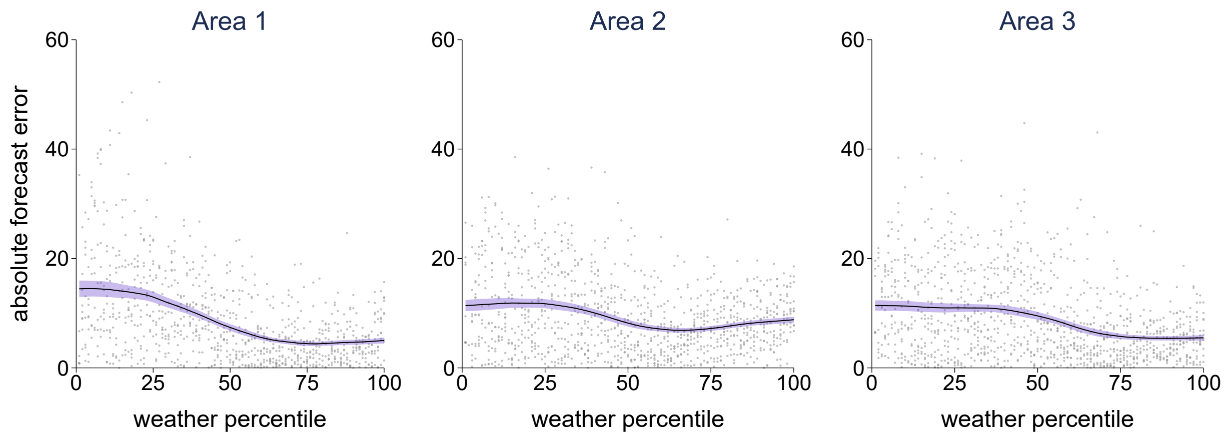

Figure Notes: The local polynomial smoothing applied here uses the kernel weighting of epanechnikov, a bandwith of 10 (arbitrary choice for illustrational purposes) and a degree of 0. See Fan and Gijbels, 1996 for a comprehensive work on the method applied here. Absolute forecast errors for horizon $h = 0$ are defined as $|f_0 - w|$ and weather percentiles are constructed from the weather index w (See Section 3.2).

is even stronger for pessimistic than optimistic forecasts.

Mixed forecasts seem inherently risky as the outcomes are a larger gamble compared to good and bad forecasts. These push the threshold c^m relative to the other two thresholds at $t = 0$ upwards. Combining this with a bad forecast, the probability of actually good weather is not as low any longer. Consequently, potential skiers have a difficult time separating a bad forecast from a mixed forecast. Then, ski enthusiasts (that cover the upper tail of the distribution of $c_i(a, 0)$) incorporate this and, thus, lower their threshold c^b. As a result, a mixed forecast induces demand just above what an area can expect from a bad forecast. Even while the chances are higher that the weather actually turns out to be much better than expected. On the other side, c^g and c^m are further apart and lead to a much higher demand after good forecasts relative to mixed forecasts.

Acknowledging the possible existence of these three channels supports the idea that the effects might appear asymmetric where *ex-post* pessimistic forecasts induce larger demand effects than *ex-post* optimistic forecasts. Thus,

Proposition 3 *Skiing demand is more volatile to mixed forecasts when the weather turns out good than when the weather turns out bad.*

Proceeding from here, the following Section describes the data that is used to test in Section 5 the three propositions.

3 Data

3.1 Demand

Demand data consists of either bookings or first-entries[8] of three ski areas during the winter season (end of November until the end of April). Data is available for different age groups and numerous pass validity types. It is provided by ski area operators located in the western Alps of Switzerland that had no dynamic pricing in place during the observed period.[9] In total the data consists of 3302 days split into 910, 1137 and 1255 days from areas 1, 2 and 3, respectively, covering all seasons between 2010 and 2020.

Unfortunately, data in area 1 is restricted to transactions, not the actual consumption of skiing. To be more certain that a transaction leads to consumption, only bookings of one-day passes that are valid on the same day as the transaction are used from area 1.[10]

The validity and age groups provide insights into the heterogeneity in behavior to weather and weather forecasts. To allow a comparison between areas the data is aggregated to three age groups, adults, juveniles and children, and five pass validity types: One-day passes, weekend passes (2-4 days), one-week passes (5-7 days), two-week passes (8-14 days) and season passes (more than 15 days).

3.2 Weather

Weather data is available from the Swiss government meteorological service MeteoSchweiz. The data is drawn for all weather stations within a 30km radius of the lowest lift in a ski area from the approximately 2,700 weather stations in Switzerland. I use a broad set of weather variables, relating them to demand and run statistical learning procedures, like random forests (RF) and forward selection, to predict skier demand. These procedures evaluate the most important variables to predict demand as accurately as possible. Appendix A.4 documents these procedures and reveals that relative sunshine duration, precipitation and minimum temperature during the day are the three key variables to be considered here.

The relative sunshine duration is the percentage share of hours of sunshine on a given day of the maximum possible hours of sunshine. Thus, it allows comparing sunny days independent of their timing within the year. An increase in sunshine duration balances

[8]First-entries are daily counts of guests entering a ski area.

[9]Dynamic prices would violate the exogeneity of the weather variables in the empirical specification and were thus essential criteria for selecting areas.

[10]It is likely that buying a seven-day pass does not necessarily resolve in seven days of actual consumption. On the contrary, it is very unlikely that buying a one-day pass leads to no consumption.

out very cold temperatures, enables a clear vision of the slope and the surroundings and encourages the consumption of food & beverages on the mountain. In line with the literature, I expect a positive relation of sunshine duration to skiing demand (Gonseth, 2013; Haugom & Malasevska, 2019; Lütolf et al., 2020; Malasevska et al., 2020; Rutty & Andrey, 2014; Scaglione & Doctor, 2008).

Precipitation is measured in millimeters throughout the daytime. During snowfall or rain, the light is often flat which exacerbates skiing and other activities on the mountain. Often it is accompanied by cold temperatures and stormy winds. I expect a negative relation to skiing demand in line with the literature (Falk, 2015; Haugom & Malasevska, 2019; Malasevska et al., 2020; Rutty & Andrey, 2014; Scaglione & Doctor, 2008).

The minimum temperature is measured in degrees Celsius throughout the daytime. Relatively warm temperatures make the snow wet and "slushy" which is perceived negatively by most skiers. However, too-cold temperatures might become unbearable for a large share of skiers. Therefore, in line with the literature, I expect a hump-shaped relation to skiing demand (Falk, 2015; Gonseth, 2013; Holmgren & McCracken, 2014; Malasevska et al., 2017a; Scaglione & Doctor, 2008; Shih et al., 2009).

3.3 Weather Forecast

The weather forecast data are midnight model outputs of COSMO-7 (MeteoSchweiz, 2012). Forecast data are available for three time horizons, 2 days, 1 day and 0 days in advance. The data covers the main weather variables presented in the previous section. That is daily relative sunshine duration [%], daytime minimum temperature [°C] and daytime precipitation [mm]. The raw data from MeteoSchweiz are spatially interpolated to the point of the lowest lift within all three areas such that they match the weather data in space (see Appendix A.3 for details).

One limitation of this data is that it is computed outputs that must not necessarily represent actually published forecasts perfectly. But, as the data are available on a very local scale, these are exactly the inputs that are used in local forecasts in mobile phone applications or online. The variation in these data likely represents actual variation in forecasts above the publication of MeteoSchweiz. Several other weather service providers draw upon the same computer model outputs to publish their forecasts. That is the main reason why these indices are preferred over pictograms (see Appendix D).

3.4 Index

In order to recover from the data whether a forecast was pessimistic or optimistic compared to the measured weather, it is necessary to reduce the multi-dimensional weather and forecast variables into a one-dimensional index that proxies the skiing preferences.

The three key variables documented in Section 3.2 are used to build the weather and forecast indices denoted as w_{ds} and f_{ds}^{d-h}, respectively. In a first step, partial indices are defined

$$\widetilde{sun}_{ds} = sun_{ds} \tag{9}$$

$$\widetilde{prec}_{ds} = \begin{cases} 100 - (|prec_{ds}| * 10), & \text{if } |prec_{ds}| \leq 10 \\ 0, & \text{otherwise} \end{cases} \tag{10}$$

$$\widetilde{\underline{temp}}_{ds} = \begin{cases} 100 - (|\underline{temp}^* - \underline{temp}_{ds}|) * 5, & \text{if } |\underline{temp}^* - \underline{temp}_{ds}| \leq 20 \\ 0, & \text{otherwise} \end{cases} \tag{11}$$

where $prec_{ds}$ is the daytime precipitation (6-18 UTC) in mm, sun_{ds} is the relative sunshine duration to the maximum daily sunshine in percentages and $\underline{temp}_{ds}$ is the daytime minimum temperature (6-18 UTC) in degrees Celsius at season day d in season s. All partial indices are computed using weather and forecast data for their respective index. $\underline{temp}^*$ is the optimal minimum temperature evaluated by regressing aggregate demand on the above three single weather variables in each area (see Appendix A.4). The partial indices are scaled from 0 to 100 where larger values are associated with better weather.

In the last step, these partial indices are uniformly weighted to build the final weather and forecast indices. More formally,

$$w_{ds} = 1/3 * \widetilde{sun}_{ds} + 1/3 * \widetilde{\underline{temp}}_{ds} + 1/3 * \widetilde{prec}_{ds} \tag{12}$$

$$f_{ds}^{d-h} = 1/3 * \widetilde{sun}_{ds}^{d-h} + 1/3 * \tilde{\underline{temp}}_{ds}^{d-h} + 1/3 * \widetilde{prec}_{ds}^{d-h}. \tag{13}$$

Using these indices in empirical models imposes several functional form assumptions that could bias the results. To address this, I transformed all weather and forecast variables to pictograms based on instructions from MeteoSchweiz, adjusted them for precipitation and run all models using those heuristics. The data processing, adapted empirical specifications and the results using the pictograms are in Appendix D. All results are robust to this check.

A comprehensive list of all weather and forecast variables considered for the index, the temporal aggregation to daytime values, the spatial interpolation to the ski area coordinates [11] and a summary of the selection procedure of the three key variables are all in Appendix A.

3.5 Summary

Table 1 shows the summary statistics of the data. Because weather and forecast variables vary little across areas only those in area 1 are displayed. The aggregate demand shows that area 3 is quite larger than the other two areas in terms of demand and covers the longest period of 10 seasons with an average season length of 119.6 days. The standard deviations of all three areas are quite large compared to the mean because a large share of the variation is driven by seasonal fluctuations[12]. It is noticeable that precipitation forecasts are on average pessimistic whereas sunshine duration forecasts are on average optimistic. In addition, the minimum temperature is often a bit warmer than predicted. Combined, these lead to a slightly optimistic 0-day forecast index because the sunshine variable varies more than precipitation[13]. To account for this, the 0-day error is demeaned in each area and hence centered with a mean zero.

In the next section I derive the empirical strategy that allows me to test propositions 1 to 3 with the data at hand.

4 Empirical Strategy

The empirical model to test proposition 1 links weather and forecast data to the individual-level decision that amounts to aggregate skiing demand. I estimate

$$log(y_{ds}) = w_{ds}\beta + e_{ds}^{d-h}\delta + \alpha_d + o_{ds}\nu + \varepsilon_{ds}, \tag{14}$$

where w_{ds} is the weather index, $e_{ds}^{d-h} = f_{ds}^{d-h} - w_{ds}$ is the forecast error, α_d is the season day fixed effect that is common across seasons for the same day but varies across season days, o_{ds} is a dummy indicating Easter holidays and ε_{ds} is the idiosyncratic error term.

The identification strategy of (14) is derived from the cost heterogeneity in type A and type B agents. First, for each season day d in season s there is a set of $\mathcal{B}_{ds}$ individuals that

[11] I apply inverse distance weighting on weather stations within 30km of the corresponding lowest lift stations in the areas. These are precisely the same coordinates whereat weather forecast data from MeteoSchweiz is available.

[12] The inclusion of season day fixed effects that capture the seasonality in the regression models explain a large share of the variation, see Appendix C.3

[13] There is no variation in precipitation on dry days

Table 1: Summary statistics

Variable	Obs	s	$\overline{d}$	Mean	SD	Min	Max
Aggregate Demand							
Area 1	910	7	130.0	777.5	631.8	17	3,768
Area 2	1,137	10	113.7	1,091.6	840.0	16	4,428
Area 3	1,196	10	119.6	4,370.1	3,182.6	15	15,205
Area 1 Daytime Precipitation [mm]							
Measurement	910	7	130.0	1.2	3.3	0.0	48.1
0-day forecast	910	7	130.0	1.9	4.6	0.0	47.5
Area 1 Relative Sunshine Duration [%]							
Measurement	910	7	130.0	50.8	34.6	0.0	100.0
0-day forecast	910	7	130.0	64.5	33.7	0.0	100.0
Area 1 Daytime Minimum Temperature [°C]							
Measurement	910	7	130.0	-5.1	4.2	-20.7	3.3
0-day forecast	910	7	130.0	-6.4	4.2	-23.5	2.1
Area 1 Indices							
Sunshine index	910	7	130.0	50.8	34.6	0.0	100.0
Precipitation index	910	7	130.0	89.7	21.2	0.0	100.0
Minimum temperature index	910	7	130.0	72.4	16.3	33.8	100.0
Weather index	910	7	130.0	70.6	17.9	0.0	99.4
0-day forecast index	910	7	130.0	74.7	22.2	0.0	98.4
0-day error (forecast − weather)	910	7	130.0	0.0	12.0	-59.4	42.6

Table Notes: Column s indicates the number of seasons that are covered and column $\overline{d}$ indicates the average number of days per season (as the panel is unbalanced).

are the potential of type B agents to ski on that day. They number to B_{ds} and are solely determined by the distance of the respective cost threshold c^w to $\bar{c}$ and the distribution of individuals with costs in that range. Second, for each season day d in season s there is a set of $\mathcal{A}_{ds}$ individuals that are the potential of type A agents to ski on that day. They number to A_{ds}. Demand on a given day can then be decomposed into

$$E[y|w,f] = E[B|w] + E[A|f] \tag{15}$$

where $E[B|w] = \sum_{i=1}^{\mathcal{B}} \mathbb{1}\left[c_i(s,t=1) \in [c^w, \bar{c}[\right]$ and $E[A|f] = \sum_{i=1}^{\mathcal{A}} \mathbb{1}\left[c_i(s,t=1) \in [c^f, 1[\right]$. The large variation in potential skiers in $\mathcal{B}_{ds}$ and $\mathcal{A}_{ds}$ between season days due to weekends, holidays and school vacation is absorbed by the fixed effect α_d and the Easter dummy o_{ds}. The coefficients $\hat{\beta} - \hat{\delta}$[14] recover the net average partial effect of the weather on the demand of type B agents $\partial y/\partial w = \partial B/\partial w$ across all seasons s and days d. This works as the weather outcome has no direct influence on the number of type A agents. Note that these partial effects are increasing in the number of potential type B agents. At the same time, a demand change induced by the forecast $\partial y/\partial f$ affects only type A agents in the model and is, thus, identified as $\partial A/\partial f = \hat{\delta}$.

To test proposition 2, whether forecast errors are more volatile the higher the share of potential type A agents, model (14) is extended by variation across different groups. The model reads then

$$log(y_{dsg}) = w_{ds}\beta_0 + e_{ds}^{d-h}\delta_0 + \sum_{g=1}^{G}(D_g\gamma_g + w_{ds} \times D_g\beta_g + e_{ds}^{d-h} \times D_g\delta_g) + \alpha_d + o_{ds}\nu + \varepsilon_{dsg}, \tag{16}$$

where D_g is a dummy variable that equals 1 for observations that belong to group $g \in G$ and 0 otherwise. γ_g recovers the group fixed effect relative to the reference group (where $D_g = 0\,\forall g$), β_g the weather interaction effect of group g relative to the reference group and δ_g the forecast error interaction effect of group g relative to the reference group. All other coefficients are defined as in (14).

I implicitly assume here that the distribution of cost heterogeneity and the cost thresholds for type A and type B agents are the same. Under this assumption, the partial effects $\hat{\beta} - \hat{\delta}$ and $\hat{\delta}$ are equal if the number of both groups and the standard deviation of w and e are of the

[14]Note that (14) can be rewritten as $log(y_{ds}) = w_{ds}\beta + (f_{ds}^{d-h} - w_{ds})\delta + \alpha_d + o_{ds}\nu + \varepsilon_{ds}$ where the average partial effect of the weather is straightforward. This model is chosen because it is easily adapted to the context of optimistic and pessimistic forecasts.

same size. From changes in type A and type B agents through weather and forecast effects, I recover the share of these groups among all weather-sensitive skiers. For example, when one standard deviation of the weather changes overall demand by, say, 30% while keeping the forecast constant (net weather effect) and one standard deviation of the forecast error changes demand of type A agents by 15% while keeping the weather constant (net forecast effect). Then the share of type A agents among all weather-sensitive agents is estimated at around $15/(15 + 30) = 1/3$. Using this property and the average partial effects from (16) recover the share of type A agents for different groups as

$$\begin{aligned} S_g^A :=& \frac{\%\Delta A_g}{\%\Delta(A_g + B_g)} \\ =& \frac{exp\big((\hat{\delta}_0 + D_g\hat{\delta}_g)\hat{\sigma}_e\big) - 1}{\Big(exp\big((\hat{\delta}_0 + D_g\hat{\delta}_g)\hat{\sigma}_e\big) - 1\Big) + \Big(exp\big((\hat{\beta}_0 + D_g\hat{\beta}_g - \hat{\delta}_0 - D_g\hat{\delta}_g)\hat{\sigma_w}\big) - 1\Big)}, \end{aligned} \tag{17}$$

where $\hat{\sigma}_e$ and $\hat{\sigma}_w$ are standard deviations of forecast errors and weather, respectively. Computing these shares for different groups allows for testing of differences across groups. For example, one-day pass owners are expected to consist of relatively more type A agents than season-pass owners because the latter are typically local residents that have relatively low switching costs. Therefore, differences across these two groups would confirm proposition 2.

To test proposition 3, whether asymmetric error effects prevail, model 16 is further extended using slope dummies. I estimate

$$\begin{aligned} log(y_{dsg}) =& w_{ds}\beta_0 + e_{ds}^{d-h}\delta_0 + [e_{ds}^{d-h} \times \tilde{D}_{ds}]\lambda_0 \\ &+ \sum_{g=1}^{G} \big(D_g\gamma_g + [w_{ds} \times D_g]\beta_g + [e_{ds}^{d-h} \times D_g]\delta_g + [e_{ds}^{d-h} \times \tilde{D}_{ds} \times D_g]\lambda_g\big) \\ &+ \alpha_d + o_{ds}\nu + \varepsilon_{dsg}, \end{aligned} \tag{18}$$

where $\tilde{D}_{ds} = \mathbb{1}[e_{ds}^{d-h} > 0]$ is a slope dummy indicating optimistic forecasts. All other variables/coefficients are defined as in (16). This model allows for heterogeneous weather effects and heterogeneous two-sided error effects across the observed groups and in the aggregate (aggregate demand is then simply specified as one group and the sum in (18) drops out). In particular, optimistic and pessimistic error effects are distinguishable by the slope change in λ_0 for each group and can be tested in line with proposition 3.

5 Results

I estimate the aggregate model (14) by a least-squares dummy variable estimator (LSDV) separately for each ski area and forecast horizon. The results are presented in Table 2. In all areas and across all forecast horizons the weather index has a larger impact on demand than the forecast error. Apart from area 3, all forecast errors are statistically significantly different from zero partially confirming proposition 1 that forecast errors affect skiing demand above the weather effect. A change in the weather index by one standard deviation is associated with a 58%[15], 41% and 63% change in skier demand in areas 1 to 3 holding all else equal, respectively.

Table 2 further indicates the effects of forecast errors. I estimate that a change of a 0-day forecast error by one standard deviation changes demand, all else equal, by 14%, 12% and 6% in area 1,2 and 3, respectively. The effects for the 1-day and the 2-day forecast errors are slightly lower but around the same magnitude. Also, the closer the forecast horizon, the better it matches the (expected) final decision timing of type A agents[16]. Next, zooming further into group heterogeneities reveals that the low coefficients on forecast errors in area 3 originate from differences in the guest structure that blur effects in the aggregate.

[15] The Taylor approximation to interpret semi-elasticities in log-linear models as percentage changes is not feasible for large coefficients. Exact values are used here, where $\%\Delta y = exp(\Delta\beta * \sigma_w) - 1$

[16] The decision on the intention to ski might happen quite earlier than the final decision. I expect type A agents to decide at the latest on the eve of the day. At this point, skiing might still be called off without any investment into the decision. But as soon as the gear is packed and the alarm clock is set, agents will be much more hesitant to call it off due to the sunk cost fallacy (Arkes & Blumer, 1985)

Table 2: Effect of weather and forecast error on aggregate log demand

Dependent variable	Log demand, area 1			Log demand, area 2			Log demand, area 3		
	0-day forecast	1-day forecast	2-day forecast	0-day forecast	1-day forecast	2-day forecast	0-day forecast	1-day forecast	2-day forecast
Main effects									
Gross weather	0.025***	0.026***	0.026***	0.017***	0.017***	0.018***	0.024***	0.024***	0.024***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Forecast error	0.011***	0.007***	0.005***	0.010***	0.009***	0.009***	0.006*	0.002	0.004
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Controls									
Easter dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Season day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Season fixed effects	No	No	No	No	No	No	No	No	No
N	910	910	910	1137	1137	1137	1196	1196	1196
R^2	0.796	0.790	0.787	0.700	0.699	0.701	0.760	0.758	0.759

Standard errors in parentheses and clustered at season day level

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table Notes: The table depicts LSDV estimates of model (14) for three areas and three forecast horizons. Standard errors are clustered at the season day level to account for intra-day correlations across seasons (seasonality). Demand in area 1 consists of one-day pass purchases valid for the day in question. Other passes in area 1 are not used due to data limitations. Demand in areas 2 and 3 are the aggregated first entries across all pass categories. The weather (w_{ds}) and (here) not visible forecast (f_{ds}^{-h}) indices are continuous, scaled between 0 and 100, and based on weighted partial indices of precipitation, sunshine and minimum temperature as defined in Section 3.2. The forecast error variable $e_{ds}^{h} = f_{ds}^{h} - w_{ds}$ is the difference between weather and forecast. The Easter dummy indicates the four Easter holidays (Good Friday to Easter Monday). All models are estimated using season day fixed effects to account for the seasonality. As no time trends in effects are expected no season fixed effects were included.

For this, demand is disaggregated into one-day and season pass owners in areas 2 and 3. The comparison between the two pass types is interesting because it allows a differentiated view of groups that closely resemble typical type A and B agents. One-day pass owners are mostly day-trippers that face large switching costs and decide relatively early. Hence, many type A agents are expected in that group. On the contrary, season pass owners tend to be second-home owners, local residents or regular overnight guests that have little or no gain from an early decision and correspond more to type B agents. On top of that, these two ticket types generate around two-thirds of all first-entries[17] and involve fewer sunk cost effects from early bought tickets compared to week passes or other multi-day passes[18]. Table 3 reveals that 0-day error effects are statistically different from zero for all one-day pass owners but not necessarily for season pass owners across both areas. Proposition 1 is confirmed for one-day pass owners in all three areas.

Furthermore, recovering the shares of type A agents using (17) and testing for the difference between the two types confirms Proposition 2: The share of type A agents in one-day pass owners is around 32 or 17 percentage points higher than in season pass owners and amount to somewhere around 55% or 25% in the preferred specification (column 2) in area 2 and 3, respectively. Notice that type A agents are probably underestimated because these types are only identified on days when forecasts deviate from the weather. During periods of good and stable large-scale weather situations forecasts and weather variables run perfectly aligned and, thus, an early decision by a type A agent would not be identified as such.

Another interesting pattern across pass validity types that fits with the theory is the difference in gross weather effects. The overall average gross weather effect is likely underestimated in multi-day pass owners and overestimated in one-day pass owners because of the overnight guests' selective behavior within the two groups. Weather-sensitive overnight guests with relatively low opportunity costs tend to buy one-day passes to keep their overall expected expenditures in line with actual consumption whereas those with a higher opportunity cost would buy multi-day passes to gain from cheaper daily prices. The former group at the left tail of the opportunity cost distribution face then additional transaction costs to buy the one-day pass at the counter, making them less likely to purchase a ticket and shifting their opportunity cost $c_i(a)$ even lower. The latter group's opportunity cost at the right tail of the alternative cost distribution rises even more as they might be susceptible to the

[17]62% in area 2 and 69% in area 3, see Figure 5 in Appendix C.1

[18]One can think of three reasons why a typical overnight stayer buys a multiday-pass: First, she is not weather-sensitive and expects to ski independent of the weather. Second, the forecast indicates good weather throughout the stay. Third, she values convenience and has no financial constraints to do so. The former two types might fall for the sunk cost fallacy and might thus decide in favor of skiing even if this does not represent their rational choice (Arkes & Blumer, 1985).

sunk cost fallacy. Furthermore, note that this behavior could be expected independently of whether an agent is of type A or B. As I cannot discriminate between different guest groups within pass owners, the evidence for this remains suggestive. In line with these theoretical derivations, the top panel in Table 3 indicates larger gross weather effects for one-day passes than season pass owners (and other multi-day pass owners as reported in Table 11 in Appendix C.4).

Table 3: Effect of weather and forecast error on log demand of one-day pass and season pass owners

Dependent variable	Log demand, area 2				Log demand, area 3			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Gross weather effects								
One-day pass owners	0.022***	0.023***	0.021***	0.021***	0.030***	0.030***	0.030***	0.031***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Season pass owners	0.016***	0.018***	0.015***	0.017***	0.024***	0.026***	0.024***	0.026***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
0-day error effects								
One-day pass owners	0.013***	0.015***	0.009***	0.011***	0.011***	0.012***	0.009***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Season pass owners	0.005***	0.007***	0.001	0.002	0.004	0.004	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Share of type A agents								
One-day pass owners	0.456***	0.548***	0.264**	0.353***	0.212***	0.247***	0.175***	0.204***
	(0.099)	(0.107)	(0.086)	(0.093)	(0.055)	(0.057)	(0.050)	(0.052)
Season pass owners	0.204*	0.233**	0.022	0.062	0.092	0.081	0.060	0.050
	(0.082)	(0.071)	(0.067)	(0.058)	(0.055)	(0.047)	(0.050)	(0.043)
Difference in shares								
One-day − Season pass	0.253**	0.315***	0.243***	0.292***	0.120**	0.166***	0.115**	0.154***
	(0.087)	(0.086)	(0.071)	(0.074)	(0.044)	(0.043)	(0.040)	(0.038)
Controls								
Easter dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pass-type fixed effects	Yes	-	Yes	-	Yes	-	Yes	-
Season day fixed effects	Yes	-	Yes	-	Yes	-	Yes	-
Day-by-pass fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Season fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
N	4,829	4,829	4,829	4,829	5,370	5,370	5,370	5,370
R^2	0.593	0.735	0.617	0.757	0.726	0.841	0.732	0.847

Standard errors in parentheses and clustered at season day level

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table Notes: The table depicts LSDV estimates of model (16) where the groups are separated by different pass validity categories using four specifications across two areas. Standard errors are clustered at the season day level to account for intra-day correlations across seasons. The weather (w_{ds}) and (here) not visible forecast (f^0_{ds}) indices are continuous, scaled between 0 and 100 and based on weighted partial indices of precipitation, sunshine and minimum temperature. The 0-day error variable $e^0_{ds} = f^0_{ds} - w_{ds}$ is the difference between weather and 0-day forecast. Demand is the aggregated first entries for one-day passes or season pass owners. Season pass owners hold a season pass or any other pass valid for more than 14 days. Shares of type A agents and differences between the shares are recovered by a nonlinear combination of point estimates using the delta method (See Equation (17)). Easter is a dummy indicating the four Easter holidays (Good Friday to Easter Monday). Each specification includes season day and pass-type fixed effects whereby specifications (2) and (4) include an interaction of the two. Season fixed effects control for possible time trends and are included in specifications (3) and (4).

In the next step, I turn to asymmetric reactions of forecast errors by including a slope dummy on the forecast error as in (18). So far I showed that most variation from error effects originate from one-day pass owners as they are the only group with a sizable share of type A agents. Therefore, restricting the sample to one-day pass owners, I find that pessimistic errors are significantly more prevalent in area 1 and yield larger but not statistically significant effects in areas 2 and 3. Consider Table 4 for this. A pessimistic 0-day forecast of one standard deviation reduces demand all else equal by 17%, 12% and 8% compared to days with accurate forecasts in areas 1, 2 and 3, respectively. An optimistic 0-day forecast of one standard deviation, on the other hand, increases demand all else equal by 3%, 8% and 8% for the respective three areas. The difference between both error directions is only in area 1 significant at the 5% level. Notice also the previously described tendency of weather-sensitive overnight guests to choose one-day passes. Such a selection would lead to a pessimistic reaction due to the right-skewed opportunity costs.

Another channel of pushing demand reactions toward pessimistic errors is risk aversion. To further investigate this, one-day pass owners are split by age groups[19]. Table 5 shows that forecast reactions are dominated by pessimistic errors in all areas and in areas 2 and 3 more so for children. This is in line with the expectation that families tend to be more risk averse than single adults (Dore et al., 2014).[20] Nevertheless, as only a few of the asymmetric effects are significant and additional robustness checks (Table 14 in Appendix D.3) neither confirm this result, the empirical investigation of Proposition 3 is only suggestive.

[19] Children enter the area most likely not on their own. As I do not observe who enters the area with whom, I allocate one adult to each child entering the area.

[20] Parents tend to make more risk averse choices for their children than for themselves (Dore et al., 2014). In this case, adults would avoid the risk of getting caught in a snowstorm with low visibility and strong winds more when the additional responsibility for a child is borne.

Table 4: Effect of weather and optimistic/pessimistic forecast errors on log demand for one-day pass owners

Dependent variable	Log demand, area 1		Log demand, area 2		Log demand, area 3	
	(1)	(2)	(1)	(2)	(1)	(2)
Main effects						
Weather	0.024^{***}	0.024^{***}	0.021^{***}	0.020^{***}	0.030^{***}	0.031^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Optimistic error	0.004	0.003	0.010^{***}	0.006	0.011^{***}	0.010^{***}
	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
Pessimistic error	0.016^{***}	0.018^{***}	0.018^{***}	0.015^{***}	0.010^{*}	0.012^{***}
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Asymmetric effects						
Optimistic − Pessimistic error	-0.012^{*}	-0.014^{*}	-0.008	-0.009	0.001	-0.002
	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.005)
Controls						
Easter dummy	Yes	Yes	Yes	Yes	Yes	Yes
Season day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Season fixed effects	No	Yes	No	Yes	No	Yes
N	910	910	1,099	1,099	1,154	1,154
R^2	0.797	0.806	0.678	0.709	0.798	0.819

Standard errors in parentheses and clustered at season day level

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table Notes: The table depicts LSDV estimates of model (18) for one-day pass owners in three areas. Standard errors are clustered on the season day to account for intra-day correlations across seasons (seasonality). To allow a comparison between the areas only one-day passes are used. The weather (w_{ds}) and (here) not visible forecast (f_{ds}^0) indices are continuous, scaled between 0 and 100 and based on weighted partial indices of precipitation, sunshine and minimum temperature. The 0-day error variable $e_{ds}^0 = f_{ds}^0 - w_{ds}$ is the difference between weather and 0-day forecast and is interacted with a dummy variable $\tilde{D}_{ds} = \mathbb{1}[(f_{ds}^0 - w_{ds}) > 0]$ to allow for a slope change in optimistic forecasts. Easter is a dummy indicating the four Easter holidays (Good Friday to Easter Monday). Each specification includes season day fixed effects and specification (2) includes season fixed effects.

Table 5: Asymmetric effects of weather and forecast error on log demand of one-day pass owners

dependent variable	log demand, area 1				log demand, area 2				log demand, area 3			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Weather effects												
Adults	0.027***	0.026***	0.027***	0.026***	0.022***	0.022***	0.021***	0.021***	0.032***	0.032***	0.033***	0.032***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Adolescents	0.012***	0.013***	0.013***	0.013***	0.017***	0.016***	0.015***	0.014***	0.017***	0.017***	0.018***	0.018***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Children	0.015***	0.017***	0.015***	0.017***	0.017***	0.017***	0.015***	0.015***	0.019***	0.020***	0.020***	0.021***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Optimistic error effects												
Adults	0.003	0.005	0.003	0.004	0.016***	0.014***	0.011***	0.009***	0.014***	0.014***	0.013***	0.014***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Adolescents	−0.001	−0.004	−0.001	−0.003	0.007	0.009	0.002	0.005	0.008*	0.009*	0.007	0.009*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)	(0.003)	(0.004)	(0.004)	(0.004)
Children	0.001	0.001	0.001	0.001	0.010*	0.008	0.004	0.003	0.009*	0.007	0.007	0.006
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Pessimistic error effects												
Adults	0.016***	0.018***	0.017***	0.019***	0.011*	0.013***	0.007	0.009*	0.013***	0.011***	0.014***	0.012***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Adolescents	0.004	0.004	0.005	0.005	0.026***	0.020***	0.019***	0.015***	0.006	0.011***	0.007*	0.012***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.006)	(0.006)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
Children	0.015***	0.012***	0.016***	0.013***	0.014***	0.017***	0.009	0.013*	0.013***	0.011***	0.014***	0.013***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)	(0.005)	(0.006)	(0.003)	(0.004)	(0.003)	(0.004)
Asymmetric effects												
Optimistic − Pessimistic, adults	−0.013	−0.013	−0.014*	−0.014*	0.005	0.001	0.004	0.001	0.001	0.004	−0.001	0.002
	(0.007)	(0.007)	(0.006)	(0.007)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Optimistic − Pessimistic, adolescents	−0.005	−0.008	−0.006	−0.008	−0.019*	−0.010	−0.017*	−0.010	0.002	−0.001	−0.000	−0.003
	(0.006)	(0.006)	(0.006)	(0.006)	(0.009)	(0.009)	(0.008)	(0.008)	(0.005)	(0.006)	(0.005)	(0.005)
Optimistic − Pessimistic, children	−0.015	−0.011	−0.015*	−0.012	−0.005	−0.009	−0.005	−0.010	−0.004	−0.005	−0.006	−0.007
	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)	(0.009)	(0.006)	(0.007)	(0.006)	(0.007)
Controls												
Easter dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age category fixed effects	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-
Season day fixed effects	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-
Day-by-age fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Season fixed effects	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
N	2,150	2,150	2,150	2,150	2,437	2,437	2,437	2,437	2,906	2,906	2,906	2,906
R^2	0.790	0.846	0.794	0.850	0.625	0.705	0.655	0.729	0.795	0.834	0.801	0.840

Standard errors in parentheses and clustered at season day level

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table Notes: The table depicts LSDV estimates of model (18) for one-day pass owners in three areas. Standard errors are clustered on the season day to account for intra-day correlations across seasons (seasonality). To allow a comparison between the areas only one-day passes are used. The weather (w_{ds}) and (here) not visible forecast (f^0_{ds}) indices are continuous, scaled between 0 and 100 and based on weighted partial indices of precipitation, sunshine and minimum temperature. The 0-day error variable $e^0_{ds} = f^0_{ds} - w_{ds}$ is the difference between weather and 0-day forecast and is interacted with a dummy variable $\tilde{D}_{ds} = \mathbb{1}[(f^0_{ds} - w_{ds}) > 0]$ to allow for a slope change in optimistic forecasts. Easter is a dummy indicating the four Easter holidays (Good Friday to Easter Monday). Each specification includes season day and pass-type fixed effects whereby specifications (2) and (4) include an interaction of the two. Season fixed effects control for possible time trends and are included in specifications (3) and (4).

6 Discussion

Regarding weather and forecasts, I suggest a few principles to what ski area operators should pay attention to when implementing new pricing schemes. Up to now, most weather-related pricing schemes only implement price increases in case of good weather expectations in order not to interfere with early bookers' discounts[21] (Lütolf et al., 2020). Yet, these price increases always build upon weather forecasts at horizons up to 5 days in advance that could potentially turn out optimistic. Worse-than-expected weather coupled with higher paid prices seems like a bad deal for anyone. Thus, pricing should not depend on supposedly precise local weather forecasts but rather on the large-scale weather situation.

Lower prices could be optimal when the large-scale situation is uncertain (i.e. Foehn or west wind situations in the Alps) and forecast errors in either direction might materialize. Then, on a day with worse-than-expected weather (i.e. optimistic forecast), lower prices reduce the individual risk of having large and salient out-of-pocket expenses for a mediocre skiing experience. The increased demand enhances reactions to optimistic forecasts as more agents decide to ski in relatively bad conditions. Conversely, on a day with better-than-expected weather (i.e. pessimistic forecast), a low price might be perceived as a win-win for the customer and potentially has a great effect on satisfaction. When the large-scale situation brings certainly good weather (i.e. high pressure system or Bise), higher prices can be set almost risk-free. Analyzing such pricing strategies based on large-scale situations is a viable road for future research.

Next, instead of using dynamic prices an operator could refund sold tickets in the case of worse-than-expected weather outcomes and allow customers to switch the paid price of ski passes for alternative activities within the destination. This counteracts the sunk cost fallacy: The customer's urge to make use of already paid tickets and ski in otherwise unwanted conditions is reduced. In practice, such a refund works better when firms are horizontally integrated within the area or agree on shared profits for refunded tickets.

In order to consider future research proceedings from the above results, some limitations are discussed here. First, the aggregate data permits a detailed analysis on an individual level. The relatively large differences in results between areas suggest that differing contexts or guest structures add up in various ways to aggregate estimates. Using more detailed individual-level data that tracks individuals in their purchase and consumption timing to

[21] Early bookers' discounts work because agents are certain that an early purchase comes at a financial benefit. Lowering prices due to bad weather forecasts would interfere with that certainty. Why would anyone buy a one-day pass early on when prices might fall below the discount later on? (Lütolf et al., 2020)

investigate asymmetric patterns is an interesting avenue for future research.

Second, the forecast data originates from one service provider and, towards the end of the time period, already outdated model outputs. Covering ten years of weather forecast data has the caveat that technological progress advances at a higher pace than a single forecast model is in use. Thus, the data of the COSMO-7 model outputs might be slightly different from what was actually depicted online or in the app via pictograms. Especially in the later seasons of data. Nonetheless, as the pictograms are monotonous transformations from forecast data, the variation from these transformations or to other forecast providers are likely substantially smaller than the variation within the forecast data itself. Using data from more than one service provider could confirm this hypothesis.

Third, the above results are documented in the context of ski area entrances. However, the relevance of winter sports activities is decreasing as many ski area operators and classic winter sports destinations are expanding their businesses to all four seasons due to rising temperatures and a decreasing snowpack (Gonseth & Matasci, 2011; Koenig & Abegg, 1997; Plaz & Schmid, 2015). Nevertheless, the decision framework applies to any outdoor activity that involves high switching costs. In particular, any outdoor activity that requires traveling, local infrastructure and technical gear. That includes mountain biking and to a lesser extent also mountaineering, climbing and hiking. More broadly, most water-related outdoor sports such as sailing or kite-surfing are to a large extent similar too. Therefore, it is a valuable avenue for further research to test the propositions from the theory in other contexts.

7 Conclusion

In this paper, I show theoretically and empirically that individuals evaluate their outdoor activities by trading off costs and values that largely depend on the weather and prior information in the form of forecasts. The theory implies that two dimensions of heterogeneities have to be considered in the case of skiing. First, whether switching costs are substantial, and second, how opportunity costs are distributed across individuals. As individuals evaluate the value and costs of skiing against alternative opportunities at different stages in time, their final decision amounts to an aggregate demand that varies with forecast errors of the weather. Sometimes, these reactions are larger when the forecast is pessimistic rather than optimistic. Such large pessimistic reactions might occur because of right-skewed opportunity costs, risk-averse agents or because good weather outcomes are easier to predict accurately than bad weather outcomes.

In the empirical part, I show that forecast errors affect aggregate demand both ways depending on the sign of the error. I find pessimistic errors reduce demand and optimistic errors increase demand relative to correct forecasts using data from three ski areas. The effects are substantial and significant in both directions across different pass owner types and age groups. Generally, weather forecasts affect only those that have high switching costs and, by that, are forced to stick to a plan. These are typically day-trippers and families. As a substantial share of potential skiers consists of overnight guests and residents with low or no switching costs at all, spontaneous skiers make up a large share of overall demand. On top of that, the estimates hint at asymmetric effects of optimistic versus pessimistic forecasts but remain suggestive overall.

The paper extends the literature that looks at how weather variables affect skiing demand (Malasevska & Haugom, 2018; Malasevska et al., 2017b; Shih et al., 2009) and pricing strategies of ski area operators (Falk, 2015; Falk & Scaglione, 2018; Lütolf et al., 2020; Malasevska et al., 2020; Wallimann, 2019) by linking it to the literature that incorporates forecast data in decision-making processes (Cerdá Tena & Quiroga Gómez, 2011; Jewson et al., 2021; Katz & Lazo, 2012; Katz et al., 1982). Going from here, there is still much to be learned for future researchers. For example, by using individual-level purchase and consumption data to study the theoretical insights more thoroughly, by looking at pricing strategies incorporating large-scale weather situations or by testing the theoretical propositions in weather-related contexts other than skiing.

8 Literature

References

Arkes, H. R., & Blumer, C. (1985). The psychology of sunk cost. *Organizational Behavior and Human Decision Processes*, *35*(1), 124–140. https://doi.org/10.1016/0749-5978(85)90049-4

Carson, R., & Yu, C. A. (2020). Sources and Nature of Measurement Error in Estimating Climate Related Impacts, 1–66.

Cerdá Tena, E., & Quiroga Gómez, S. (2011). Economic value of weather forecasting: the role of risk aversion. *TOP*, *19*(1), 130–149. https://doi.org/10.1007/s11750-009-0114-3

Dore, R. A., Stone, E. R., & Buchanan, C. M. (2014). A Social Values Analysis of Parental Decision Making. *The Journal of Psychology*, *148*(4), 477–504. https://doi.org/10.1080/00223980.2013.808603

Elsasser, H., & Bürki, R. (2002). Climate change as a threat to tourism in the Alps. *Climate Research*, *20*(3), 253–257. https://doi.org/10.3354/cr020253

Falk, M. (2015). Return on Investments in New Ski Lifts : The Importance of Weather Conditions and Elevation. (February).

Falk, M., & Scaglione, M. (2018). Effects of ski lift ticket discounts on local tourism demand. *Tourism Review*, *73*(4), 480–491. https://doi.org/10.1108/TR-08-2017-0133

Fan, J., & Gijbels, I. (1996). *Local Polynomial Modelling and Its Applications: Monographs on Statistics and Applied Probability 66* (1st). Routledge. https://doi.org/https://doi.org/10.1201/9780203748725

Gonseth, C. (2013). Impact of snow variability on the Swiss winter tourism sector: Implications in an era of climate change. *Climatic Change*, *119*(2), 307–320. https://doi.org/10.1007/s10584-013-0718-3

Gonseth, C., & Matasci, C. (2011). Analysis of the sensitivity of ski tourism demand to climate change in Switzerland. *Managing Alpine Future II - Inspire and drive sustainable mountain regions*, 257–267. http://infoscience.epfl.ch/record/167138

Gössling, S., Scott, D., Hall, C. M., Ceron, J. P., & Dubois, G. (2012). Consumer behaviour and demand response of tourists to climate change. *Annals of Tourism Research*, *39*(1), 36–58. https://doi.org/10.1016/j.annals.2011.11.002

Hastie, T., Tibishirani, R., & Friedman, J. (2008). *The Elements of Statistical Learning*. https://doi.org/10.1111/j.1532-5415.1984.tb02220.x

Haugom, E., & Malasevska, I. (2019). The relative importance of ski resort- and weather-related characteristics when going alpine skiing. *Cogent Social Sciences*, *5*(1). https://doi.org/10.1080/23311886.2019.1681246

Holmgren, M. A., & McCracken, V. A. (2014). What Affects Demand for "The Greatest Snow On Earth?". *Journal of Hospitality Marketing and Management*, *23*(1), 1–20. https://doi.org/10.1080/19368623.2012.746212

Jewson, S., Scher, S., & Messori, G. (2021). Decide Now or Wait for the Next Forecast? A Decision Framework Based on an Extension of the Cost-Loss Model. *Monthly Weather Review*, *149*(6). https://doi.org/https://doi.org/10.1175/MWR-D-20-0392.1

Katz, R. W., & Lazo, J. K. (2012). *Economic Value of Weather and Climate Forecasts*. https://doi.org/10.1093/oxfordhb/9780195398649.013.0021

Katz, R. W., Murphy, A. H., & Winkler, R. L. (1982). Assessing the Value of Frost Forecasts to Orchardists: A Dynmaic Decision-Making Approach. *Journal of Applied Meteorology*, *21*.

Koenig, U., & Abegg, B. (1997). Impacts of climate change on winter tourism in the swiss alps. *Journal of Sustainable Tourism*, *5*(1), 46–58. https://doi.org/10.1080/09669589708667275

Lütolf, P., Stettler, J., Wagenseil, U., Wallimann, H., & Rohrer, B. (2020). Auswirkungen der neuen Preismodelle - Erkenntnisse für die Bergbahnbranche. *SBS Schriften*, *10*, 241.

Malasevska, I., & Haugom, E. (2018). Optimal prices for alpine ski passes. *Tourism Management*, *64*, 291–302. https://doi.org/10.1016/j.tourman.2017.09.006

Malasevska, I., Haugom, E., Hinterhuber, A., Lien, G., & Mydland, Ø. (2020). Dynamic pricing assuming demand shifting: the alpine skiing industry. *Journal of Travel and Tourism Marketing*, *37*(7), 785–803. https://doi.org/10.1080/10548408.2020.1835787

Malasevska, I., Haugom, E., & Lien, G. (2017a). Modelling and forecasting alpine skier visits. *Tourism Economics*, *23*(3), 669–679. https://doi.org/10.5367/te.2015.0524

Malasevska, I., Haugom, E., & Lien, G. (2017b). Optimal weather discounts for alpine ski passes. *Journal of Outdoor Recreation and Tourism*, *20*(May), 19–30. https://doi.org/10.1016/j.jort.2017.09.002

MeteoSchweiz. (2012). Dem Wetter einen Schritt voraus: Von der Messung bis zur Prognose, 24 pp.

MeteoSchweiz. (2015). *Typische Wetterlagen im Alpenraum* (tech. rep.).

Murphy, A. H. (1969). On Expected-Utility Measures in Cost-Loss Ratio Decision Situations. *Journal of Applied Meteorology*, *8*(6), 989–991. https://www.jstor.org/stable/26174709

Osczevski, B. Y. R., & Bluestein, M. (2005). Equivalent Temperature. *Van Nostrand's Scientific Encyclopedia*, (May), 1453–1458. https://doi.org/10.1002/0471743984.vse3032

Plaz, P., & Schmid, S. (2015). Aussichten für das Geschäft mit den alpinen Schneesportlern in Graubünden. Grundlagenberichtim Rahmen des Projekts „Strategien für Bündner Tourismusorte". https://www.wirtschaftsforum-gr.ch/uploads/files/a2_aussichten_schneesport.pdf

Rutty, M., & Andrey, J. (2014). Weather forecast use for winter recreation. *Weather, Climate, and Society*, *6*(3), 293–306. https://doi.org/10.1175/WCAS-D-13-00052.1

Scaglione, M., & Doctor, M. (2008). The impact of inaccurate weather forecasts on cable-car use, 1–12.

Scott, D., & Gössling, S. (2022). A review of research into tourism and climate change - Launching the annals of tourism research curated collection on tourism and climate change. *Annals of Tourism Research*, *95*, 103409. https://doi.org/10.1016/j.annals.2022.103409

Shih, C., Nicholls, S., & Holecek, D. F. (2009). Impact of Weather on Downhill Ski Lift Ticket Sales. *Journal of Travel Research*, *47*(3), 359–372. https://doi.org/10.1177/0047287508321207

Steiger, R., & Abegg, B. (2017). Aktuelle und zukünftige Schneesicherheit der Skigebiete in Graubünden. (January 2015). https://www.researchgate.net/publication/271210835

Steiger, R., & Abegg, B. (2018). Ski areas' competitiveness in the light of climate change: Comparative analysis in the Eastern Alps. *Tourism in Transitions*, 187–199. https://doi.org/10.1017/CBO9781107415324.004

Steinacker, R. (2006). Alpiner Föhn – eine neue Strophe zu einem alten Lied. *Promet*, *10*(1), 3–10.

Wallimann, H. (2019). A Substantial Discount on Ski Passes: A Synthetic Control Analysis. *Working Papers SES*, *507*.

Winkler, R. L., Murphy, A. H., & Katz, R. W. (1983). The value of climate information: A decision-analytic approach. *Journal of Climatology*, *3*(2), 187–197. https://doi.org/10.1002/joc.3370030208

Appendix

A Weather and Forecast Data Processing

A.1 Pool of Weather and Forecast Variables

Next to the weather variables described in Section 3.2, I additionally considered the following variables: Daytime maximum and mean temperature [°C], wind chill temperature [°C][22], fresh snow accumulated [cm][23], daily average wind speed [m/s], daily maximum wind speed (from hourly averages) [m/s], daily maximum in gusts [m/s], wind direction [°], relative humidity (daily minimum, mean and maximum) [%] and daily average air pressure [hPa].

The forecast data covers additionally to the variables described in Section 3.3 the following hourly variables released at midnight for the three time horizons described above: Average wind speed [m/s], maximum and mean temperature [°C], snowfall [kg/m^2], snowpack [cm].

All forecast data are in hourly values and weather variables such as minimum temperature and precipitation are as well. Most other values are in daytime (6-18 UTC) or in daily granularity available (0-24 UTC). Not all hours matter for the purpose of skiing the same as the ski areas are normally operating between 8 a.m. and 4 p.m. CET. Therefore, the data is aggregated into the relevant hours as shown in the next section.

A.2 Temporal Aggregation

All weather and forecast data from MeteoSchweiz are specified in coordinated universal time (UTC). However, the pictograms and the published data that users actually observe are specified in central european time (CET). In the winter months CET=UTC+1 whereas in the summer months CET=UTC+2. The time intervals used for aggregating weather and

[22] A combination of wind and temperature gives the Wind Chill Temperature (WCT). This variable indicates the perceived temperature and as such adds wind to the equation which decreases the WCT as it gets stronger. Temperatures that are too warm wet the snow that is perceived negatively by many skiers but, on the contrary, too-cold temperatures might become unbearable for a large share of skiers. (Malasevska et al., 2017a; Osczevski & Bluestein, 2005)

[23] Snowfall is already measured in the precipitation variable. Thus, the precipitation of snow is lagged one day into the future to represent the fresh snow fallen within the last 24 hours. Then the precipitation variable depicts immediate snowfall or rain. Fresh snow is expected to have a different effect on demand than daily precipitation. The former is sought by freeride-enthusiasts whereas the latter is generally considered as being bad for skiing - clouds dim the light and the falling snow or rain enhances the bad sight further (Falk, 2015; Gonseth, 2013; Holmgren & McCracken, 2014; Shih et al., 2009).

forecast data to daily observations are presented in Table 6. In order to perform a precise temporal aggregation to the depicted intervals hourly data is required. Hourly data is only for precipitation and temperature available at this granularity. All other weather data is either measured or made available at daily or daytime aggregates. As the main specifications involve temperature, precipitation and sunshine, a precise aggregation to the stated daytime intervals is only exacerbated in the sunshine variable. Fortunately, the sun shines mostly[24] within the time interval of 6.00 − 18.00 CET at the observed periods during the winter season which means that hourly and daily data are of the same quality.

Table 6: Temporal aggregation for different weather and forecast variables

variable	season time	UTC	CET
weather and forecast indices	winter	5.00 − 17.00	6.00 − 18.00
	summer	4.00 − 16.00	6.00 − 18.00
weather and forecast pictogram	winter	5.00 − 17.00	6.00 − 18.00
	summer	4.00 − 16.00	6.00 − 18.00

The three main variables used for the weather index are temporally aggregated according to the following rules:

Relative Sunshine Duration: The measured variables are in daytime values available and cover the sunshine duration relative to the maximum possible sunshine duration in percentages. The forecast values are separated into hourly sunshine duration [s] and maximum possible hourly sunshine duration [s]. Both variables are aggregated to daily values (that remain between 6-18 CET on most days) and are then divided such that the same percentage value for the forecast as in the measurement is received.

Precipitation: Precipitation measurements and forecasts are both available in hourly aggregates. Thus the daytime values are sums over the daytime hours for both variables.

Minimum Temperature: The measured as well as the forecast values are available in hourly minimum (i.e. the minimum that is measured within an hour). The resulting daytime

[24] At the very end of the season the sunshine duration might exceed 18 CET in the evening. These small overlaps should affect the measured relative sunshine duration from the effective relative sunshine duration only marginally and are also calculated in the forecast variable outside this time limit.

minimum temperature is then the lowest hourly value within the daytime hours for both variables.

A.3 Spatial Interpolation

To spatially join the highest and lowest lift with all weather stations within 30km, we use ArcGIS software to match geo-referenced data of our highest and lowest lifts and of all weather stations from MeteoSchweiz[25]. We find two types of weather stations: Those only measuring precipitation and those measuring almost all variables. The distance weighting has to be calculated for each variable in each year to account for missing data in a given year and station. The calculations are drawn from (Carson & Yu, 2020) section 3.1.2:

$$\hat{w}_{it} = \frac{\frac{w_{A,t}}{d^p_{A,i}} + \frac{w_{B,t}}{d^p_{B,i}}}{\frac{1}{d^p_{A,i}} + \frac{1}{d^p_{B,i}}} \tag{19}$$

where i is area i, t is the year, and A and B are the two weather stations within the 30km radius. $\hat{w}$ depicts the estimated weather variable, w the weather input variables and d the distance between stations A and B and area i. p is a power parameter that penalizes distance (usually $p = 2$ according to (Carson & Yu, 2020)). Rearranged and evaluated for n weather stations in the vicinity of 30km yields

$$\omega_{A,t} = \frac{\frac{1}{d^p_{A,i}}}{\sum_{s=A}^{n} \frac{1}{d^p_{s,i}}} \tag{20}$$

for station A at time t. The final weather variable is then the sum of all weather variables weighted by stations:

$$\hat{w}_{it} = \sum_{s=A}^{n} w_{s,t} \cdot \omega_{s,t}. \tag{21}$$

A.4 Variable Selection

The weather and forecast indices are derived from the three variables relative sunshine duration, precipitation and minimum temperature. To give an idea of how these raw variables relate to skiing demand and what other variables contribute to the question of how potential

[25]Weather station data is retrieved from https://www.meteoschweiz.admin.ch/home/messwerte.html?param=messnetz-automatisch

skiers react to the weather, I set up the model

$$log(y_{ds}) = W_{ds}\beta + \alpha_d + o_{ds}\nu + \varepsilon_{ds}, \tag{22}$$

where y_{ds} is the aggregate demand in one-day passes, W_{ds} is a row-vector of weather variables, α_d is the season day fixed effect that is common across seasons for the same day but varies across season days, o_{ds} is a dummy indicating Easter holidays and ε_{ds} is the idiosyncratic error term. This regression is estimated using OLS and presented in Tables 7, 8 and 9 for the three areas, respectively. The specification in column (1) uses the three main variables only. Column (2) adds season fixed effects and column (3) adds a squared term for the minimum temperature. The latter column represents basically what is used in the specifications with the weather index as temperature enters the index in a quadratic way as well. All further columns show additional weather variables that could be relevant for skiing but turn out to be of relatively little importance compared to the four main variables.

The relative relevance of weather variables is further investigated by the use of random forests (RF). The idea is to find the key variables explaining skiing demand to create a weather and forecast index that proxies actual and expected skiing conditions in a single variable. First, I grow a RF on (22) including the full set of available weather variables (described in Appendix A.1) in addition to all season day dummy variables. Then, the out-of-bag (OOB) root-mean-squared error (RMSE) rate for the RF is computed. This validation technique uses part of the data as training set and the remaining data as test set to validate the prediction accuracy of the RF. The RF grows random trees and uses for each tree around two-thirds of the bootstrapped observations. On top of that, it tests the accuracy with the remaining third of observations that were not used in growing the tree. If the number of trees grown is sufficiently large, the OOB can be shown to be equivalent to the leave-one-out cross validation (LOOCV) (Hastie et al., 2008).

The OOB is also used to estimate variable importance. By randomly permuting a variable in the OOB sample, comparing the MSE to the one obtained by the original variable and averaging this over all trees, the decrease in the prediction accuracy of each variable is measured (Hastie et al., 2008). Another option would be to use the Lasso estimator and evaluate which parameters of weather variables are shrunk to zero at the latest (while increasing the shrinking parameter λ). Because the data includes many potential predictors that are highly collinear (e.g. maximum and minimum temperature) OLS and likewise Lasso might struggle in separating the effects of the collinear variables. The variable importance measure com-

Table 7: Variable selection area 1

Dependent variable	log demand, area 1						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Weather variables							
Relative sunshine duration [%]	0.009***	0.009***	0.010***	0.009***	0.009***	0.009***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Precipitation [mm]	−0.065***	−0.064***	−0.065***	−0.064***	−0.064***	−0.066***	−0.065***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.015)	(0.015)
Minimum temperature [°C]	−0.010	−0.008	−0.031*	−0.031*	−0.031*	−0.029*	−0.033*
	(0.006)	(0.006)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Minimum temperature^2 [°C]			−0.002*	−0.046*	−0.002	0.017	−0.005*
			(0.001)	(0.018)	(0.006)	(0.011)	(0.002)
Average wind speed [m/s]				−0.046*	−0.002	0.017	−0.005*
				(0.018)	(0.006)	(0.011)	(0.002)
Fresh snow [cm]					−0.045*	−0.001	0.019
					(0.018)	(0.006)	(0.011)
Maximum gust of wind [m/s]						−0.083*	0.001
						(0.030)	(0.006)
Relative humidity [%]							−0.093***
							(0.031)
Controls							
Easter dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Season day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Season fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
N	910	910	910	910	910	910	910
R^2	0.778	0.785	0.786	0.789	0.789	0.790	0.793

Standard errors in parentheses and clustered at season day level

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table Notes: The table depicts LSDV estimates of model (22) for area 1. Standard errors are clustered at the season day level to account for intra-day correlations across seasons (seasonality). Demand consists of one-day pass purchases valid for the day in question. Other passes in area 1 are not used due to data limitations. The weather variables are daytime aggregates and scaled according to their unit in square brackets. The Easter dummy indicates the four Easter holidays (Good Friday to Easter Monday). All models are estimated using season day fixed effects to account for the seasonality.

Table 8: Variable selection area 2

Dependent variable	log demand, area 2						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Weather variables							
Relative sunshine duration [%]	0.006***	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Precipitation [mm]	−0.047***	−0.040***	−0.040***	−0.040***	−0.040***	−0.043***	−0.041***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)
Minimum temperature [°C]	−0.029***	−0.021***	−0.048***	−0.048***	−0.048***	−0.047***	−0.048***
	(0.006)	(0.006)	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)
Minimum temperature^2 [°C]			−0.002*	−0.003	−0.001	0.028	−0.004
			(0.001)	(0.033)	(0.003)	(0.017)	(0.002)
Average wind speed [m/s]				−0.003	−0.001	0.028	−0.004
				(0.033)	(0.003)	(0.017)	(0.002)
Fresh snow [cm]					−0.002	−0.001	0.028
					(0.034)	(0.003)	(0.017)
Maximum gust of wind [m/s]						−0.088	−0.000
						(0.064)	(0.003)
Relative humidity [%]							−0.106
							(0.068)
Controls							
Easter dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Season day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Season fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
N	1,099	1,099	1,099	1,099	1,098	1,098	1,098
R^2	0.654	0.695	0.696	0.696	0.696	0.697	0.698

Standard errors in parentheses and clustered at season day level

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table Notes: The table depicts LSDV estimates of model (22) for area 2. Standard errors are clustered at the season day level to account for intra-day correlations across seasons (seasonality). Demand is aggregated first entries across all pass categories. The weather variables are daytime aggregates and scaled according to their unit in square brackets. The Easter dummy indicates the four Easter holidays (Good Friday to Easter Monday). All models are estimated using season day fixed effects to account for the seasonality.

Table 9: Variable selection area 3

Dependent variable	log demand, area 3						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Weather variables							
Relative sunshine duration [%]	0.010***	0.011***	0.011***	0.011***	0.011***	0.011***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Precipitation [mm]	−0.093***	−0.093***	−0.094***	−0.092***	−0.091***	−0.091***	−0.083***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Minimum temperature [°C]	−0.024***	−0.023***	−0.044***	−0.041***	−0.043***	−0.043***	−0.051***
	(0.005)	(0.006)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Minimum temperature^2 [°C]			−0.002***	−0.023	−0.004	0.014	−0.010***
			(0.001)	(0.037)	(0.004)	(0.013)	(0.002)
Average wind speed [m/s]				−0.023	−0.004	0.014	−0.010***
				(0.037)	(0.004)	(0.013)	(0.002)
Fresh snow [cm]					−0.021	−0.004	0.009
					(0.037)	(0.004)	(0.012)
Maximum gust of wind [m/s]						−0.072	0.001
						(0.050)	(0.004)
Relative humidity [%]							−0.101*
							(0.048)
Controls							
Easter dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Season day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Season fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
N	1,154	1,154	1,154	1,154	1,153	1,153	1,153
R^2	0.786	0.809	0.812	0.812	0.812	0.813	0.818

Standard errors in parentheses and clustered at season day level

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table Notes: The table depicts LSDV estimates of model (22) for area 3. Standard errors are clustered at the season day level to account for intra-day correlations across seasons (seasonality). Demand is aggregated first-entries across all pass categories. The weather variables are daytime aggregates and scaled according to their unit in square brackets. The Easter dummy indicates the four Easter holidays (Good Friday to Easter Monday). All models are estimated using season day fixed effects to account for the seasonality.

puted by RF does not suffer from this limitation. Hence, I refrain from other methods to compute variable importance.

Even though the prediction performance of this RF is very inaccurate (it predicts only around 0.2 of the variation in demand accurately), it delivers valuable estimates of variable importance. Figure 4 indicates the three variables that contribute the most to the reduction in the MSE: The relative sunshine, the minimum temperature through the day and precipitation. Further below those three, the variables show no clear ordering across areas. Some measures of wind and humidity have predictive power too, but at a much lower magnitude than the first three.

Figure 4: Variable importance measure of RF including all available predictors

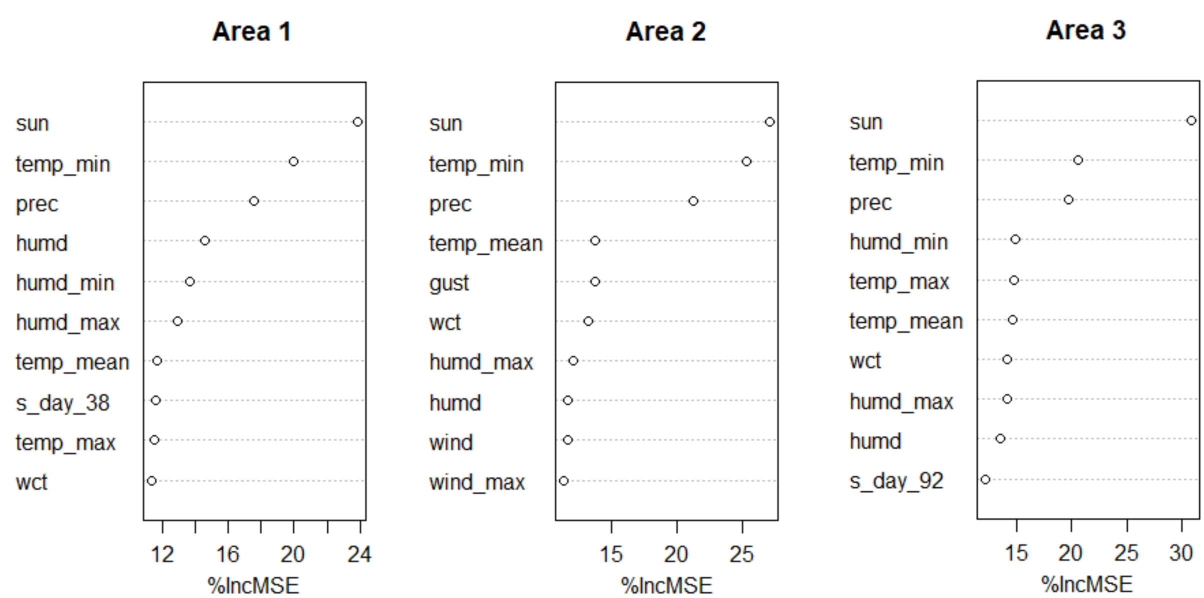

Figure Notes: Variable importance estimated by Random Forests for each area. The measure on the x-axis indicates by how much the MSE would increase leaving the variable on the y-axis out of the random forest.

Having identified the three main variables relative sunshine duration, precipitation and minimum temperature by two methods (OLS and RF), these are used to create the weather and forecast indices described in Section 3.2. As the minimum temperature is inversely u-shaped to demand, I recover an estimate for the optimal temperature

$$\underline{t}^* = -\frac{\hat{\beta}_t}{2\hat{\beta}_{t^2}} \tag{23}$$

using specification (7) in Tables 7, 8 and 9 for each area, respectively. The deviation from that optimum is then related to lower partial temperature indices as shown in (11).

B Additional Theoretical Results

B.1 Asymmetric Effects Through Risk Aversion

The second channel that affects the symmetry of reactions to forecast errors is the degree of risk aversion. Using (8) for the distance of thresholds under good and mixed weather forecasts and comparing it to the distance of thresholds under mixed and bad weather forecasts allow me to formally compare these distances.

$$u(v(a,g)-c^g)-u(v(a,g)-c^m)=\left(\frac{1-p_m}{p_m}-\frac{1-p_g}{p_g}\right)V_b \tag{24}$$

$$u(v(a,g)-c^m)-u(v(a,g)-c^b)=\left(\frac{1-p_b}{p_b}-\frac{1-p_m}{p_m}\right)V_b. \tag{25}$$

Suppose agents are risk neutral and the forecaster is equally good in predicting bad and good weather outcomes (s.t. $p_g-p_m=p_m-p_b$), then

$$\underbrace{\frac{p_g-p_m}{p_g p_m}V_b}_{=c^m-c^g}<\underbrace{\frac{p_m-p_b}{p_m p_b}V_b}_{=c^b-c^m}. \tag{26}$$

Thus, in the risk-neutral case (where $u(x)=x$) with uniformly distributed costs $c_i(a,0)$ mixed forecasts that turn out optimistic induce larger shifts in demand than mixed forecasts that turn out pessimistic. However, risk aversion counteracts this implied demand asymmetry due to the concavity of the utility function. Risk aversion implies that

$$c^{m,RA}-c^{g,RA}=(v-c^{g,RA})-(v-c^{m,RA})>u(v-c^{g,RA})-u(v-c^{m,RA}) \tag{27}$$

and risk neutrality that

$$c^{m,RN}-c^{g,RN}=(v-c^{g,RN})-(v-c^{m,RN})=u(v-c^{g,RA})-u(v-c^{m,RA}) \tag{28}$$

where $v=v(a,g)$ to simplify notation. From this it follows that the distance c^m-c^g is larger for risk averse agents ($[c^{m,RA}-c^{g,RA}]-[c^{m,RN}-c^{g,RN}]>0$). By the same argument, c^b-c^g is larger for risk-averse agents. Thus, the more concave the utility function is, the larger the differences in distances between c^b and c^g and also the larger the differences between c^m and

c^g. Comparing the differences in these distances yields

$$\left\{\left[c^{m,RA} - c^{g,RA}\right] - \left[c^{m,RN} - c^{g,RN}\right]\right\} - \left\{\left[c^{b,RA} - c^{g,RA}\right] - \left[c^{b,RN} - c^{g,RN}\right]\right\} \tag{29}$$

$$=(c^{m,RA} - c^{m,RN}) - (c^{b,RA} - c^{b,RN}) > 0 \tag{30}$$

due to the concavity of the utility function. Consequently, as $c^m - c^g$ surpasses $c^b - c^g$ with increasing concavity, the distance between c^b and c^m decreases.

C Additional Empirical Results

C.1 Summary Statistics

Figure 5 indicates the share in aggregate demand, measured as first-entries or bookings (area 1), that different pass validity types generate across the three areas. Notice that area 1 is artificially restricted to one-day passes as only the purchase of passes is registered and not the consumption. In area 2 one-day pass and season pass owners generate each 31%, and one-week pass owners 26% of all first entries. First entries from other pass validity types generate the remaining 12%. In area 3 one-day pass owners generate 30%, season pass owners 39% and one-week pass owners 20% of all first-entries. The other pass types generate the remaining 11%.

Figure 5: Shares in aggregate demand by validity types

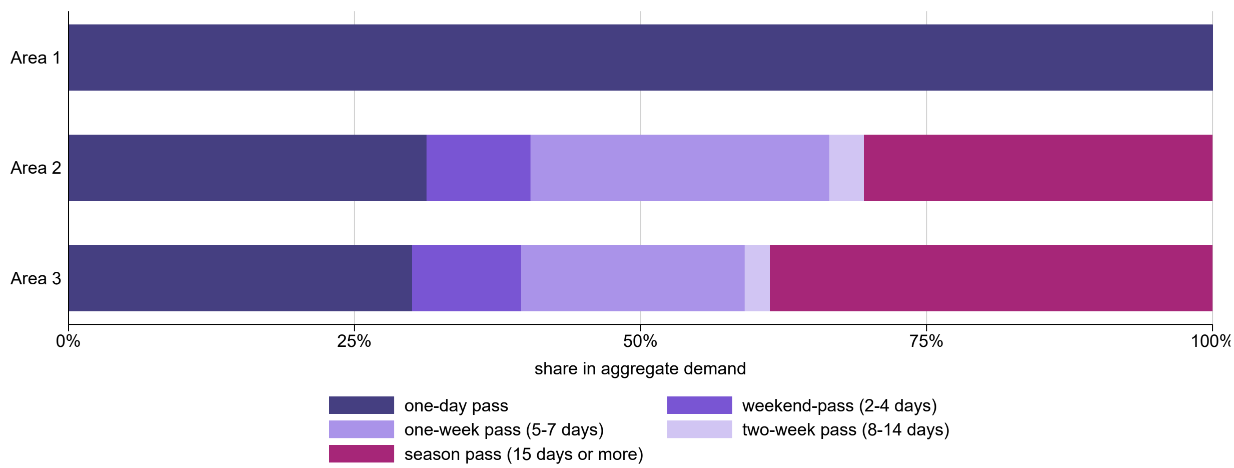

Figure Notes: The share of first-entries generated by agents owning different pass validity type categories across the three areas is indicated. Pass validity types in area 1 are restricted to one-day passes.

Figure 6 indicates the share in aggregate demand (top panel) and one-day pass owners (bottom panel), measured as first-entries or bookings (area 1), that different age groups generate across the three areas. Adults make up between 68% and 81% of overall demand whereas children make up between 13% and 24% in the three areas. The remaining shares around 5% are generated by adolescents. The share of adults is slightly larger in one-day passes compared to the aggregate demand at the expense of children. Notice that the groups might not be identically defined regarding the exact age. The groups are built from pass types that indicate age categories as defined by the ski areas themselves.

Figure 6: Shares in aggregate demand by age groups

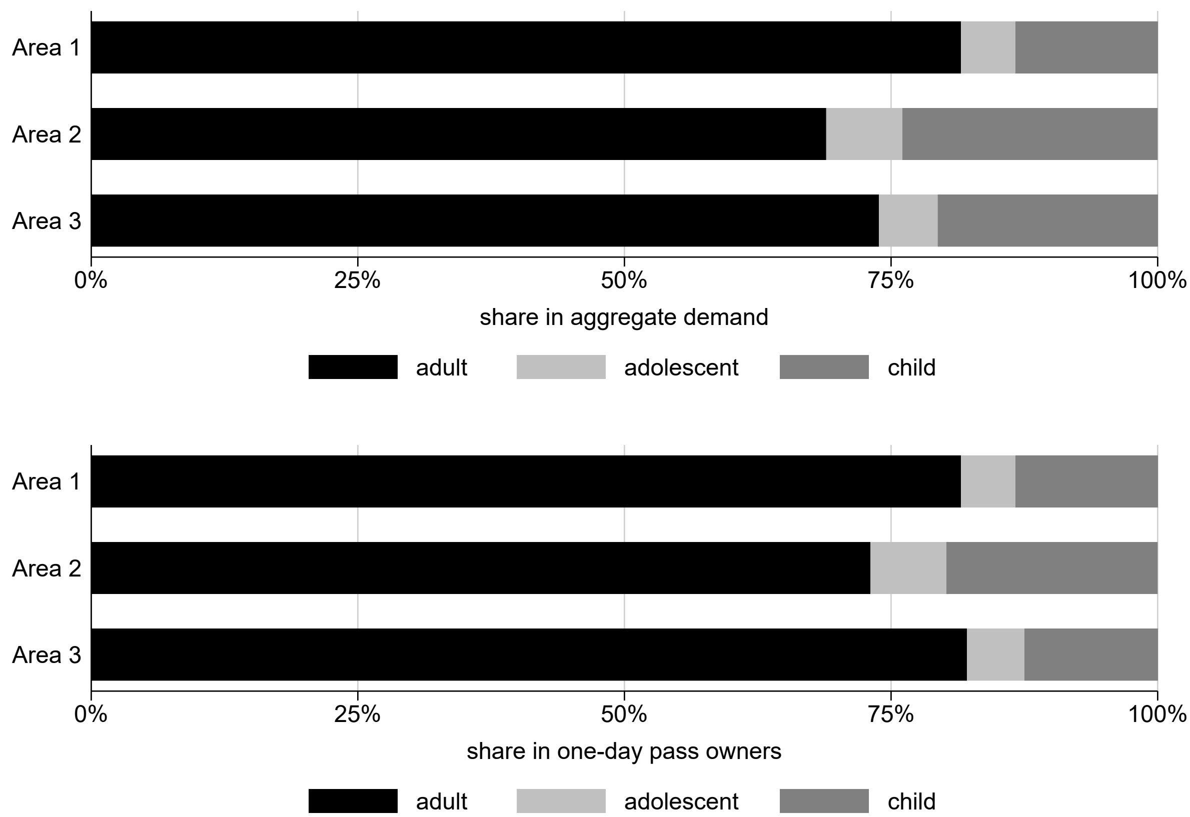

Figure Notes: The top panel indicates the share of first-entries generated by agents of different age groups in overall demand across the three areas. The bottom panel indicates the share of first entries generated by agents of different age groups in one-day passes across the three areas.

C.2 Uneven Weather Probabilities across Switzerland

In Figure 3 I show that the forecaster makes larger errors in bad weather (measured *ex post*) compared to good weather for the three areas discussed throughout the paper. However, this phenomenon is not a random occurrence but rather a pattern that is observed all over the Swiss Alps. Figure 7 displays estimates from a linear regression of absolute forecast errors on weather percentiles interacted by spatial units of 202 major Swiss Ski Areas. In particular, I estimate

$$|e_{dsj}^{d-0}| = w_{dsj}\beta + \gamma_j D_j + w_{dsj} \times D_j\delta + \varepsilon_{dsj} \tag{31}$$

where $|e_{dsj}^{d-0}| = |f_{dsj}^{d-0} - w_{dsj}|$ is the absolute value of the 0-day forecast error, D_j is a vector of dummies that is equal to 1 if $j = j$ and 0 if otherwise, w_{dsj} is the weather index and $w_{dsj} \cdot D_j$ is the interaction between the latter two at day d in season s at ski area j. The interaction allows for heterogeneous effects of the predictability gap at different spatial units. These units correspond to ski areas' entrance lifts. Estimates at these geographical locations are displayed in Figure 7. The intensity of red indicates a higher gap in the predictability of bad weather to good weather. It is visible that the forecaster faces increasing difficulties predicting accurately bad weather outcomes the more a ski area lies in inner-alpine regions. As bad weather in the northern alps is often brought by strong northern or western winds, it is inherently difficult to predict how far these weather fronts reach into the alps. The same is true for more southern exposed territories such as the canton of Ticino and the Oberengadin.

Figure 7: OLS estimates of absolute forecast errors on weather percentiles by ski areas

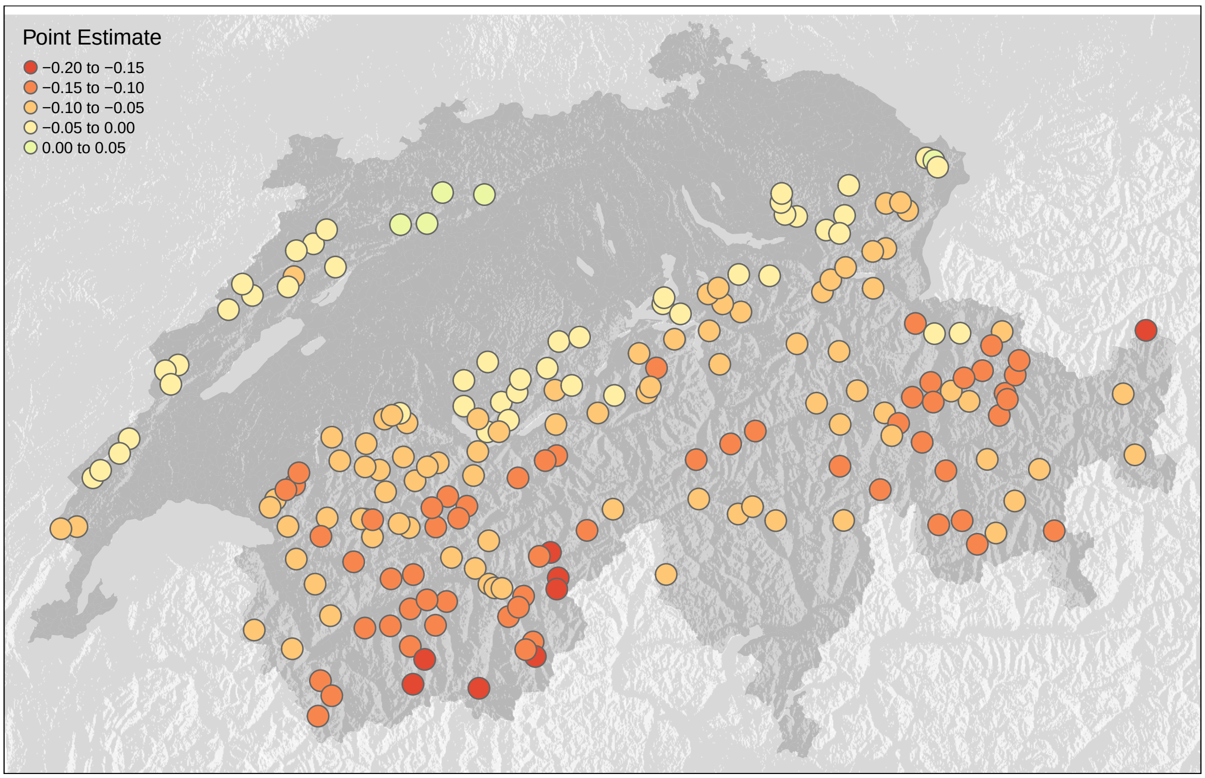

Figure Notes: The points indicate the geographic locations of two hundred major ski areas across Switzerland. The point's color shading from light yellow to red depicts the effect size of individual weather effects on forecast errors in model (31). A higher intensity of red is associated with a larger gap in the ability to accurately predict the weather in good relative to bad weather outcomes.

C.3 Effects of Partial Weather Indices

To give an idea how the partial weather indices of sunshine (9), precipitation (10), minimum temperature (11) and their respective forecast errors relate to the aggregate demand, I estimate

$$log(y_{ds}) = \widetilde{W}_{ds}\beta + \widetilde{E}^{d-h}_{ds}\delta + [\widetilde{E}^{d-h}_{ds} \times \widetilde{D}_{ds}]\lambda_0 + \alpha_d + o_{ds}\nu + \varepsilon_{ds}, \tag{32}$$

where $\widetilde{W}_{ds} = [\widetilde{sun}_{ds} \;\; \widetilde{prec}_{ds} \;\; \widetilde{temp}_{ds}]$ is a row-vector of partial weather indices defined by Equations (9), (10) and (11), $\widetilde{E}^{d-h}_{ds}$ is a row vector of partial forecast errors based on the same weather and forecast indices as $\widetilde{W}_{ds}$ and $\widetilde{D}_{ds}$ is a vector of slope dummy for the same partial indices that are equal to 1 whenever the allocated partial index is optimistic. It is crucial to note that the estimates from that model are mere associations between demand and the exogenous partial indices but lack a causal interpretation. The reason is that the *ceteris paribus* assumption is likely violated whenever a coefficient is interpreted. For example, interpreting the coefficient of sunshine duration - the change in demand that happens through a change in sunshine duration - would suggest that the minimum temperature stays constant at the same time. This is hardly realistic and is the reason why I defined one-dimensional weather and forecast indices in the first place.

The results of estimating (32) are presented in Table 10. The top panel indicates that demand is indeed positively related to all three partial weather indices. This supports the idea of using these three variables as inputs for the weather and forecast indices. Comparing optimistic and pessimistic error effects in the second and third panels shows how the sunshine error is significantly related to optimistic effects and precipitation to pessimistic effects only. One possible explanation for this could be that the salient feature of a bad weather forecast is precipitation whereas the salient feature of a good forecast is sunshine duration. Thus, when a forecast is framed around more or less precipitation, it is, so to speak, in the realm of bad weather occurrences[26].

Consider the counterfactual situations in Figure 2: The thresholds c^m and c^b are close because mixed forecasts in precipitation is close to what is considered bad skiing weather. Comparing a forecast in the realm of precipitation to a good weather counterfactual (as in the case of pessimistic forecasts) affects demand much more than a bad weather counter-

[26]For example a forecast might be mixed because two days prior to the event it indicates 5mm precipitation and one day prior to the event only 0.5mm. Then it is likely that the sunshine variable is predicted correctly but the precipitation forecast turns out optimistic or pessimistic.

Table 10: Effect of weather and forecast error using partial indices with slope dummy on log demand for one-day pass owners

Dependent variable	Log demand, area 1		Log demand, area 2		Log demand, area 3	
	(1)	(2)	(1)	(2)	(1)	(2)
Partial weather index effects						
Sunshine	0.006^{***}	0.005^{***}	0.008^{***}	0.007^{***}	0.010^{***}	0.011^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Precipitation	0.013^{***}	0.014^{***}	0.007^{***}	0.007^{***}	0.013^{***}	0.013^{***}
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Minimum temperature	0.004^{***}	0.004^{***}	0.006^{***}	0.004^{***}	0.007^{***}	0.007^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Optimistic error effects						
Sunshine error	-0.001	-0.001	0.006^{***}	0.004^{*}	0.004^{*}	0.003^{*}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Precipitation error	0.006	0.007	0.003	0.004	0.008	0.008
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Minimum temperature error	0.003	0.003	-0.003	-0.011	-0.010	-0.007
	(0.003)	(0.003)	(0.005)	(0.005)	(0.006)	(0.005)
Pessimistic error effects						
Sunshine error	0.002	0.003	0.004	0.002	0.003	0.005
	(0.004)	(0.004)	(0.003)	(0.002)	(0.003)	(0.002)
Precipitation error	0.009^{***}	0.010^{***}	0.006^{***}	0.007^{***}	0.005^{*}	0.004^{*}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Minimum temperature error	-0.000	0.004	0.004	0.000	0.004	0.005
	(0.005)	(0.005)	(0.002)	(0.003)	(0.004)	(0.004)
Controls						
Easter dummy	Yes	Yes	Yes	Yes	Yes	Yes
Season day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Season fixed effects	No	Yes	No	Yes	No	Yes
N	910	910	1,099	1,099	1,154	1,154
R^2	0.803	0.812	0.682	0.717	0.803	0.824

Standard errors in parentheses and clustered at season day level
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table Notes: The table depicts LSDV estimates of model (32) for one-day pass owners in three areas. Standard errors are clustered on the season day to account for intra-day correlations across seasons (seasonality). To allow a comparison between the areas only one-day passes are used. The partial weather ($\tilde{W}_{ds}$) and (here) not visible partial forecast ($\tilde{F}^0_{ds}$) indices are continuous, scaled between 0 and 100 and include partial indices of precipitation, sunshine and minimum temperature. The 0-day partial error variables in $\tilde{E}^0_{ds} = \tilde{F}^0_{ds} - \tilde{W}_{ds}$ are the difference between each partial weather and 0-day forecast index and are interacted with slope dummy variables $\tilde{D}_{ds} = \mathbb{1}[(\tilde{F}^0_{ds} - \tilde{W}_{ds}) > 0]$ to allow for a slope change in optimistic forecasts. Easter is a dummy indicating the four Easter holidays (Good Friday to Easter Monday). Each specification includes season day fixed effects and specification (2) includes season fixed effects.

factual. On the other hand, when the prevalent variable in a forecast is sunshine, then the forecast is in the realm of good weather occurrences[27]. Uncertainties reflected in the threshold c^m are more often close to the good weather threshold c^g. Then, demand is much more shifted when compared to a bad weather counterfactual as in the case of optimistic reactions.

C.4 Shares of Type A Agents by All Pass Validity Types

Table 11 provides LSDV results of all pass validity types of model (16). It represents the same estimates as in Table 3 and recovers shares of type A agents also by (17). Most noticeable is how weekend, one-week and two-week pass owners have smaller effect sizes in gross weather effects than the other pass types. This might have two causes: First, those pass types attract enthusiasts that expect to make a lot out of their passes and overtake some of the weather risks from ski area operators. Second, once they bought the pass they are subject to the sunk cost fallacy (Arkes & Blumer, 1985). Looking at the shares of type A agents and neglecting the discussion about one-day and season pass owners (as these are already discussed in Section 5), only weekend pass owners have significant shares in some specifications.

[27]For example a forecast might be mixed because two days prior to the event it indicates 80% sunshine and one day prior to the event only 50%. Then it is likely that the sunshine forecast turns out optimistic or pessimistic but the precipitation is predicted correctly at zero.

Table 11: Effect of weather and forecast error on log demand for different pass validity types

Dependent variable	Log demand, area 2				Log demand, area 3			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Gross weather effects								
One-day pass owners	0.022***	0.023***	0.021***	0.021***	0.030***	0.030***	0.030***	0.031***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Weekend pass owners	0.015***	0.014***	0.013***	0.013***	0.014***	0.014***	0.014***	0.014***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
One-week pass owners	0.009***	0.006***	0.007***	0.005***	0.010***	0.007***	0.010***	0.008***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
Two-week pass owners	0.006***	0.007***	0.004*	0.006***	0.006***	0.006***	0.006***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Season pass owners	0.016***	0.018***	0.015***	0.017***	0.024***	0.026***	0.024***	0.026***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
0-day error effects								
One-day pass owners	0.013***	0.015***	0.009***	0.011***	0.011***	0.012***	0.009***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Weekend pass owners	0.005*	0.004	0.000	−0.000	0.007***	0.008***	0.006*	0.006***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
One-week pass owners	0.006*	0.005	0.002	0.000	0.008*	0.008***	0.007*	0.006***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
Two-week pass owners	0.012***	0.011***	0.008*	0.007*	0.007***	0.008***	0.006*	0.006***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Season pass owners	0.005***	0.007***	0.001	0.002	0.004	0.004	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Share of type A agents								
One-day pass owners	0.456***	0.548***	0.264**	0.353***	0.212***	0.247***	0.175***	0.204***
	(0.099)	(0.107)	(0.086)	(0.093)	(0.055)	(0.057)	(0.050)	(0.052)
Weekend pass owners	0.218	0.172	0.013	−0.016	0.370*	0.379**	0.247*	0.253*
	(0.112)	(0.120)	(0.085)	(0.090)	(0.144)	(0.140)	(0.116)	(0.109)
One-week pass owners	0.627	0.640	0.166	0.014	0.689	1.085	0.480	0.692
	(0.417)	(0.449)	(0.282)	(0.264)	(0.408)	(0.618)	(0.317)	(0.389)
Two-week pass owners	5.718	2.112	3.589	1.273	1.400	1.701	0.808	0.989
	(6.443)	(1.129)	(4.126)	(0.789)	(1.058)	(1.029)	(0.592)	(0.555)
Season pass owners	0.204*	0.233**	0.022	0.062	0.092	0.081	0.060	0.050
	(0.082)	(0.071)	(0.067)	(0.058)	(0.055)	(0.047)	(0.050)	(0.043)
Differences in shares								
One-day − Weekend	0.238	0.375**	0.252*	0.369***	−0.158	−0.132	−0.072	−0.048
	(0.122)	(0.131)	(0.098)	(0.107)	(0.126)	(0.120)	(0.101)	(0.094)
One-day − One-week	−0.170	−0.092	0.098	0.339	−0.477	−0.838	−0.305	−0.487
	(0.431)	(0.424)	(0.298)	(0.251)	(0.416)	(0.605)	(0.325)	(0.380)
One-day − Two-week	−5.262	−1.564	−3.325	−0.920	−1.188	−1.454	−0.633	−0.785
	(6.428)	(1.104)	(4.118)	(0.772)	(1.049)	(1.016)	(0.586)	(0.545)
One-day − Season	0.253**	0.315***	0.243***	0.292***	0.120**	0.166***	0.115**	0.154***
	(0.087)	(0.086)	(0.071)	(0.074)	(0.044)	(0.043)	(0.040)	(0.038)
Controls								
Easter dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pass-type fixed effects	Yes	-	Yes	-	Yes	-	Yes	-
Season day fixed effects	Yes	-	Yes	-	Yes	-	Yes	-
Day-by-pass fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Season fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
N	4,829	4,829	4,829	4,829	5,370	5,370	5,370	5,370
R^2	0.593	0.735	0.617	0.757	0.726	0.841	0.732	0.847

Standard errors in parentheses and clustered at season day level

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table Notes: The table depicts LSDV estimates of model (16) where the groups are separated by different pass validity categories using four specifications across two areas. Standard errors are clustered at the season day level to account for intra-day correlations across seasons. The weather (w_{ds}) and forecast (f^0_{ds}) indices are continuous variables scaled between 0 and 100 and based on weighted partial indices of precipitation, sunshine and minimum temperature. The 0-day error variable $e^0_{ds} = f^0_{ds} - w_{ds}$ is the difference between weather and 0-day forecast. One-day pass owners possess and use a one-day pass, weekend pass owners a two- to four-day pass, week pass owners a five- to seven-day pass, two-week pass owners an eight- to fourteen-day pass and season pass owners a season pass or any other pass valid for more than 14 days. Shares of type As and differences between the shares are recovered using (17) by a nonlinear combination of point estimates using the delta method. Easter is a dummy indicating the four Easter holidays (Good Friday to Easter Monday). Each specification includes season day and pass-type fixed effects whereby specifications (2) and (4) include an interaction of the two. Season fixed effects control for possible time trends and are included in specifications (3) and (4).

D Robustness Check Using Pictograms

D.1 Data Processing to Weather and Forecast Classes

With the purpose of creating one-dimensional weather and forecast classes from hourly observations of the COSMO-7 model outputs several data-cleaning steps are necessary that are based on the algorithms MeteoSchweiz uses for the creation of pictograms. The pictograms are published in their forecast and represent what the individuals observe in the app or online. Although the representation endured some changes over the covered years, the three key variables sunshine duration, precipitation and temperature were always presented in a similar fashion. A recent representation is depicted in Figure 8 where on top pictograms of sunshine/clouds/precipitation are presented in 3-hour aggregates, the temperature is depicted as a red line and precipitation is additionally presented as blue bars.

Figure 8: Example of a typical representation of a local weather forecast

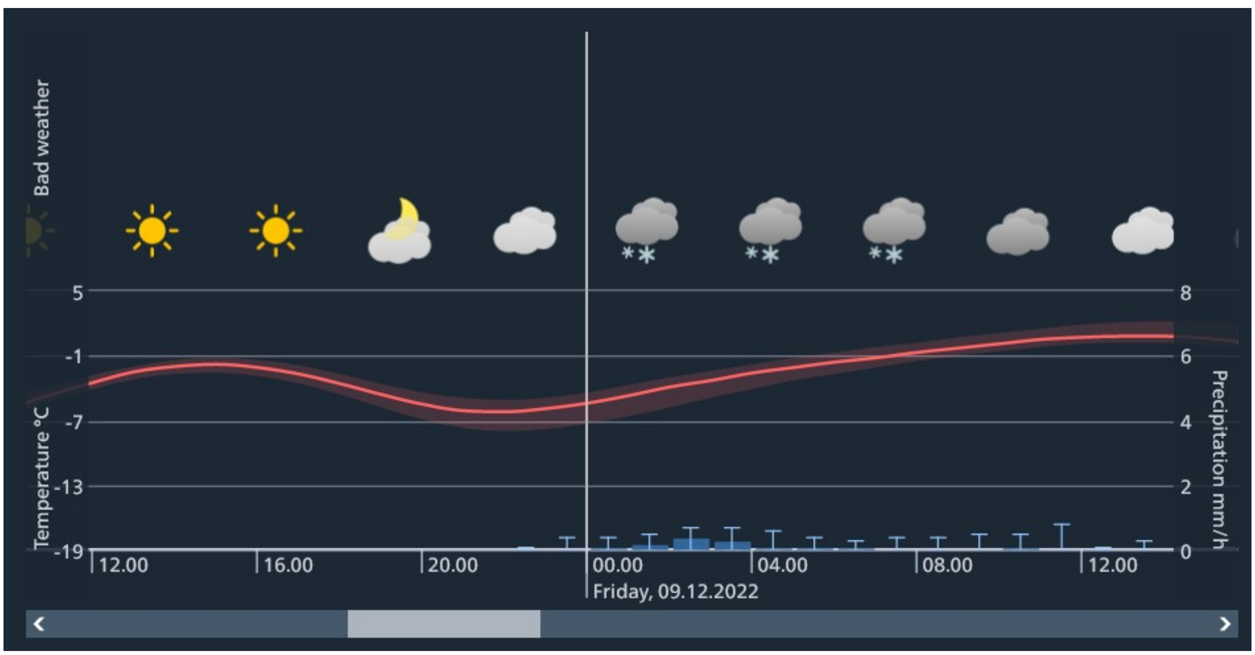

Figure Notes: A typical representation of a local weather forecast from https://www.meteoschweiz.admin.ch.

MeteoSchweiz provided their exact decision node to recreate each of their 35 possible daytime pictograms[28] on an hourly basis and how each of the pictograms is aggregated to 3-hour, 6-hour or 12-hour aggregates. Please contact the author if these exact decision nodes are of

[28]MeteoSchweiz extended their pictograms to 42 in recent years to include thunderstorms in summer and winter which are both of minor importance here and would fall under the same classes.

interest as these are not meant to be published here.

My approach is then to classify the weather and forecast variables on a certain day into four classes that represent the 35 (daytime) pictograms as closely as possible. In my approach, it might be possible to classify the same pictogram (=icon) into up to three different classes because combined with the precipitation bars and disaggregated to 3-hour periods a quite different weather outcome could be expected from the same temporally aggregated pictogram. For example, in an extreme case (which is very rare) it is possible that a day with 80% relative sunshine duration with 2mm precipitation of snow over the period of three hours (e.g. at the beginning or end of the day) is aggregated to the same icon as a day with just 20% relative sunshine duration with 15mm precipitation of snow over the period of eight hours (never exceeding 2mm per hour). MeteoSchweiz has good reasons to aggregate these situations to the same pictogram as in both situations the sun is shining and some snow is falling (and never really strong), but users will see the difference between the two days by looking at the error bars and disaggregated 3-hour pictograms. Therefore, the four resulting classes are not based on pictograms only but rather on pictograms combined with precipitation.

The four classes are bad weather, predominantly cloudy, predominantly sunny and good weather. These classes are based on daytime aggregated pictograms taking five opacity classes (*clear*, *few*, *scattered*, *broken*, *overcast*)[29], four precipitation intensity classes (*very weak*, *weak*, *moderate*, *strong*)[30] and three significant weather situations (*no significant weather*, *rain*, *snow*)[31] into account. In Table 12 the classification into the four weather and forecast classes based on the MeteoSchweiz pictogram classes is depicted. Cells' values range from 1 to 4 indicating the classes 1 = bad weather, 2 = predominantly cloudy, 3 = predominantly sunny and 4 = good weather.

[29] MeteoSchweiz uses opacity classes based on cloud coverage, I use for the same classes the relative sunshine duration. I assume here that the aggregated fraction of sky covered by clouds on a given day at a certain point of interest is well represented by the respective relative sunshine duration measure. That means when the relative sunshine duration on a certain day is 20%, then the sky is assumed to be covered by clouds by 80%.

[30] MeteoSchweiz has the additional precipitation intensity class of *nil* which is unnecessary due to the other classes.

[31] MeteoSchweiz defines additional classes for *cirrus*, *rain and snow*, *thunderstorm rain* and *thunderstorm snow*. I classify *cirrus* into *no significant weather* (as it makes very little to no difference to skiers) *rain and snow* as well as *thunderstorm snow* into *snow* and *thunderstorm rain* into *rain*.

Table 12: **Classification of pictogram classes into four weather/forecast classes**

Sig. weather \ Opacity	Clear	Few	Scattered	Broken	Overcast
No sig. weather	4	4	3	2	2
Snow (intensity = [v|w|m|s])	[4|3|3|3]	[3|3|2|2]	[3|3|2|2]	[2|2|1|1]	[2|2|1|1]
Rain (intensity = [v|w|m|s])	[4|3|3|2]	[3|3|2|1]	[3|2|2|1]	[2|2|1|1]	[2|1|1|1]

Table Notes: Each column depicts an opacity class which is derived from relative sunshine duration. Each row depicts a significant weather class which is further classified into four intensity classes in the case of precipitation. These are v = very weak, w = weak, m = moderate, s = strong. Exact values of thresholds for the classification are drawn from MeteoSchweiz directly and not published here. The values in the cells indicate the four resulting classes where 1 = bad weather, 2 = predominantly cloudy, 3 = predominantly sunny, 4 = good weather.

D.2 Empirical Model

Proposition 1 to 3 are additionally tested using the following model:

$$\begin{aligned} log(y_{dsg}) =& W_{ds}\beta_0 + D^{opt}_{ds}\delta_0 + D^{pes}_{ds}\lambda_0 + \underline{\widetilde{temp}}_{ds}\eta \\ &+ \sum_{g=1}^{G} \left(D_g\delta_g + [D_g \times W_{ds}]\beta^w_g + [D_g \times D^{opt}_{ds}]\delta_g + [D_g \times D^{pes}_{ds}]\lambda_g\right) \\ &+ \alpha_d + o_{ds}\nu + \varepsilon_{dsg} \end{aligned} \tag{33}$$

where $W_{ds}\beta_0 = D^2_{ds}\beta^2_0 + D^3_{ds}\beta^3_0 + D^4_{ds}\beta^4_0$ for the four weather classes with class 1 as baseline category. D^{opt}_{ds} is a dummy that fulfills $\mathbb{1}[F]_{ds} - W_{ds} > 0]$ meaning that forecasts predicted optimistic weather by at least one class. D^{pes}_{ds} is a dummy that fulfills $\mathbb{1}[F_{ds} - W_{ds} < 0]$ meaning that forecasts predicted pessimistic weather by at least one class. The group dummies D_g indicate again the heterogeneous groups in either pass validity types or age and interactions with the weather classes as well as with optimistic and pessimistic errors allow for group-specific weather and forecast error effects. $\underline{\widetilde{temp}}_{ds}$ is the partial minimum temperature index that is added because weather classes reflect temperature differences only implicitly. So far it enters the weather classes via the distinction between rain and snow classes which does not account for temperature variations in sunny weather situations (without any precipitation).

D.3 Results

Table 13 shows the estimates of model (33) across three specifications per area for one-day pass owners in the aggregate. Therefore, these results represent the same estimates as Table 4 in Section 5. In contrast to the results using equally weighted indices are the error effects in area 1 not asymmetric towards pessimistic errors but, on the opposite, asymmetric towards optimistic effects in area 2. The difference between the two is that in the equally weighted indices, precipitation is weighted more heavily than in the pictograms. Considering again Table 10, where I found that precipitation errors tend to lead to stronger pessimistic effects and sunshine errors tend to lead to stronger optimistic effects, explains why giving less weight to precipitation raises optimistic effects at the expense of pessimistic effects.

Table 14 shows the estimates of model (33) across four specifications per area for one-day pass owners across age groups. Therefore, these results represent the same estimates as Table 5 in Section 5. Comparing the results of the two tables lead to the same observation as described above. Using pictograms instead of continuous indices gives more weight to sunshine duration relative to precipitation and, thus, leads to somewhat stronger optimistic effects. All asymmetric effects tend to be rather small and just slightly above the 5% significance threshold. Therefore, I do not confirm Proposition 3.

Table 13: Effect of weather and forecast error on log demand for one-day pass owners using pictograms

dependent variable	log demand, area 1			log demand, area 2			log demand, area 3		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Weather effects									
Weather class 2	0.506***	0.508***	0.502***	0.571***	0.527***	0.491***	0.724***	0.683***	0.691***
	(0.081)	(0.081)	(0.079)	(0.089)	(0.090)	(0.084)	(0.079)	(0.076)	(0.072)
Weather class 3	0.873***	0.870***	0.863***	0.963***	0.900***	0.884***	1.143***	1.099***	1.085***
	(0.079)	(0.078)	(0.078)	(0.100)	(0.100)	(0.098)	(0.097)	(0.092)	(0.088)
Weather class 4	1.269***	1.300***	1.306***	1.103***	1.034***	1.024***	1.552***	1.502***	1.579***
	(0.084)	(0.081)	(0.081)	(0.087)	(0.088)	(0.084)	(0.071)	(0.070)	(0.068)
Error effects									
Optimistic error	0.313***	0.320***	0.335***	0.296***	0.273***	0.199*	0.290***	0.259***	0.251***
	(0.062)	(0.061)	(0.062)	(0.070)	(0.069)	(0.070)	(0.061)	(0.062)	(0.057)
Pessimistic error	−0.341***	−0.348***	−0.343***	−0.000	0.050	−0.013	−0.296***	−0.275***	−0.309***
	(0.107)	(0.108)	(0.108)	(0.096)	(0.100)	(0.102)	(0.078)	(0.076)	(0.076)
Asymmetric effects									
Optimistic + Pessimistic error	−0.028	−0.028	−0.008	0.296*	0.322*	0.185	−0.005	−0.016	−0.058
	(0.145)	(0.145)	(0.146)	(0.142)	(0.144)	(0.149)	(0.109)	(0.108)	(0.105)
Controls									
Partial temperature index		0.005***	0.005***		0.006***	0.005***		0.007***	0.007***
		(0.002)	(0.002)		(0.001)	(0.001)		(0.001)	(0.001)
Easter dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Season day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Season fixed effects	No	No	Yes	No	No	Yes	No	No	Yes
N	910	910	910	1,099	1,099	1,099	1,154	1,154	1,154
R^2	0.774	0.778	0.784	0.659	0.668	0.699	0.766	0.775	0.795

Standard errors in parentheses and clustered at season day level
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table Notes: The table depicts LSDV estimates of model (33) for three specifications in three areas. Standard errors are clustered on the season day to account for intra-day correlations across seasons (seasonality). To allow a comparison between the areas only one-day passes are used. The weather classes are dummies from classes 2 to 4, where class 1 (=bad weather) builds the baseline and is omitted. 0-day forecast classes are similarly defined. The error effects are dummies indicating differences between forecast and weather classes of at least one. Asymmetric effects are tested by the linear combination of optimistic and pessimistic dummies. Easter is a dummy indicating the four Easter holidays (Good Friday to Easter Monday). All models are estimated using season day fixed effects to account for the seasonality.

Table 14: Asymmetric effects of weather and forecast error on log demand of one-day pass owners using pictograms separated by age groups

dependent variable	log demand, area 1				log demand, area 2				log demand, area 3			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Weather effects												
Class 2, adults	0.527***	0.524***	0.521***	0.515***	0.499***	0.490***	0.461***	0.451***	0.790***	0.767***	0.793***	0.768***
	(0.088)	(0.091)	(0.087)	(0.090)	(0.080)	(0.083)	(0.076)	(0.079)	(0.069)	(0.076)	(0.068)	(0.073)
Class 2, adolescents	0.202*	0.261*	0.203*	0.255*	0.352***	0.354***	0.270***	0.284***	0.382***	0.392***	0.411***	0.423***
	(0.095)	(0.106)	(0.092)	(0.104)	(0.100)	(0.103)	(0.086)	(0.083)	(0.091)	(0.093)	(0.092)	(0.096)
Class 2, children	0.343***	0.301*	0.338***	0.292*	0.414***	0.452***	0.376***	0.416***	0.474***	0.494***	0.490***	0.514***
	(0.095)	(0.106)	(0.092)	(0.104)	(0.093)	(0.103)	(0.094)	(0.105)	(0.080)	(0.087)	(0.080)	(0.088)
Class 3, adults	1.001***	0.967***	0.997***	0.962***	0.878***	0.895***	0.868***	0.880***	1.248***	1.228***	1.239***	1.220***
	(0.083)	(0.086)	(0.084)	(0.087)	(0.087)	(0.091)	(0.086)	(0.090)	(0.089)	(0.090)	(0.087)	(0.087)
Class 3, adolescents	0.437***	0.468***	0.440***	0.472***	0.610***	0.591***	0.555***	0.543***	0.568***	0.554***	0.586***	0.573***
	(0.093)	(0.099)	(0.091)	(0.096)	(0.095)	(0.103)	(0.095)	(0.095)	(0.097)	(0.102)	(0.099)	(0.105)
Class 3, children	0.612***	0.617***	0.614***	0.617***	0.685***	0.704***	0.660***	0.682***	0.635***	0.696***	0.639***	0.702***
	(0.089)	(0.098)	(0.087)	(0.096)	(0.107)	(0.114)	(0.110)	(0.119)	(0.105)	(0.106)	(0.107)	(0.108)
Class 4, adults	1.350***	1.352***	1.345***	1.338***	1.001***	1.031***	0.965***	0.990***	1.641***	1.643***	1.684***	1.687***
	(0.083)	(0.088)	(0.084)	(0.089)	(0.078)	(0.084)	(0.075)	(0.080)	(0.070)	(0.070)	(0.070)	(0.069)
Class 4, adolescents	0.567***	0.611***	0.572***	0.612***	0.721***	0.682***	0.649***	0.627***	0.809***	0.854***	0.866***	0.913***
	(0.100)	(0.108)	(0.100)	(0.109)	(0.103)	(0.094)	(0.088)	(0.080)	(0.076)	(0.080)	(0.078)	(0.084)
Class 4, children	0.825***	0.842***	0.823***	0.834***	0.792***	0.807***	0.729***	0.755***	1.027***	1.067***	1.079***	1.120***
	(0.114)	(0.119)	(0.115)	(0.120)	(0.086)	(0.096)	(0.090)	(0.100)	(0.073)	(0.077)	(0.075)	(0.079)
Optimistic error effects												
Adults	0.317***	0.334***	0.324***	0.342***	0.281***	0.303***	0.201***	0.225***	0.319***	0.333***	0.307***	0.324***
	(0.066)	(0.067)	(0.066)	(0.067)	(0.057)	(0.059)	(0.059)	(0.060)	(0.057)	(0.057)	(0.055)	(0.054)
Adolescents	0.117	0.096	0.127	0.103	0.191*	0.185	0.129*	0.131	0.197***	0.251***	0.175*	0.232***
	(0.072)	(0.074)	(0.072)	(0.074)	(0.078)	(0.092)	(0.061)	(0.075)	(0.063)	(0.070)	(0.064)	(0.070)
Children	0.204***	0.161*	0.211***	0.168*	0.201***	0.171*	0.112	0.090	0.265***	0.206*	0.244***	0.185*
	(0.070)	(0.072)	(0.069)	(0.071)	(0.068)	(0.068)	(0.072)	(0.075)	(0.080)	(0.082)	(0.081)	(0.084)
Pessimistic error effects												
Adults	−0.275*	−0.315***	−0.271*	−0.313*	0.025	0.026	−0.025	−0.019	−0.330***	−0.296***	−0.356***	−0.319***
	(0.104)	(0.109)	(0.105)	(0.111)	(0.072)	(0.083)	(0.075)	(0.086)	(0.075)	(0.071)	(0.075)	(0.070)
Adolescents	−0.059	−0.091	−0.054	−0.089	−0.076	−0.036	−0.083	−0.050	−0.125	−0.166	−0.145	−0.182*
	(0.114)	(0.120)	(0.118)	(0.122)	(0.139)	(0.145)	(0.108)	(0.108)	(0.075)	(0.085)	(0.076)	(0.087)
Children	−0.112	−0.117	−0.105	−0.113	−0.058	−0.041	−0.094	−0.077	−0.149	−0.183*	−0.171*	−0.206*
	(0.106)	(0.123)	(0.104)	(0.120)	(0.099)	(0.104)	(0.099)	(0.109)	(0.080)	(0.087)	(0.080)	(0.087)
Asymmetric effects												
Optimisitc + Pessimistic, adults	0.042	0.019	0.053	0.029	0.306***	0.330*	0.176	0.206	−0.010	0.038	−0.049	0.005
	(0.146)	(0.151)	(0.148)	(0.154)	(0.106)	(0.120)	(0.112)	(0.123)	(0.106)	(0.099)	(0.105)	(0.097)
Optimisitc + Pessimistic, adolescents	0.059	0.005	0.073	0.013	0.115	0.149	0.046	0.081	0.073	0.085	0.029	0.050
	(0.149)	(0.157)	(0.152)	(0.159)	(0.185)	(0.206)	(0.144)	(0.157)	(0.107)	(0.122)	(0.108)	(0.123)
Optimisitc + Pessimistic, children	0.092	0.045	0.106	0.055	0.143	0.130	0.018	0.013	0.116	0.023	0.073	−0.021
	(0.148)	(0.164)	(0.144)	(0.159)	(0.131)	(0.135)	(0.139)	(0.149)	(0.132)	(0.140)	(0.132)	(0.141)
Controls												
Easter dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age category fixed effects	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-
Season day fixed effects	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-
Day-by-age fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Season fixed effects	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
N	2,150	2,150	2,150	2,150	2,437	2,437	2,437	2,437	2,906	2,906	2,906	2,906
R^2	0.773	0.832	0.776	0.834	0.608	0.690	0.647	0.722	0.779	0.819	0.784	0.824

Standard errors in parentheses and clustered at season day level
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table Notes: The table depicts LSDV estimates of model (33) for four specifications in three areas. Standard errors are clustered on the season day to account for intra-day correlations across seasons (seasonality). To allow a comparison between the areas only one-day passes are used. The weather classes are dummies from classes 2 to 4, where class 1 (=bad weather) builds the baseline and is omitted. 0-day forecast classes are similarly defined. The error effects are dummies indicating differences between forecast and weather classes of at least one. Asymmetric effects are tested by the linear combination of optimistic and pessimistic dummies. Easter is a dummy indicating the four Easter holidays (Good Friday to Easter Monday). All models are estimated using season day fixed effects to account for the seasonality.

Center for Regional Economic Development (CRED)

University of Bern

Schanzeneckstrasse 1

P.O.Box

CH-3001 Bern

Telephone: +41 31 684 37 11

E-Mail: info@cred.unibe.ch

Website: http://www.cred.unibe.ch

The Center for Regional Economic Development (CRED) is an interdisciplinary hub for the scientific analysis of questions of regional economic development. The Center encompasses an association of scientists dedicated to examining regional development from an economic, geographic and business perspective.

Contact of the author:

Pascal Troxler

University of Bern

Schanzeneckstrasse 1

P.O.Box

CH-3001 Bern

Telephone: +41 31 684 39 54

Email: pascal.troxler@unibe.ch

This paper can be downloaded at:

https://www.cred.unibe.ch/forschung/publikationen/cred_research_papers/index_ger.html