The Demand, Supply and Regional Economic Development of Swiss Ski Areas

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Preface

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Bern, Dezember 2023 *Pascal Troxler*

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Introduction

Since the emergence of skiing tourism in Switzerland, the Swiss have developed a deep connection to this sport, its traditions and the mountain landscapes involved. The skiing boom after the Second World War fuelled economic growth in otherwise laggard regions and helped to reduce regional economic disparities. However, the growth happened in a fragile environment, requiring the utmost care to conserve its appeal. Almost 40 years ago, Jost Krippendorf investigated the Alpine tourism development in Switzerland in a national research project with the help of Hansruedi Müller and numerous researchers across various fields. At the time, he described it this way:

The connections are obvious: a living space that is not also an economic space is dead. A recreational space that is not also a living and economic space is sterile. An economic space that is not also a living space endangers the environment and resources. The aim must therefore be to coordinate the complementary functions of living, economic activity, recreation and to bring them into harmony with nature. (Krippendorf & Müller, 1986)

His fear that the economic space would outgrow the living and recreational space, which is why the economic space exists in the first place, is a topic more relevant and present than ever. The climate change caused by economic activity threatens the snow reliability of most ski areas and, with it, the sustainability of ski areas' recreational space and connected municipalities' economic space. At the same time, ski area capacities keep growing despite a stagnation in demand for more than twenty years. Is it thus possible that the provision of skiing infrastructure mismatches its demand? How does demand arise in the first place? How much was the economic space growing due to ski area expansion and is it still growing today?

This thesis tackles these questions in three chapters by investigating the demand, supply and regional economic development of Swiss ski areas. Chapter One starts at the individual level by studying the potential skier's activity choice with limited information through weather forecasts and how that translates to the aggregate demand in a ski area. Chapter Two addresses the ski area operator level and investigates the effect of ski lift investments on own and neighboring ski area outcomes. Chapter Three concerns the municipality level and investigates the regional economic impact of ski area access through the widespread emergence of ski areas after the Second World War.

In the first chapter, I investigate the effects of the weather and its forecasts on skiing demand. To this end, I develop a theory where individuals choose their activity based on imperfect information about weather outcomes from forecasts. So far, most scholars consider only actual weather measurements in describing individuals' weather preferences for skiing. However, as conditions in an unstable weather environment only become visible at the site, the decision to go skiing hinges on uncertain weather forecasts. They provide a missing piece of information for those individuals who cannot spontaneously take the skis out of their basement and enter the nearby ski area effortlessly. Forecast errors might thus affect the decision to engage in skiing of individuals with high switching costs. Furthermore, as ski area operators often claim that wrong forecasts ruin their business, the question arises as to whether pessimistic forecasts deter more skiers from skiing than optimistic forecasts induce. In theory, such asymmetric reactions can occur when agents are risk-averse, tend to have higher opportunity costs for skiing, or when a ski area is located far in the Alps, where forecasting errors are more asymmetric.

In the empirical part, I first generate one-dimensional weather and forecast indices through statistical learning techniques that closely represent skiers' weather preferences. Linking these indices to daily demand data from three Swiss ski areas and estimating linear panel data models confirms that forecast errors impact skiing demand beyond the variations attributed solely to weather conditions. In one of the three observed areas, I find that a one standard deviation change in the weather index changes demand by 30% on average. In contrast, the average effect of a standard deviation change in the forecast error is 14%. Thus, optimistic forecasts increase demand above, while pessimistic forecasts reduce demand below expected demand without the error. The differences in effect size point to many spontaneous skiers in all three observed ski areas. Moreover, I find suggestive evidence of stronger reactions to pessimistic than optimistic forecasts.

With this paper, I contribute to three strands of the literature. First, to research that investigates tourists' choices on whether, where, and for how long to take a vacation (Nicolau & Más, 2005, 2008; Yang et al., 2013). Secondly, scholars that relate weather and snow conditions to skiing demand (Haugom & Malasevska, 2019; Malasevska et al., 2017b; Shih et al., 2009) and, thirdly, literature about the use of meteorological information in economic decision-making (Jewson et al., 2021; Wegelin et al., 2022; Zirulia, 2016). My contribution is to link these bodies of work by providing a theory about skiing tourists' behavior, exploiting novel weather forecast data and testing the propositions from the theory with a relevant application.

In the second chapter, co-authored by Monika Bandi Tanner and Marcus Roller, our attention turns to the ski area operators and the effectiveness of ski area investments to retain demand. Skiing demand in Switzerland is dampened by many challenges, encompassing climate change, exchange rate pressures, and demographic changes. Operator firms react to this by leveraging their attractiveness with new high-capacity ski lifts and snowmaking facilities to gain a competitive advantage. These changes at the ski area level raise operation and procurement costs and are often financially supported by public actors across the three federal tiers of Switzerland. However, by supplying more capacities at higher costs while demand deteriorates and prices remain constant (Vanat, 2023), the public interventions might encapsulate an inherent inefficiency. Thus, we set out to study ski area investments in snowmaking facilities and new ski lifts and capture their relationship to own and neighboring ski area outcomes.

Regarding snowmaking, we study the effect of natural snow on ski area demand and transportation revenue and distinguish ski areas by increasing levels of snowmaking capability. We find that ski area operators with snowmaking capability above the median (covering more than 30% of their slopes) reduce their dependency on natural snow by two-thirds. The demand for ski areas at the lowest quartile changes by 5.3% due to a standard deviation change in the number of consecutive days with sufficient snow (a snowpack above 30cm), whereas the demand for ski areas at the highest quartile no longer varies with natural snow. With regard to lift investments, we find that a new ski lift increases demand and revenues in the winter of the lift opening by, on average, 4.1% and 1.9%, respectively, before the effect decays to almost zero after five years. We show that these effects are driven by daytrippers consuming more as a response to the new lift. Furthermore, we find that ski area expansions at the extensive margin (developing new terrain) generate new short-term demand but also attract skiers from neighboring competitors within 25 kilometers. In contrast, ski area expansions at the intensive margin only generate new demand.

With this research, we provide a missing piece to the policy debate about the financial stability of ski area operator firms and the government's involvement and legitimization of it (Derungs et al., 2019; Lengwiler & Bumann, 2018). Furthermore, we link the literature that investigates the relationship between snowmaking investments and ski area demand (Berard-Chenu et al., 2021; Falk & Vanat, 2016; Gonseth, 2013) and the literature that relates quantity and quality of ski areas to firm outcomes (Alessandrini, 2013; Falk, 2008; Falk & Tveteraas, 2020). We contribute to both by using state-of-the-art methods to identify and estimate causal effects, incorporating the effects of nearby competitors by exploiting road distances, using various novel data sources and applying this to the case of Switzerland.

The third chapter, co-authored by Marcus Roller and Monika Bandi Tanner, explores the historical significance of ski area access for alpine municipalities. We find that skiing tourism emerged in two periods. First, during the pioneering period between 1890 and

1940, innovative engineers competed to create the most effective and secure way of transporting tourists close to the famous mountain peaks. At the time, skiing helped merely to operate the first racket railroads, funiculars and aerial cable cars in winter. The second period began after the Second World War when immense economic growth and increasing leisure led to a nationwide skiing boom that changed the primary purpose of cableways. Until 1980, almost all ski areas operating today were opening up. We thus aim to answer how municipalities that gained access to a ski area during this period developed economically relative to comparable alpine municipalities that did not gain such access.

The study utilizes comprehensive historical data on cableways in Switzerland linked to federal tax and population data. Employing a difference-in-differences strategy, we show how the presence of a ski area influences the economic trajectory of municipalities. Access municipalities have a 16% larger population on average, enabling substantially more employment in tourism-related services. As these services are more labor-productive than the otherwise dominating agricultural sector and, at the same time, are within the services more labor-productive in access municipalities than in non-access municipalities, taxable incomes at access municipalities are 15% higher after accounting for population growth. These higher individual incomes and a larger population translate to substantial tax gains for the access municipalities, amounting to an average of 66% higher tax revenues.

This chapter can be seen as part of the growing body of work on the emergence of tourism and its socio-economic impact (Faber & Gaubert, 2019; Favero & Malisan, 2021; Nocito et al., 2021). Furthermore, it informs the policy debate on the effectiveness and efficiency of public involvement in ski areas. We show that access municipalities gain from the involvement by earning higher municipal tax revenues but generate at the same time tight path dependencies between the two because municipal governments invest in ski area infrastructure themselves (Derungs et al., 2019; Schuck & Heise, 2020). In light of climate change, this poses a challenge for municipal governments that face the decision of whether to continue this support, even though natural snow reliability is no longer given.

Chapter 1

The Impact of Weather Forecasts on Skiing Demand

Acknowledgments: I am very grateful to Marcus Roller, Michael Gerfin and Jean-Michel Benkert for their insights and help in modeling and structuring the paper. Additionally, I would like to thank Monika Bandi Tanner, Maximilian von Ehrlich, Samuel Wirth for valuable comments, Max and Irene Gsell from the IMG Stiftung for the funding, and participants at the Brownbag Seminar at the University of Bern, the 2021 AIEST conference in Lucerne, and the 2022 VfS conference in Basel.

1.1 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 skiers likely base their decisions on forecasts rather than the actual weather. Weather forecasts provide information about possible skiing conditions, shape the expectations of skiers and have become considerably more accurate (Bauer et al., 2015). This helps 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 driving to the area entrance. Therefore, switching to another activity is more expensive the more planning is involved and the higher the costs for the alternative. The ability to assess the conditions at the site and make a spontaneous decision is thus only feasible for those already close by. Consequently, weather forecasts might explain demand fluctuations better than the weather itself, especially when the forecasts deviate from the actual weather and when agents face high switching costs.

In this paper, I therefore 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.

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 to go skiing or postpone the decision to when they observe the weather. With all the 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 switching costs. For some agents (Type A), switching costs are high (typically daytrippers). For others (Type B), switching costs are low (typically overnighters). The former base their decision on weather forecasts, whereas the latter postpone the decision to the second period and react accordingly to the weather outcome.

From these individual choices, it appears that optimistic forecasts increase and pessimistic forecasts decrease aggregate skiing demand. However, depending on the circumstances, the effect of pessimistic forecast errors might turn out larger than that of optimistic errors and vice versa. One channel that leads to such asymmetric reactions is that the provider's accuracy in predicting the weather appears to be lower in precipitation-prone large-scale weather situations. In other words, the probability of a forecast error is higher in bad large-scale situations than in typical good weather situations. In the model, I show that such a forecasting asymmetry translates directly into an asymmetric reaction toward pessimistic forecasts. Moreover, risk aversion and a skewed cost distribution of alternative activities among heterogeneous type A agents can foster similar reactions.

Exploiting panel data of daily skiing demand across ten seasons from three large ski areas paired with local weather and weather forecast data allows me to study these patterns empirically.[1] Using a one-dimensional weather index comprising of sunshine duration, precipitation and minimum temperature with data from Federal Office of Meteorology and Climatology (MeteoSwiss), I find that a one standard deviation change in the weather affects demand 58% in area 1. This gross weather effect is a non-linear combination of the net weather 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 demand change of 30% in area 1, is across most groups larger than the forecast error effect, which changes demand on average by 14% in the same area. These differences in effect sizes suggest that a large share 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 shares of the two

[1] In the present work, I exploit variation in daily aggregate demand that fits the theoretical predictions from modeling individuals. Estimating a nested logit model that captures the complete decision process of individuals would be optimal. However, such data does not exist in this context (to our knowledge) (see e.g. Nicolau & Más, 2008; Yang et al., 2013).

types. The share of type A agents among all weather-sensitive one-day pass owners is estimated to lie between 25% and 55% depending on the area.

Finally, I find suggestive evidence of stronger reactions to pessimistic forecasts relative to optimistic forecasts. Further research is necessary to empirically evaluate for which type of agents an asymmetric reaction could be confirmed regarding their opportunity costs, risk aversion or other personal characteristics.

With this paper, I link and contribute to three strands of literature. In the first strand, the researchers model the sequential choices of potential tourists on whether, where and for how long to take a vacation (Nicolau & Más, 2005, 2008; Yang et al., 2013). The model I propose is different as it combines the activity choices of overnighters already on vacation and daytrippers considering plans to ski at a specific ski area. In that sense, I study an additional sequence of the tourist's choice of how to spend a given day, conditional on the weather and its forecast. Generally, weather affects the demand for short trips more than for longer trips (Bausch et al., 2021; Zirulia, 2016) and is therefore precisely relevant for daytrippers and overnighters choosing their activity.

The second strand of literature considers skiing demand and its relation to weather outcomes (Haugom & Malasevska, 2019; Malasevska et al., 2017b; Shih et al., 2009) and dynamic pricing (Lütolf et al., 2020; Malasevska et al., 2020). 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 adaptation investments (Falk, 2015; Falk & Scaglione, 2018; Lütolf et al., 2020; Malasevska et al., 2020; Wallimann, 2022). 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,[2] and it increases pricing efficiency for those areas with

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

dynamic prices.[3] The main contribution here is to empirically incorporate the effect of local weather forecasts on skiing demand.[4]

Lastly, the third strand of literature studies the use of meteorological information in economic decision-making (e.g Cerdá Tena & Quiroga Gómez, 2011; Hewer & Gough, 2016; Katz et al., 1982; Wegelin et al., 2022). The present work is closest related to the papers of Zirulia (2016) and Jewson et al. (2021). The first, by Zirulia (2016), develops a theory of how daytrippers incorporate weather forecasts in their decision to go on excursions. In a sequential model where firms set prices before the guests receive the signal of weather forecasts, he finds that inaccurate forecasts benefit firms and hurt customers because demand elasticities change with the accuracy of forecasts. In contrast to Zirulia (2016), I model the complete demand, including overnighters, and allow forecast accuracy to be heterogeneous for different weather outcomes (which matters because the forecast accuracy varies with large-scale weather situations). Also, I focus solely on aggregate demand, neglecting any supply-side responses (this works as the observed ski pass prices remain static within a season). The second, by Jewson et al. (2021), builds 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 two papers by Zirulia (2016) and Jewson et al. (2021) describe the optimal decision based on forecasts but lack an empirical part to test whether the theory is an accurate model of reality. My contribution is to provide all of that: How decisions are formed, how that translates to the aggregate and whether these theoretical reactions coincide with

[3]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 and thus try to achieve the highest possible capacity utilization. In practice, most operators offer early bookers a substantial discount to hedge the weather risk.

[4]Scaglione and Doctor, 2008 have 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).

observed behavior.

Section 1.2 covers the activity choice model and the propositions that follow from it. Section 1.3 presents the data used for the empirical part. Section 1.4 derives the empirical strategy to evaluate the propositions and Section 1.5 covers the results. I discuss limitations and conclude in Section 1.6.

1.2 Theory

1.2.1 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 remaining home or engaging in the 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 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 1.1.

The weather and forecast states materialize with the probabilities in Table 1.1. 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 agents) cheaper when skiing is planned

Figure 1.1: Decision nodes faced by the agents

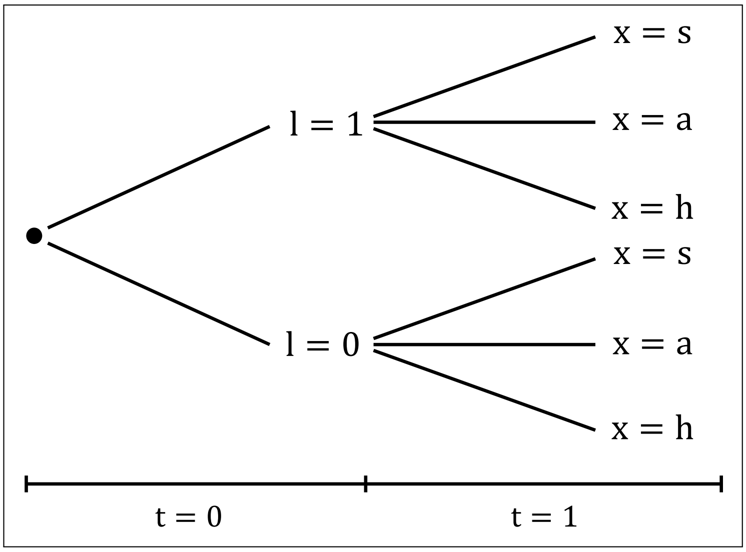

Figure Notes: The first decision node represents the plan $l \in \{1, 0\}$ whether to ski or not to ski and the choice $x \in \{s, h, a\}$ whether to ski, remain home or engage in an alternative outdoor activity. Forecasts are available at period $t = 0$ and the weather at $t = 1$.

Table 1.1: Weather and forecast probabilities

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

($l = 1$) than when it is not planned ($l = 0$). Following the alternative is better than remaining 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 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, that is, 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. They depend on the agent's preferences and costs.

Suppose there are two types of skiers, type A and type B. Type A faces high 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, has no change in cost over time.

Switching costs are higher than sticking to the plan for some agents because it involves 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 carried out 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 from the fact that some individuals choose to ski at all. The second inequality is due to the high switching costs. That is, a large difference between $c(s,0)$ and $c(s,1)$. The last inequality 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

$$\begin{aligned} & p_{\mathrm{f}} \cdot u\big(v(s,g) - c(s,1)\big) + (1-p_{\mathrm{f}}) \cdot u\big(v(s,b) - c(s,1)\big) \\ \geq\ & p_{\mathrm{f}} \cdot \underbrace{u\big(v(a,g) - c(a,0)\big)}_{\text{good weather outcomes}} + (1-p_{\mathrm{f}}) \cdot \underbrace{u\big(v(h,b) - c(h,0)\big)}_{\text{bad weather outcomes}} \end{aligned} \tag{1.1}$$

for 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 always stick to the plan at $t = 0$ because switching is too expensive.

Conversely, type B agents always switch 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 resident or overnighter, will favor then skiing over the alternative. Therefore, in good weather conditions, these types decide to ski no matter what the forecast signals. The type B plans to ski ($l = 1$) whenever

$$\begin{aligned} & p_{\mathrm{f}} \cdot u\big(v(s,g) - c(s,1)\big) + (1-p_{\mathrm{f}}) \cdot u\big(v(s,b) - c(s,1)\big) \\ \geq\ & p_{\mathrm{f}} \cdot \underbrace{u\big(v(s,g) - c(s,0)\big)}_{\text{good weather outcomes}} + (1-p_{\mathrm{f}}) \cdot \underbrace{u\big(v(h,b) - c(h,0)\big)}_{\text{bad weather outcomes}} \end{aligned} \tag{1.2}$$

for f $\in \{g, m, b\}$. As Equation 1.2 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 accepting 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. I start at the more straightforward case of type B.

1.2.2 Heterogeneity in the Cost of the Alternative

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 at $t = 1$ when

$$u\big(v(s,w) - c(s)\big) = u\big(v(a,w) - c(a)\big). \tag{1.3}$$

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

$$\{c_i(a) : \underline{c} \leq c_i(a) < \overline{c}\} \tag{1.4}$$

where $\underline{c}$ is the lowest possible cost of the alternative a and $\overline{c} = c(s)$. From Equation 1.3 I define implicit cost thresholds c^w that satisfy

$$u\big(v(s,w) - c(s)\big) = u\big(v(a,w) - c^w\big) \tag{1.5}$$

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 1.4, the weather is continuous, and so are the implicit cost thresholds.

Type A

For the type A agents, the forecast has decision value and the decision at $t = 0$ is thus 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 ($l = 1$) and engaging in the alternative when skiing is not planned ($l = 0$) at $t = 0$. From Equation 1.1 it follows that the type A is indifferent between skiing and waiting at $t = 0$ when

$$u\big(v(s,g) - c(s,1)\big) = u\big(v(a,g) - c(a,0)\big) + \frac{(1-p_{\mathrm{f}})V_b}{p_{\mathrm{f}}} \tag{1.6}$$

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

$$\{c_i(a,0) : \underline{c} \leq c_i(a,0) < \overline{c}\} \tag{1.7}$$

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

From Equation 1.6 I define three implicit cost thresholds $c^{\mathrm{f}} \in \{c^g, c^m, c^b\}$ that satisfy

$$u\big(v(s,g) - c(s,1)\big) = u\big(v(a,g) - c^{\mathrm{f}}\big) + \frac{(1-p_{\mathrm{f}})V_b}{p_{\mathrm{f}}}. \tag{1.8}$$

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 the 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 1.2 depicts four typical counterfactual situations. An optimistic forecast increases demand by all individuals with cost $c_i(a,0) \in [c^m, c^b)$. Conversely, 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.*

Figure 1.2: Cost heterogeneity and related outcomes under different scenarios

(a) Optimistic error (b) Pessimistic error

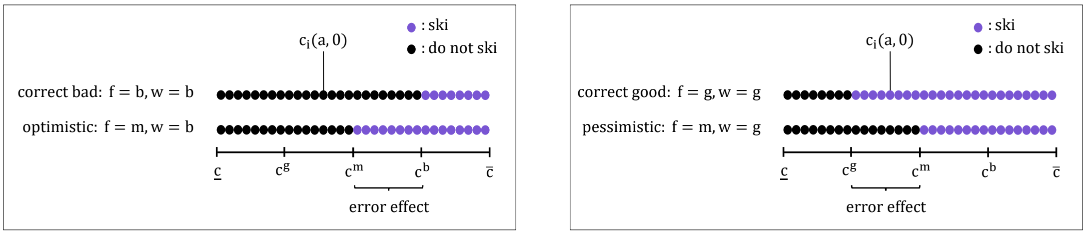

Figure Notes: Both panels indicate two counterfactual situations where the weather turns out bad (in panel a) or good (in panel b) and how type A agents (depicted as dots) decide according to their preferences as idiosyncratic costs of the alternative. On the top line, the forecast is correct and all 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.

On top of that, from the derivation of cost thresholds for both types, it follows that skiing demand on a certain day always consists 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 high switching costs, as, e.g., daytrippers or families, then I would expect a larger volatility of their demand to forecast errors.

1.2.3 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 cost of the alternative $c_i(a, 0)$ is uniform across $[\underline{c}, \overline{c})$. The symmetry of the effects hinges on (i) the alternative's 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 cost distribution of the alternative among type A agents is not uniform (not as drawn in Figure 1.2). The cost of the alternative hinges to a large extent on the guest composition of the ski area, its available opportunities, and its saturation from skiing. For example, daytrippers from urban areas might have fewer alternative outdoor activities than rural ones. A ski area with primarily urban guests facing high costs for the alternative would lead to a left-skewed distribution. In such a setting, optimistic error effects exceed pessimistic error effects.

The second channel works through risk aversion. It makes planning to ski at $t = 0$ for mixed forecasts less attractive because 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 A.2.1.

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 than bad weather. Typical bad-weather situations such as west wind and Foehn exacerbate the prediction in inner-alpine regions because it is *ex-ante* uncertain how far the clouds reach into the Alps.[5] The

[5] 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

complex topography of the mountains makes it almost impossible to precisely predict when clouds appear and where some mountains protect certain places from unfortunate weather outcomes. On the contrary, in typical good weather situations such as high-pressure and Bise situations, the weather is relatively easy to predict accurately as unexpected storms are almost impossible to hit certain inner-alpine areas.[6] See Appendix A.3.2 for an empirical investigation of this phenomenon and how it leads formally to asymmetric reactions.

The existence of these three channels supports the idea that the effects materialize asymmetrically, with pessimistic forecasts inducing larger demand effects than 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.*

The following Section describes the data used to test the three propositions in Section 1.5.

1.3 Data

1.3.1 Demand

Demand data consists of either bookings or first entries[7] 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 during the observed

on the lee side and to precipitation and thick clouds on the windward side of the mountains (Federal Office of Meteorology and Climatology, 2015; Steinacker, 2006).

[6]Bise is 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 overcasts the Swiss midlands and an inversion (temperatures are higher above the fog than below)(Federal Office of Meteorology and Climatology, 2015).

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

period.[8] 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 valid on the same day as the transaction are used from area 1.[9]

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). The shares of pass validity types and age groups among all passes in the three areas are depicted in Appendix A.3.1.

1.3.2 Weather

Weather data is available from MeteoSwiss. The data is drawn for all weather stations within a 30km radius of a chosen lift station[10] 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 Forest (RF) and forward selection, to predict skier demand. These procedures evaluate the most important variables to predict demand as accurately as possible. I document the identification of relative sunshine duration, precipitation and minimum temperature during the day as the key variables in Appendix A.1.4.[11]

[8] A dynamic price system with price adjustments for certain weather situations would violate the exogeneity of the weather variables in the empirical specifications and was thus an essential criterion for selecting ski areas.

[9] 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.

[10] I take the lowest lift within a ski area apart from the access lift. This lift lies at altitudes higher than 1500 m.a.s.l. in all three areas.

[11] Wind, wind chill temperature and snowfall are often also cited as key variables for skiing (e.g., in Falk, 2015; Gonseth, 2013; Haugom & Malasevska, 2019; Malasevska et al., 2017a). Strong winds or substantial snowfalls can even force an operator to close ski areas for some days. However, the results are not sensitive to the inclusion of any of those variables in the analysis (see Appendix A.1.4.)

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

Precipitation is measured in millimeters throughout the daytime. During snowfall or rain, the light is often flat, exacerbating 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).

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; Shih et al., 2009). This non-linear representation implicitly captures the negative impact of the snow conditions of warm, sunny spring days as well as the negative impact of the very icy cold days.

1.3.3 Weather Forecast

The weather forecast data are midnight model outputs of COSMO-7 (Consortium for Small-scale Modeling) obtained from MeteoSwiss (Federal Office of Meteorology and Climatology, 2012, see e.g.). 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 are spatially interpolated to the point of the chosen lift within all three areas to match the weather data in space (see Appendix A.1.3 for details).

One limitation of this data is that it is computed outputs that do not necessarily match actual published forecasts perfectly. However, as the data are available on a very local scale, these represent the inputs 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 MeteoSwiss. Several other weather service providers publish their forecasts using the same computer model outputs. That is why I prefer the indices over pictograms (see Appendix A.4 for an alternative forecast measure using pictograms).

1.3.4 Index

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. Combining three (negatively) correlated weather variables into one index might seem counter-intuitive. However, it is simple and allows a clear-cut depiction of forecast errors and preferences.[12] Furthermore, it works as a proxy for the perceived weather while the information loss is negligible. As we show, the results do not change qualitatively when using single weather variables instead (see Appendix A.3.3) and the performance of the index to predict skier attendance remains at the same level as with single weather variables (see Appendix A.3.4).

The three key variables documented in Section 1.3.2 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

[12]Regressing demand on single weather variables has the caveat that the coefficients lack a *ceteris paribus* interpretation exactly because the variables are interrelated.

defined

$$\widetilde{sun}_{ds} = sun_{ds} \tag{1.9}$$

$$\widetilde{prec}_{ds} = \begin{cases} 100 - (|prec_{ds}| * 10), & \text{if } |prec_{ds}| \leq 10 \\ 0, & \text{otherwise} \end{cases} \tag{1.10}$$

$$\widetilde{\underline{temp}}_{ds} = \begin{cases} 100 - (|\underline{temp}^{*} - \underline{temp}_{ds}|) * 5, & \text{if } |\underline{temp}^{*} - \underline{temp}_{ds}| \leq 20 \\ 0, & \text{otherwise} \end{cases} \tag{1.11}$$

where $prec_{ds}$ is the daytime precipitation (6-18 Coordinated Universal Time (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 indices. $\underline{temp}^{*}$ is the optimal minimum temperature evaluated by regressing aggregate demand on the three single weather variables in each area (see Appendix A.1.4). The partial indices are scaled from 0 to 100, with larger values associated with better weather.

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

$$w_{ds} = 1/3 * \widetilde{sun}_{ds} + 1/3 * \widetilde{\underline{temp}}_{ds} + 1/3 * \widetilde{prec}_{ds} \tag{1.12}$$

$$f_{ds}^{d-h} = 1/3 * \widetilde{sun}_{ds}^{d-h} + 1/3 * \widetilde{\underline{temp}}_{ds}^{d-h} + 1/3 * \widetilde{prec}_{ds}^{d-h}. \tag{1.13}$$

The question may arise why I weight the three variables uniformly. The variable importance results and Ordinary Least Squares (OLS) estimates in Appendix A.1.4 show that relative sunshine duration should be weighted the most. But, once the three variables are equally scaled, precipitation should be weighted the most (see Appendix A.3.3). At the same time, considering the literature would suggest that temperature should be weighted the most (see, e.g. Haugom & Malasevska, 2019). The compromise is thus to weigh all three variables equally. In Appendix A.3.3, I discuss what implications other weightings have on the results.

Another concern is the functional form assumptions imposed through the index and how these could potentially bias the results. To address this, I transformed all weather and forecast variables to pictograms based on instructions from the data provider MeteoSwiss, adjusted them for precipitation and ran all models using those heuristics. In this robustness check, the variables are essentially transformed into pictograms that the end-user sees in the web browser or the phone application. The data processing, adjusted empirical specifications and the results using the pictograms are in Appendix A.4. 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 and a summary of the selection procedure of the three key variables are all in Appendix A.1.

1.3.5 Summary

Table 1.2 shows the summary statistics of the data. Because weather and forecast variables vary little across the three areas, only those from area 1 are displayed. The aggregate demand shows that area 3 is 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 relatively large because the fluctuations within a season are substantial. Noticeably, precipitation forecasts are pessimistic on average, whereas sunshine duration forecasts are optimistic on average. 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 (within each area) and hence centered with a mean zero.

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

Table 1.2: Summary statistics

Variable	Obs	s	$\bar{d}$	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 $\bar{d}$ indicates the average number of days per season (as the panel is unbalanced).

In the next section, I derive the empirical strategy that allows me to empirically test propositions 1 to 3.

1.4 Empirical Strategy

The empirical model to test proposition 1 links weather and forecast data to aggregate skiing demand. I estimate

$$log(y_{ds}) = w_{ds}\beta + e_{ds}^{d-h}\delta + \alpha_d + o_{ds}\nu + \varepsilon_{ds}, \tag{1.14}$$

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 the model in Equation 1.14 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 are the potential of type B agents to ski 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 that day. They number to A_{ds}. Demand on a given day can then be decomposed into

$$E[y|w,f] = E[B|w] + E[A|f] \tag{1.15}$$

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 does not directly influence 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

[14] Note that the model in Equation 1.14 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.

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, the model in Equation 1.14 is extended by variation across different groups. The model reads then

$$log(y_{dsg}) = w_{ds}\beta_0 + e_{ds}^{d-h}\delta_0 + \sum_{g=1}^{G}(D_g\gamma_g + w_{ds} \times D_g\beta_g + e_{ds}^{d-h} \times D_g\delta_g) + \alpha_d + o_{ds}\nu + \varepsilon_{dsg}, \tag{1.16}$$

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 and variables are defined as in Equation 1.14.

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 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 with the average partial effects from the model in Equation 1.16. Formally,

$$\begin{aligned} S_g^A :=& \frac{\%\Delta A_g}{\%\Delta(A_g + B_g)} \\ =& \frac{exp\big((\hat{\delta}_0 + D_g\hat{\delta}_g)\hat{\sigma}_e\big) - 1}{\Big(exp\big((\hat{\delta}_0 + D_g\hat{\delta}_g)\hat{\sigma}_e\big) - 1\Big) + \Big(exp\big((\hat{\beta}_0 + D_g\hat{\beta}_g - \hat{\delta}_0 - D_g\hat{\delta}_g)\hat{\sigma}_w\big) - 1\Big)}, \end{aligned} \tag{1.17}$$

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 residents with relatively low switching costs. Therefore, differences across these two groups would confirm proposition 2.

To test proposition 3, whether asymmetric error effects prevail, the model in Equation 1.16 is further extended using slope dummies. I estimate

$$
\begin{aligned}
log(y_{dsg}) = & w_{ds}\beta_0 + e_{ds}^{d-h}\delta_0 + (e_{ds}^{d-h} \times \tilde{D}_{ds})\lambda_0 \\
& + \sum_{g=1}^{G} \left(D_g\gamma_g + (w_{ds} \times D_g)\beta_g + (e_{ds}^{d-h} \times D_g)\delta_g + (e_{ds}^{d-h} \times \tilde{D}_{ds} \times D_g)\lambda_g \right) \\
& + \alpha_d + o_{ds}\nu + \varepsilon_{dsg},
\end{aligned}
\tag{1.18}
$$

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 Equation 1.16. 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 specified as one group and the sum in Equation 1.18 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.

1.5 Results

I estimate the aggregate model in Equation 1.14 separately for each ski area and forecast horizon. The results are presented in Table 1.3. 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 show positive and statistically significant coefficients 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%, 41% and 63% change in skier demand in areas 1 to 3, respectively.[15]

[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 $\%\Delta y = exp(\Delta\beta * \sigma_w) - 1$.

Table 1.3: 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

Table Notes: The table depicts OLS estimates of the model in Equation 1.14 for three areas and three forecast horizons. 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 1.3.2. 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). Standard errors are in parentheses and clustered at the season day level.

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

Table 1.3 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] Zooming further into group heterogeneities in the next step reveals that the low coefficients on forecast errors in area 3 originate from differences in the guest composition that blur effects in the aggregate.

To this end, 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 closely resembling typical type A and B agents. One-day pass owners are mostly daytrippers who face high 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, residents or overnighters with 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 1.4 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 Equation 1.17 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

[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)

[17]62% in area 2 and 69% in area 3, see Figure A.2 in Appendix A.3.1.

[18]One can think of three reasons why a typical overnighter buys a multiday-pass: First, she is not weather-sensitive and skis either way. 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 thus favor skiing even if this does not reflect their rational choice (Arkes & Blumer, 1985).

Table 1.4: Effect of weather and forecast error on log demand by pass types

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

Table Notes: The table depicts OLS estimates of the model in Equation 1.16 where the groups are separated by different pass validity categories using three specifications across two ski areas. 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 1.17). The Easter dummy indicates the four Easter holidays (Good Friday to Easter Monday). Standard errors are in parentheses and clustered at the season day level. The full table with all pass type groups is in Appendix A.3.6.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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 good and stable large-scale weather situations, forecasts and weather variables run perfectly aligned. Thus, an early decision by a type A agent would not be identified as such.

In the next step, I turn to asymmetric reactions of forecast errors by including a slope dummy on the forecast error as in Equation 1.18. So far, I have shown that most variation from error effects originate from one-day pass owners as they are the only group with a sizeable share of type A agents. Therefore, by 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 1.5 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 contrary, increases demand all else equal by 3%, 8% and 8% for the respective areas. The difference between both error directions is only in area 1 significant at the 5% level. Because neither looking at heterogeneity by age type (Table A.7 in Appendix A.3.5) nor considering additional robustness checks confirm asymmetric reactions (see Tables A.10 and A.11 in Appendix A.4.3), the empirical investigation of Proposition 3 remains suggestive.

Table 1.5: Effect of weather and 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

Table Notes: The table depicts OLS estimates of the model in Equation 1.18 for one-day pass owners in three areas. 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. The Easter dummy indicates the four Easter holidays (Good Friday to Easter Monday). Standard errors are in parentheses and clustered at the season day level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

1.6 Conclusions

I show that potential skiers evaluate their outdoor activities by trading off costs and values that largely depend on the weather, prior information in the form of forecasts and individual costs for the alternatives. Aggregate skiing demand varies accordingly with forecast errors of the weather and the observed weather. This holds in theory as well as empirically. Under specific circumstances regarding the distribution of costs for the alternatives, the degree of risk aversion or the probabilities of forecasts to turn out correctly, aggregate reactions are larger when the forecast is pessimistic rather than optimistic. However, the empirical evidence of such asymmetries remains suggestive and has yet to be confirmed.

Some limitations are discussed here to consider future research proceedings from the above results. First, the aggregate data hinders a detailed analysis on an individual level. The relatively large differences in results between areas suggest that differing contexts or guest compositions add up to aggregates in various ways. Using more detailed individual-level data that tracks individuals' purchase and consumption choices to 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 forecasting progresses at a higher pace than a particular model is in use. Thus, the data of the COSMO-7 model outputs might differ slightly from what was depicted via pictograms in the application. Nonetheless, as the pictograms are monotonous transformations from forecast data, the variation from these transformations or to other forecast providers is likely substantially smaller than the variation within the forecast data itself. Using data from more than one service provider could confirm this.

Third, the above results are documented in the context of ski area entrances with limited relevance. However, the decision framework applies to any outdoor activity with 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, mountaineering, climbing and hiking. More broadly, most water-related outdoor sports such as sailing or surfing are similar too. Therefore, it is a valuable avenue for further research to test the propositions from the theory in other contexts.

Chapter 2

The Investment Competition among Swiss Ski Areas

joint with Monika Bandi Tanner and Marcus Roller

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2.1 Introduction

Ski areas in Switzerland generate winter transportation revenues of around 700 million CHF (Vanat, 2023), operate 1,380 ski lifts and have a vertical capacity of almost 500,000 persons per hour by one kilometer at the end of the winter 2018.[1] The operator firms are often the largest employers in the Alps and can reduce regional economic disparities (Ehrler, 2022, see also Chapter 3). Recently, Swiss ski areas have been exposed to two opposing trends. On the one hand, skiing demand is shrinking due to a warming climate and its detrimental effect on the snowpack (Elsasser & Bürki, 2002; Gössling et al., 2012; Koenig & Abegg, 1997; Marty et al., 2017), exchange rate pressure (Abrahamsen & Simmons-Süer, 2011; Plaz & Schmid, 2015), price reductions for air travel (Müller-Jentsch, 2017) and demographical changes (Lütolf et al., 2020; Plaz & Schmid, 2015). In Figure 2.1, we show that ski area first entries have decreased by 12% between 2010 and 2018 alone. Moreover, notice the visual correlation between natural snow days and demand.

On the other hand, the ski area's supply has been growing by 7% in terms of average capacities over the same period and sample. This raises the question of why ski area capacities are still growing despite any growth in demand. One reason is that ski area operators try to increase their attractiveness by investing in new ski lifts with higher capacities to gain a competitive advantage (Falk & Tveteraas, 2020; Mayer, 2009).[2] On top of this motive, governments alleviate such investments by financially supporting ski area operators through subsidized funds or ownership (Derungs et al., 2019; Lengwiler & Bumann, 2018). However, higher capacities and accompanying snowmaking facilities

[1] In the remainder, we use the term ski lift to generalize all facilities that transport skiers (or other persons following a snowsports activity) uphill. These include all surface lifts (such as t-bar and platter lifts), aerial cableways (such as chairlifts, gondolas, cablecars, funitels, funitors and hybrid lifts), cable railways, funiculars and, in some instances, racket railways. Additionally, the term capacity describes a ski lift's vertical transportation capacity (persons per hour times one kilometer).

[2] Because of technological advances, a new ski lift is faster and more comfortable and is often endowed with larger cabins than its predecessor (Falk & Tveteraas, 2020; Mayer, 2009). Such product innovations are generally viewed to increase the profitability of a ski area through a higher willingness to pay and, potentially, more skiers (Alessandrini, 2013; Falk, 2008; Malasevska, 2018).

Figure 2.1: Development of ski area supply and demand

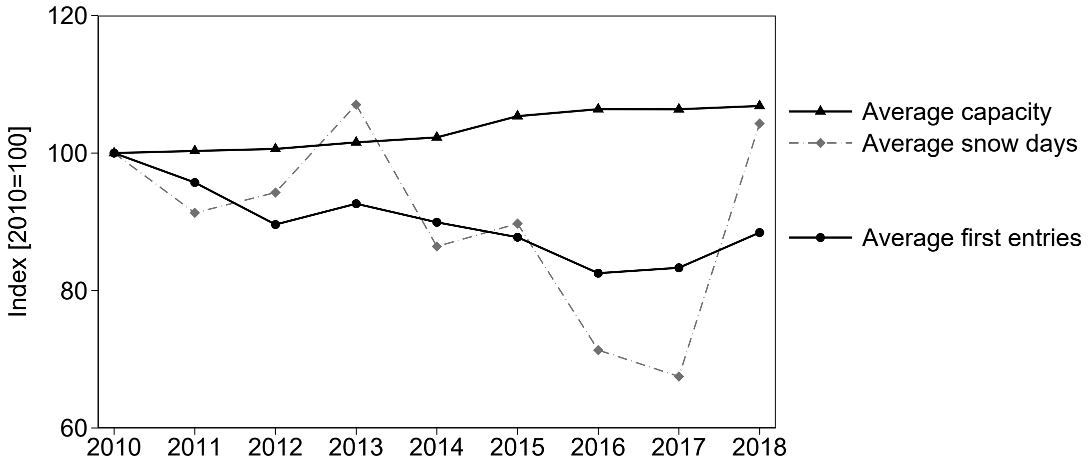

Figure Notes: Average ski area capacities (data from *bergbahnen.org*, measured as persons per hour transported times vertical kilometers) and first entries (data from Seilbahnen Schweiz (SBS) and annual reports of ski area operator firms) of a balanced panel with 46 Swiss ski areas and their mean consecutive days with a snow cover of $\geq$ 30 cm (data from the WSL Institute for Snow and Avalanche Research (SLF)). The averages are indexed to 100 in 2010. Snow days and first entries in year t correspond to the winter season $t-1/t$ (e.g., first entries in 2018 correspond to the winter season 2017/18). The sample accounts for 24% of all ski areas and 46% of all ski lift capacities in Switzerland and is, thus, skewed towards larger ski areas of which more data is available.

increase procurement, operation and environmental costs.[3]

Despite the rising costs, the average firm has expanded its capacities and snowmaking capabilities without enforcing higher prices (average prices remained constant between 2010 and 2018, see Vanat, 2023)[4] all the while demand has deteriorated. It is therefore crucial to study how ski area investments affect skiing demand and, if so, whether it creates new demand or attracts skiers from competing areas. Until now, no research has employed a rigorous identification of ski area investment's demand-side effects that simultaneously consider the local competition.

[3]New ski lifts are often accompanied by snowmaking facilities that guarantee the operation of connected slopes (Falk & Tveteraas, 2020) while increasing water consumption (Cognard & Berard-chenu, 2023). Furthermore, operation and procurement costs increase with the length, speed and size of the cabins (Kremer, 2015; Schibli, 1999).

[4]Notice that the relationship between ski area size and prices was further shocked when Saas Fee introduced an 80% discount on season passes in the winter of 2016/17. Suddenly, skiers could ski at a large resort for barely profitable prices for small lift operators. Even though this pricing strategy was likely unsustainable (Falk & Scaglione, 2018), it launched the widespread introduction of dynamic prices across Switzerland (Lütolf et al., 2020; Wallimann, 2022).

The goal of this paper is thus to close this research gap by estimating the effect of Swiss ski area investments on firm-level outcomes. In particular, (i) whether snowmaking investments help to overcome the operator firm's dependency on natural snow, (ii) how much ski lift investments increase the operator firm's demand and revenue in the short term and (iii) whether and how much demand reacts to neighboring ski lift investments.

We answer these questions by combining novel data with a state-of-the-art empirical strategy to identify causal effects. The investment data is from the online platform *bergbahnen.org* and linked to firm-level outcomes from Seilbahnen Schweiz (SBS), the national cableways association. We add snowmaking data from SBS, natural snow and weather data from the WSL Institute for Snow and Avalanche Research (SLF) and the Federal Office of Meteorology and Climatology (MeteoSwiss).

We first follow Gonseth (2013) and analyze the effect of natural snow variability on ski area demand and transportation revenue and test whether a high snowmaking capability reduces these effects.[5] Estimating a linear panel data model using a Two-Way Fixed Effect (TWFE) estimator, we find that ski area operators with snowmaking capability above the median (covering more than 30% of their slopes) reduce their dependency on natural snow coverage by two-thirds. Instead of a 4.8% change in demand and a 4.1% change in revenue due to a standard deviation change in the number of consecutive days with sufficient snow cover, they vary on average only by 1.4% and 1.6%, respectively. The ski areas at the highest quartile in snowmaking capabilities reduce their natural snow dependency to effects statistically indistinguishable from zero.

We then employ a Difference-in-Differences (DiD) strategy (using TWFE estimators or so-called event study specifications, see e.g. Freyaldenhoven et al., 2021; Roller, 2023;

[5]We believe that the approach of Gonseth (2013) and Berard-Chenu et al. (2022) to use snowmaking investments as a moderating variable on the relationship between natural snow variability and outcomes is more valid than investigating the direct effect of snowmaking investments on outcomes. Above all, because the latter relationship is highly endogenous. For example, as firms invest in snowmaking facilities mostly in dry years (Berard-Chenu et al., 2021), their demand and revenues often increase one year later because of reversion to the mean. On such occasions, the snowmaking investments could easily be confused to cause an increase in demand.

Schmidheiny & Siegloch, 2023) for the Swiss market to study the events of new lift installations. We find that a lift investment increases demand on average by 4.1% and revenue by 1.9% in the first winter season of the lift opening. The effects become statistically insignificant in the second year and converge to zero after five years.[6] Adding hotel demand data from the Federal Statistical Office (FSO) to our model shows that daytrippers, not overnight stayers, drive the positive demand effects.

Finally, we add ski lift investments in neighboring ski areas to our empirical model and distinguish new ski lifts by 25km road distance rings and by whether they expand a ski area extensively to new terrain or not (intensive versus extensive ski lift investments). We find no spatial competition for new ski lifts at the intensive margin. However, demand decreases in the first season after a neighboring extensive investment within 25km by 10% on average and all else equal. The effect remains negative for road distances between 25 and 50km but decays to zero after 50 kilometers. Together, our results imply that intensive ski lift investments create (or retain) business at the operator's ski area without affecting neighbors. This result is likely driven by a behavioral change of skiers consuming more because the new lift provides more comfort, is more beginner-friendly or has a protective bubble against bad weather. Extensive ski lift investments, however, create business and attract daytrippers from neighboring ski areas. Most likely, the ski lift attracts skiers from nearby competitors who aim to explore the new terrain. Both effects materialize primarily during the first winter season and diminish after five years.

We contribute to three strands of the literature. The first strand looks at the financial stability of ski area operator firms and documents the government's involvement and legitimization of it. In Switzerland, the three federal tiers all take part in financially supporting the ski areas: The federal government and cantons implement together the New Regional Policy (NRP) in which projects receive subsidies[7] (Hoff et al., 2021; Lengwiler & Bumann, 2018) and the municipal governments act as owners or lenders to investment

[6]Notice that the estimates include effects of all ski area-related changes on top of the lift investment. For instance, the effect of accompanying snowmaking facilities to ensure the operations of the new lift.

[7]Depending on the canton, ski area related projects receive subsidized loans (with a low or zero interest rate) build or renew ski area infrastructure and direct payments (called "à fonds perdu" - without having to pay back) for projects at the concept stage (Ehrler, 2022; Hoff et al., 2021).

projects at their local ski area (Derungs et al., 2019; Lengwiler & Bumann, 2018). Public actors legitimize financial aid through the positive spillovers to complementary tourism-related services such as the accommodation, gastronomy and retail industry (Lohmann & Crasselt, 2012; Lütolf et al., 2020; Wallimann, 2022, Chapter 3) and to support typical winter destinations toward year-round infrastructure utilization (Hoff et al., 2021). We contribute here by showing the average effectiveness of ski lift investments to retain demand and that extensive investments increase competition. By that, we provide a missing piece to the debate about the effectiveness of public involvement in Swiss ski areas.

The second strand concerns the relationship between snowmaking investments and ski area outcomes. Research indicates a positive correlation between snowmaking and ski area demand in Australia, France, Canada and the USA (Bark et al., 2010; Berard-Chenu et al., 2021; Falk & Vanat, 2016; Pickering, 2011; Scott et al., 2019). Regarding Switzerland, Gonseth (2013) finds that an increase in snowmaking facilities from covering zero to 30% of the slopes' length reduces the natural snow sensitivity of skier visits from 0.41% to 0.25% per day with sufficient snow in Swiss ski areas. Although our snow dependency estimates are lower (a reduction from 0.26% to 0.09% per snow day), they lie within the confidence intervals of the results from Gonseth (2013). Still, they may indicate a decreasing natural snow dependency over time. Our work contributes here by showing the Swiss ski area's dependency on snow (natural or artificial) covering a longer period with recent data and providing a benchmark against which other investments can be compared.

The third strand of the literature looks at the quantity and quality of ski lifts and relates these to ski area outcomes (Alessandrini, 2013; Falk, 2008; Falk & Steiger, 2019; Falk & Tveteraas, 2020; Lütolf, 2016; Malasevska, 2018). Several studies have shown that larger ski areas tend to be more profitable by looking at correlations between the size and outcomes of ski areas (see e.g. Falk & Steiger, 2019; Lütolf, 2016) but refrain from identifying causal effects. In that regard, the most similar work to ours is from Falk and Tveteraas (2020). Using data from South Tyrol, they estimate that a lift investment leads to a higher demand between 6 and 10% in the following winter season before returning to the baseline two years later. Furthermore, they find ski lift investments cannibalize demand within the wider ski area because the effect is lower and insignificant when the investment effects include the whole ski destination. However, their identification strategy is not transparent. They neglect potential pretrends and do not discuss other potential violations of crucial assumptions in the DiD setup (i.e., parallel trends, the stable unit treatment value assumption and treatment heterogeneity). We contribute to this literature by using state-of-the-art methods to estimate causal effects, discussing all pitfalls to the identification, incorporating the effects of nearby competitors by taking road distances, using various novel data sources and applying this to the case of Switzerland.

We continue by providing background information in Section 2.2 and present the data in Section 2.3. Then, we show our empirical and identification strategy in Section 2.4 that we use to compute the results in Section 2.5. Finally, we discuss our findings in Section 2.6 and conclude in Section 2.7.

2.2 Background

2.2.1 Firms' Investment Objectives

Faced with the decision of whether to invest in ski area infrastructure, we identify three possible investment objectives of operator firms:

1. Raise the attractiveness of the ski area (Alessandrini, 2013; Ehrler, 2022; Falk & Steiger, 2019; Gonseth, 2013)
2. Overcome congestion (Barro & Romer, 1987; Falk, 2008; Pullman & Thompson, 2003; Walsh et al., 1983)
3. Replace outdated lifts (Falk & Tveteraas, 2020; Federal Office of Transport, 2021)

The first objective is referred to as the *induced-demand effect*: An increase in investments is coupled with the belief to attract more demand and to raise revenues. It can create new demand (the *business-creation effect*), attract skiers away from competing areas (*business-stealing effect*) or have no effect at all. On top of that, seasons tend to become shorter and the snowpack decreases ever more (Abegg et al., 2021; Gonseth, 2013). Thus, the longer a ski area can guarantee operations, the more demand it serves and the more revenue it generates (see Section 2.5.1). The season can be prolonged by building new lifts at higher altitudes or investing in snowmaking facilities. Notice that the business-creation effect does not necessarily imply that investments induce non-skiers to pick up skiing. More likely, it induces a behavioral change in skiers already practicing the sport to consume more skiing days. For example, to explore the new infrastructure and slopes that come with it.

The second objective is referred to as the *induced-investment effect*: A change in demand induces investments. Supply reacts to changes in demand or expected changes in demand. This effect directly threatens the identification of the above-discussed *induced-demand effect*. However, we will show in Section 2.4.2 that this channel is barely any longer a reason to invest in ski lifts. Ski areas only face congestion for a couple of days per season (e.g., during the Christmas holidays or sunny weekends) at a few locations within the ski area. Thus, operator firms aiming to lower congestion fare better by allocating demand more efficiently across time (Lütolf et al., 2020; Malasevska et al., 2020) and existing facilities than by increasing lift capacities (Pullman & Thompson, 2003).

The third objective becomes relevant when concessions are ending. Lifts at sufficiently attractive spots are then often replaced by more comfortable and capacity-intensive lifts. Others might be renewed to the newest standards to extend the concession or are closed altogether. We show in Appendix B.3.2 that a switch in concession status is a good predictor of when ski lifts are replaced.

Notice that the three objectives are not mutually exclusive: A new high-capacity lift built at the main junction in a ski area can meet all three objectives at the same time.

2.2.2 Construction Permits and Concessions

In this section, we briefly describe the formal process of requesting a concession for the operation and construction permit for a new ski lift in Switzerland. The construction permit and concession for cablecars and chairlifts are granted by the Swiss Federal Office of Transport (FOT) and for small lifts by a similar cantonal institution.[8]

In the case of a new large lift, the operator firm has to follow a preliminary inspection that takes around ten months. If the project surpasses that phase, it enters the plan approval phase of another nine months. Many formalities must be addressed during this phase. For example, an environmental impact assessment or reporting the lift to the Federal Office of Civil Aviation (FOCA) as an aviation obstacle (Federal Office of Transport, 2021). Regarding small lifts, the cantonal institution is responsible for a process similar to the plan approval phase. When the ski lift is finally built, the concession is granted for at most 25 years for large and 10 years for small lifts. Both concessions can be extended for a case-by-case settled period at the respective institutions (Federal Assembly of Switzerland, 2010).

With regard to the previously described *induced-investment effect*, the demand of the preceding season cannot influence the construction of a ski lift but rather at least one or two years later. Furthermore, the FOT recommends starting discussions and planning for large projects quite further in advance because the preliminary inspection could lead to additional delays (Federal Office of Transport, 2021). Thus, it is likely that most projects are planned up to five or even ten years before construction and the exact date of a lift opening remains uncertain for quite some time.

2.3 Data

2.3.1 Sample

We gathered an unbalanced sample on outcomes (revenue and demand) from 83 ski areas using data from SBS and annual reports of individual firms. At the same time, we have data on the characteristics of all ski lifts from 186 ski areas within Switzerland from the

[8]The FOT defines small lifts as surface lifts and small cablecars with a capacity of a maximum of 8 persons per direction of travel (Swiss Federal Council, 2020).

online platform *bergbahnen.org* (Gross, 2023).[9] Accordingly, we built the sample to contain as much information as possible about the outcomes. The data is depicted on a map in Figure 2.2. All points indicate a ski area in Switzerland and correspond to the ski lift data from *bergbahnen.org*. The grey and black points indicate the ski areas of which we have additional information on outcomes (grey points only revenue, black points also demand data) from SBS. White points indicate data with no information on outcomes.

Figure 2.2: Ski areas in Switzerland and coverage of samples

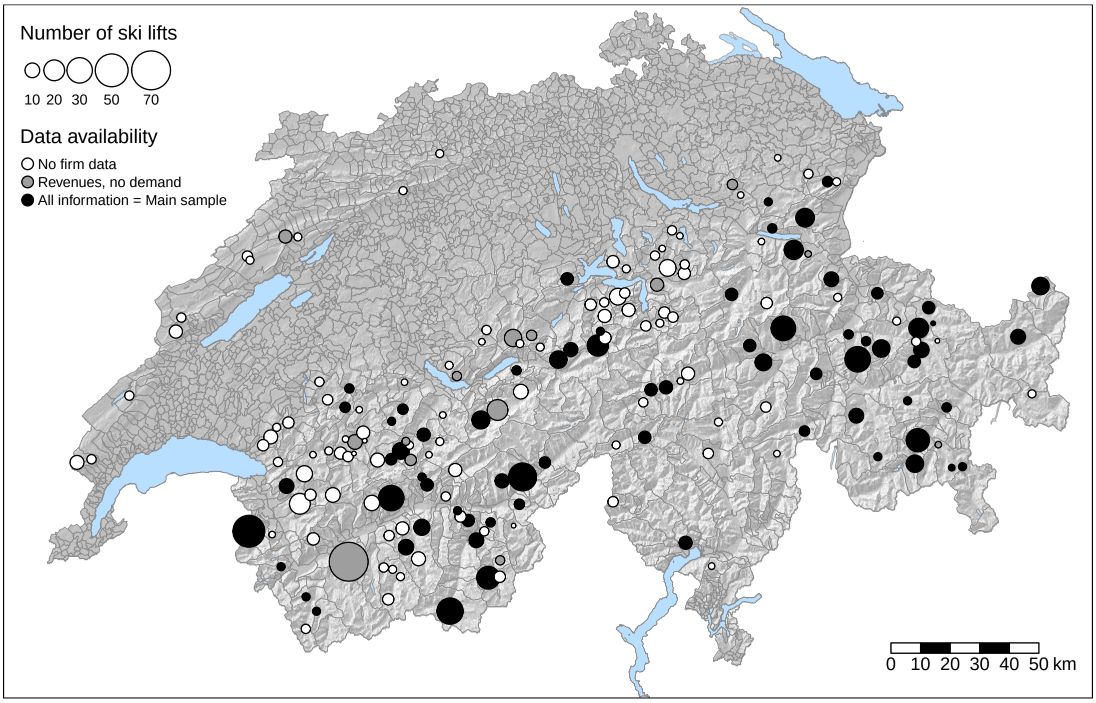

Figure Notes: Points indicate the centroid (in 2009) of Swiss ski areas. The point size depicts the number of ski lifts per ski area in 2018. Black points show ski areas from which all data is available (including revenue and demand data from SBS) and correspond to the main sample. Grey points show areas from which all data except demand is available and white points show all other areas from which outcome data is missing.

Table 2.1 shows the data coverage of the main sample. On the supply side, we count 186 ski areas in Switzerland that built 156 new ski lifts between 2009 and 2018. The new ski lift investments contain 33 lifts at additional sites and 124 replacement lifts, whereby 146 ski lift investments act at the intensive margin (within the original terrain of the ski area,

[9] We define a ski area as a cluster of lifts that consists, on average, of at least two lifts throughout its existence. See Appendix B.1.1 for details.

mostly replacement lifts) and 10 at the extensive margin (expanding the ski area to new terrain, including ski lifts that link ski areas).[10] We narrowed down the observations to our main sample along two objectives. First, to get the most comprehensive coverage of firm data and second, to ensure comparability across the two firm outcomes. Thus, the main sample contains all pairs of non-missing revenue and demand observations available. The resulting sample supports around 64% of all ski area capacities, including 72 ski areas and 83 ski lift investments, of which 9 are extensive and 74 intensive investments.[11] To ensure that our results are not driven by sample selection, we use other samples (e.g. balanced samples) for sensitivity checks. These are described in Appendix B.3.5.

Table 2.1: Data coverage of the samples

[Period] Sample	N	n	T	New	Ext	Int	Capc 2009 [%]	Capc 2018 [%]
[2009 – 2018] Overall	1,849	186	9.9	156	10	146	100	100
[2009 – 2018] Main sample	581	72	8.1	83	9	74	63.2	64.9

Table Notes: The table shows the number of observations (N), the number of panels (n) (= ski areas), the average time periods (T), the number of new ski lifts (New) distinguished by lifts that expand the ski area's terrain extensively (Ext) and those that affect the intensive margin of ski area supply (Int). The last two columns show the share of aggregate capacities that the sample covers from all Swiss ski areas in 2009 and 2018 (Capc). Notice that the overall data is also unbalanced due to ski areas that stopped operations within those years.

2.3.2 Ski Lift Investments

Data on ski lift investments is from the online platform *bergbahnen.org* (Gross, 2023). It contains geo-referenced data on all ever-built ski lifts in Switzerland until 2020. Each lift is assigned to a ski area and contains detailed characteristics such as the lift type, length

[10] We take here the consumer's perspective and conjecture that additional skiing terrain is differently valued than just new ski lifts. Accordingly, linking two ski areas raises the attractiveness in the same way as new terrain in a single area. On the contrary, we count ski lifts at new sites within the terrain of the original ski area to the intensive category. These are, for example, ski lifts that facilitate the crossing of the ski area without adding new skiing terrain or beginner lifts that are typically installed next to flat terrain within the ski area.

[11] The extensive investments are 1 ski lift in Aletschregion (2010), 2 ski lifts in Flumserberg (2013), 2 lifts linking Arosa-Lenzerheide (2013, 2015), 3 lifts linking Andermatt-Sedrun (2017, 2018), 1 lift linking Grimentz-Zinal (2013). Not in our sample is 1 extensive ski lift investment in Sörenberg (2018).

and capacity. Because we are interested in local competition, we identify ski lift investments in neighboring areas using road distances between ski area access points. First, we detect the ski area access points at the surrounding municipalities in a related project (see Chapter 3 for details). Then, with the access points at hand, we compute the shortest road distances between all pairs of ski areas using the Here Application Programming Interface (API) and assign the number of extensive and intensive ski lifts built in road distance rings of 25 kilometers for each ski area .[12] Notice that we only retain ski lifts from areas under the ski area definition stated above.

2.3.3 Ski Area Operator Firms

The firm data on ski area operators is provided by SBS and includes self-reported figures from annual reports. Similar to the ski lift data, we drop excursion lifts that operate only in summer and small ski lifts outside of ski areas. In some instances, the firms did not permit us to match their data with other information, so we dropped these observations. Finally, we fill gaps in winter first entries and transportation revenues and validate the data for as many firms as possible with annual reports from the web (see Table B.1 in Appendix B.1.4 for a comprehensive list of all reports found and used).

The self-reported information on snowmaking capabilities (the share of the slopes that can be prepared with artificial snow) is typically not stated in annual reports. Thus, we cannot perform plausibility checks and have no means to fill the gaps. Moreover, as the snowmaking variable barely varies over time, is often incomplete and contains a few contradictory values, we take the average of the first and last plausible value for each ski area as a proxy for the area's snowmaking capabilities. We then match all firm-level data to the ski lift data and aggregate the variables to the ski area level if two or more firms operate in the same ski area.

In a last step, we split demand at ski areas into two groups: The overnighters and the daytrippers. For this, we first link the first entries of ski areas to hotel demand data by the FSO at the ski area locations. Then, we estimate the travel time for each ski area to all

[12] We compute the road distances with the Stata command *georoute* (Weber & Péclat, 2017).

Swiss agglomerations and compute a gravity-based average travel time that is commonly used in the economic geography literature (see Gutiérrez et al., 2010, for an overview of studies that use such measures and Appendix B.1.7 on details how we implement this). The population data of the agglomerations is drawn from Francelet et al. (2020) and the travel times are computed using the Here API.[13] The resulting remoteness measure captures the daytripper potential for each ski area. Together with changes in overnight stays and first entries across time, we estimate the demand composition of these two types for each area. See Appendix B.1.8 for details on constructing the composition.

Making this distinction in demand imposes two assumptions that must be reconsidered when interpreting the results later. First, changes in overnight stays proxy one-to-one changes in demand from overnighters. It implies that guests do not change their behavior when an investment is made. In other words, if demand increases due to a new ski lift while we observe no change in overnight stays, then all demand changes are attributed to daytrippers. Secondly, year-to-year changes in demand from these two types depend on the baseline level inferred from the remoteness measure. We report additional results in Appendix B.3.10, where we change the baseline level to see whether this assumption drives the results.

2.3.4 Snow and Weather

Snow data are from an ongoing research project of the SLF and MeteoSwiss. In this project, the researchers estimate the snowpack at a detailed spatial and temporal resolution using historical snow, precipitation and temperature measurements (see Michel et al., 2023, for details). They provided us with their most recent estimates, which have not been published to date. The data are modeled water equivalent of the snowpack in meters for each day from 1961 to 2021 in a spatial resolution of 1,000 by 1,000 meters. Then, we match the snowpack data to all ski area centroids and count the number of consecutive days with a snowpack above 30cm (we follow Vorkauf et al., 2022, and assume

[13]We compute the travel times with the Stata command *georoute* (Weber & Péclat, 2017).

120mm snow water equivalent with a snow density of 400kg/m^3 to reach a 30cm thickness of a groomed slope) for each ski area centroid and winter season (typically between the first Saturday in December and the last Sunday in April).[14] We compute the ski area centroids as of 2009 and keep them constant to avoid endogeneity issues.[15] Notice that we exploit solely the within ski area variation of the snowpack in our empirical strategy. Using ski area fixed effects, we purge all time-invariant characteristics such as the ski area centroid or the snow density. Changing these assumptions has, therefore, little to no impact on our final estimates.[16]

We combine daily weather data from MeteoSwiss and daily first entries from three ski areas to construct a weather index (based on the weather index in Chapter 1). The index consists of daily variation from relative sunshine duration and minimum temperature.[17] The data is drawn from 190 weather stations and spatially aggregated to the centroid of each ski area using inverse distance weighted averaging (a widely used method in geography-related sciences to interpolate spatial data, see e.g. Burrough et al., 1998). Then we construct a weighted average of the weather, whereby the days are weighted based on season-day fixed effects from a regression of daily skiing demand on the weather variables.[18] Thus, the weather index is larger the more favorable the weather is for skiing throughout the season and more so when the weather is good on high-season days. See Appendix B.1.6 for a detailed description of how the weather index is constructed.

[14]The centroid of a ski area is simply the average latitude and longitude value of all of its ski lifts. In 6 cases, we manually adjusted the centroids because their altitude was more than 200 meters off from the ski area's capacity-weighted average altitude. See Appendix B.1.5 for details.

[15]The centroid is endogenous to the snow conditions. For example, a ski area operator that has to endure repeatedly bad snow conditions might decide to build new lifts at higher altitudes. This leads to better snow conditions at the new, higher-lying centroid.

[16]Essentially, these choices affect only the few border cases of ski areas where we measure either zero or all 149 consecutive days with sufficient snow at its centroid. See the results in Appendix B.3.3 where we use the substantially lower snow density of 190kg/m^3 corresponding to the median snowpack without grooming.

[17]We refrain from adding precipitation to the index as it highly correlates with our snowpack data. More precipitation in winter clearly leads to a larger snowpack.

[18]A season-day is defined as a day relative to the beginning of the winter season, typically the first Saturday in December. Comparing demand across more than one season is more accurate using season days than the calendar date because weekdays shift from year to year in their calendar date.

2.3.5 Summary Statistics

We provide summary statistics of the main sample in Table 2.2. It shows statistics for different variables with a mean comparison in the last column to check the sample's representativeness.

Table 2.2: Summary statistics of the sample versus all data

	Overall		Sample					
	N	Mean	N	Mean	SD	Min	Max	Diff
bergbahnen.org								
Number of lifts [#]	1,849	7.6	581	10.8	8.7	2.0	49.0	3.2***
Aggregate capacity [(pers./h)×km]	1,849	2,678	581	4,703	4,672	214	22,704	2,025***
Lift investments [#]	1,849	0.08	581	0.14	0.45	0.00	3.00	0.06**
Capacity-weighted average altitude [masl]	1,849	1,676	581	1,881	340	1,106	2,764	205***
SBS								
Winter first entries [1,000 pers.]	-	-	581	261	342	5	2,950	-
Winter transportation revenue [CHF 1,000]	-	-	581	7,648	9,938	30	50,214	-
Artificial snowmaking [%]	-	-	545	35	25	0	98	-
SLF, MeteoSwiss								
Consecutive snow days [#]	1,849	82	581	97	46	0	149	15***
Weather index	1,849	44	581	45	12	17	74	1*

Table Notes: The table shows summary statistics of the sample and compares it to all ski areas in Switzerland (columns under Overall). The last column (Diff) indicates the difference in means of all ski areas and the sample. A two-sided t-test is performed to test whether the differences are statistically distinguishable from zero.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The sample is not representative in terms of ski area size and altitude. Sampled ski areas, on average, contain 42% more lifts, provide a 76% higher vertical capacity, invest in around 56% more lifts and lie about 200 meters higher than the average Swiss ski area. Connected to the higher altitude, sampled ski areas have better snow and weather conditions.[19] Also, larger ski areas naturally require more lift replacements and thus investments. This selection bias means that the results are more valid for relatively large and higher-lying ski areas that invest considerably more than the average ski area in

[19]Clearly, the snowpack persists longer at higher altitudes. The more favorable weather results from fewer overcast days at high altitudes. For instance, high altitudes are free from the typical fog layer at so-called "Bise" situations.

Switzerland. In other words, the results are more valid for ski areas that actually invest frequently.

2.4 Method

2.4.1 Natural Snow Dependency

In this section, we describe the empirical strategy to estimate the firm's ability to reduce natural snow dependency by investing in snowmaking facilities. Before adding variation in snowmaking capability, we model the natural snow and weather dependency of ski areas by a two-way fixed effect model. In particular, we estimate the following specification:

$$\ln Y_{it} = \alpha_i + \delta S_{it} + \eta W_{it} + \theta_t + \varepsilon_{it}, \tag{2.1}$$

where Y_{it} is either demand or revenues at time t in ski area i. α_i and θ_t are ski area and time fixed effects, respectively. S_{it} are the consecutive days with a snow cover above 30cm at t in area i and W_{it} is a weather index. The weather index is constructed using only days between Christmas and March and the larger it is, the more favorable the weather is for skiing on high-season days (see again Section 2.3.4). As both weather and snow conditions are exogenous to the outcome, the coefficients δ and η identify causal effects of the two variables conditional on keeping the other variable constant.[20]

We add an interaction to the specification in Equation 2.1 to estimate whether ski areas with a high snowmaking capability can reduce their dependency on natural snow. In particular, we estimate

$$\ln Y_{it} = \alpha_i + \delta_0 S_{it} + \sum_{g=1}^{G} \delta_g D_g S_{it} + \eta W_{it} + \theta_t + \varepsilon_{it}, \tag{2.2}$$

[20]Towards the end of our observation period few areas have introduced dynamic prices depending on the weather and thus violating strict exogeneity. We exclude those areas in Appendix B.3.6 and report qualitatively and quantitatively similar results to our main specifications.

where all parameters and variables are defined as in the model in Equation 2.1 except the interactions between the consecutive snow days S_{it} and the indicators D_g that equal one if the ski area operator firm has a snowmaking capability between the g^{th} and $(g+1)^{\text{th}}$ quartile of snowmaking capability and zero otherwise. We identify accordingly three group effects ($G = 3$) relative to the reference group below the first quartile.

Notice again that the snowmaking capability variable remains constant over time due to data restrictions. Furthermore, we do not identify a causal effect of single snowmaking facilities on the outcome due to the difficulties in excluding reverse causality and selection into treatment bias.[21] Therefore, we merely compare ski areas with a high tendency with areas having a low tendency to produce snow and whether this reduces natural snow dependency.

2.4.2 Lift Investments

Estimation

In this section, we describe the empirical strategy to estimate the effect of ski lift investments on ski area outcomes and the effect of neighboring investments on ski area outcomes. To this end, we use an event study approach based on Schmidheiny and Siegloch (2023) with multiple treatments and varying treatment intensity. In particular, we allow for multiple investments across the observation period and (neighboring) investments of several lifts per year. The empirical model is

$$\ln Y_{it} = \alpha_i + \sum_{k=-3}^{5} \beta_k C_{i,t-k} + \delta S_{it} + \eta W_{it} + \theta_t + \varepsilon_{it}, \tag{2.3}$$

where $C_{i,t-k}$ are a set of binned event variables that indicate the number of ski lifts built $k \in [-3, ..., 5]$ years ago at time t in ski area i. All other parameters and variables are defined as in the model in Equation 2.1. The binning at the endpoints is crucial because we assume that treatment effects remain constant beyond the event window. The maximum

[21] Ski area operator firms likely react to winter seasons with poor snow coverage by investing in snowmaking capabilities (see Berard-Chenu et al., 2021). At the same time, firms probably invest more in snowmaking facilities when they have a high chance of reducing natural snow dependency.

lag reflects all observable past events before the event window and the maximum lead reflects all observable future events after the event window (Freyaldenhoven et al., 2021; Schmidheiny & Siegloch, 2023). Formally,

$$C_{i,t-k} = \begin{cases} \sum_{s=-\infty}^{-3} c_{i,t-s}, & \text{if } k = -3 \\ c_{i,t-s}, & \text{if } -3 < k < 5 \\ \sum_{s=5}^{\infty} c_{i,t-s}, & \text{if } k = 5, \end{cases} \tag{2.4}$$

where $c_{i,t}$ equals the number of new lifts at t in area i. In a year with no lift investments, $c_{i,t}$ equals zero. An example of the data with binned endpoints is in Appendix B.1.9. For our last objective, the effect of neighboring investments on ski area outcomes, we add the investments at neighboring ski areas to the model in Equation 2.3 using four road distance rings r. This yields

$$\ln Y_{it} = \alpha_i + \sum_{k=-3}^{5} \beta_k C_{i,t-k} + \sum_{r=1}^{4} \sum_{k=-3}^{5} \gamma_{rk} \tilde{C}_{ir,t-k} + \delta S_{it} + \eta W_{it} + \theta_t + \varepsilon_{it}, \tag{2.5}$$

where all coefficients and variables are defined as in the model in Equation 2.3 except $\tilde{C}_{ir,t-k}$ are a set of binned event variables that indicate the number of ski lifts built $k \in [-3, ..., 5]$ years ago in neighboring ski areas at a road distance ring r from ski area i. The binned variables are defined as in Equation 2.4 with $\tilde{c}_{irt}$ and all its leads and lags instead of c_{it} as inputs. $\tilde{c}_{irt}$ denotes all new ski lifts that are built in ski areas $j \neq i$ in road distance rings of $(0, 25]$, $(25, 50]$, $(50, 75]$ and $(75, 100]$ kilometers from ski area i at t. The rings are calculated using the closest access points between ski area i and neighboring ski areas j. In the final step, we separate $\tilde{C}_{irt}$ into two sets of binned event variables (and corresponding coefficients) of new ski lifts that expand the ski area's slopes extensively ($\tilde{C}_{irt}^{ext}$) and new ski lifts without such an expansion ($\tilde{C}_{irt}^{int}$).

All estimates in the models in Equation 2.3 and 2.5 are interpreted relative to the year of the lift construction at $t = 0$. Therefore, we normalize at $t = 0$ by dropping $C_{i,t-0}$

or $\tilde{C}_{ir,t-0}$. The normalization is at the year of the lift construction because it affects demand at the earliest in the winter after construction, which is at $t+1$.[22] In that regard, the normalization is quite standard as we drop the variable one period before the event unfolds.

Notice additionally that we restrict the effect window based on the data availability of the outcome variable. We use 3 leads because we have investment data up to 2020 but outcomes only up to 2018. When an event takes place in 2021, it is unobserved and would be represented by the third lead in 2018. But because endpoints are binned, this unit's third lead is equal to 1 across all years and is absorbed by the unit fixed effect α_i. Hence, although the investment data covers only two more years than the outcome variable, we still identify three leads (See Section 2.1.2 in Schmidheiny & Siegloch, 2023, for a comprehensive discussion of data requirements in binned event study specifications).

Since we have data on lift investments back to 1890, we are almost unrestricted in including lags. Nonetheless, we use lags only up to 5 years. First, because we assume that guests get accustomed to new lifts at least after five years (and thus, it does not make a difference whether a lift is 5, 10 or even 20 years old, the benefit in comfort and capacity remains the same). Second, the event study is symmetric in that we include four pre-treatment periods (3 leads plus the normalized period at $t=0$) and four post-treatment periods (lag 2 up to lag 5).

Lastly, notice that the coefficients of interest (β_k and γ_k in Equations 2.3 and 2.5) include all effects of infrastructural changes at the ski area that happened over the same summer. We assume hereby that the new ski lift is the most salient change to be recognized by the skiers and thus primarily induces the effects. In many cases, a new ski lift is only built when the connected slopes can be supported by additional snowmaking facilities (Falk & Tveteraas, 2020). The resulting estimates are thus valid for overall changes in the proximity of the new ski lift, including accompanying snowmaking facilities, and also need to be interpreted as such.

[22] We denote a winter season that typically starts at mid-December of year t and ends in April of year $t+1$ as being in the year $t+1$ for simplicity.

By estimating the model in Equation 2.3, we are confident in identifying a causal effect of lift investments (and accompanying infrastructure) on the outcome. Thus, in the following sections, we address the assumptions for the identification of β_k in the specification in Equation 2.3 as the Average Treatment Effect on the Treated (ATT). These are (I) no reverse causality, (II) no effect on the pre-treatment population, (III) parallel trends, (IV) stable unit treatment value assumption (see e.g. Lechner, 2010) and (V) treatment homogeneity (see e.g. Schmidheiny & Siegloch, 2023).

Identifying Assumption I: No Reverse Causality

First and foremost, we must exclude the possibility of reverse causality. That is, we have to be certain that a change in demand does not induce ski lift investments. It might very well be the case that lift investments are revenue-driven or demand-driven to resolve congestion (see *induced-investment effect* in Section 2.2.1). The former potentially goes both ways. Firms might invest whenever they stocked sufficient capital or, on the contrary, might be urged to invest as a reaction to bad years.[23] In the following, we argue why lift investments are not induced through the outcome but rather by the concession status of lifts about to be replaced.

We find in Section 2.5.1 that ski areas depend on variation in natural snow and the more so, the fewer snowmaking capabilities they have. Thus, natural snow variation can be used as a proxy for winter revenues much further back in time as our firm data goes. With this, we show that over the period of almost 60 years, snow conditions do not influence the timing of lift replacements. Instead, the concession status is a much better predictor of when lifts are replaced (see Appendix B.3.2 for the empirical evidence on this).

To illustrate this, consider Figure 2.3. It shows the number of replaced lifts and their concession status across the development periods of ski areas (see Chapter 3 for a detailed description of those periods). In the aggregate, 71% of concessions of all ever-replaced lifts in ski areas were initially prolonged. That figure changed from 43% to 74% to 87%

[23] For example, having bad snow conditions for several years induces operators to build lifts at higher altitudes.

across the three time periods (access, expansion, concentration). Most strikingly, in our event window (between 2009 and 2018), barely any lifts were replaced when concessions ended for the first time.

Figure 2.3: Concession status of replaced lifts at replacement

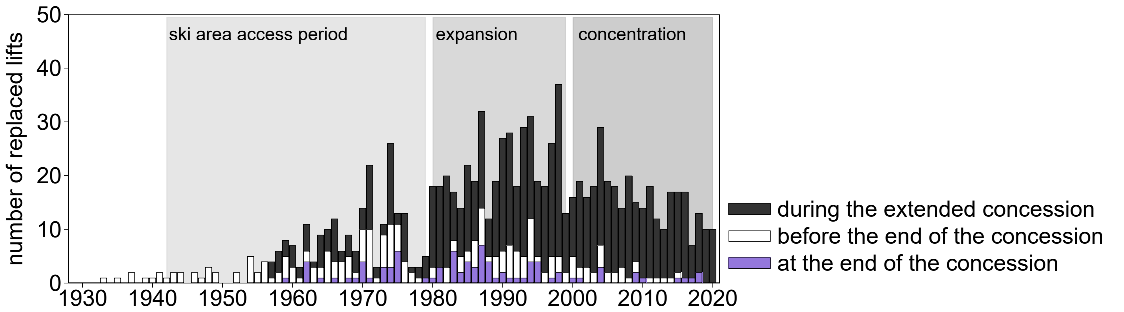

Figure Notes: A concession of a large lift is granted for 25 years (covers most lifts) and for 10 years for a small lift (covers ground-based lifts such as t-bars and very small cablecars with a capacity of maximum 8 persons per direction of travel, see Swiss Federal Council, 2020). At the end of the concession means the concession was within its last two years (t-2, t-1 and t=0).

Identifying Assumption II: No Effect on the Pre-Treatment Population

The second assumption to hold for identification is no effect on the pre-treatment population. This assumption is violated when skiers anticipate the opening of a ski lift and change their behavior before the opening because of it. As most ski area operators replace their lifts when concessions end and often communicate such a change beforehand, skiers anticipating an opening is plausible. However, the bureaucratic obstacles that operators face when new lifts are planned imply that the exact timing of a lift opening is somewhat random. The decision to build a ski lift within the next few years is not random, but when exactly it opens can *ex-ante* be unclear. Since ski area operators find it increasingly difficult to finance investments on the capital markets (due to insecure snow coverage default risk is too high, see e.g. Ehrler, 2022), they often turn to public support where they have even less say on the investment timing (due to the political decision-making process).

Furthermore, such anticipation leads only to biased estimates when the demand side changes its behavior prior to the event. For example, it is conceivable that skiers reduce their demand for a certain ski area, knowing they would want to ski it one year later when the new lift opens. Our results cannot confirm such an Ashenfelter dip (see Section 2.5.2). Including all our sensitivity checks, we estimate more than twenty event studies and find not a single pre-treatment effect that is significantly different from zero. Moreover, testing the pre-treatment coefficients jointly in all these estimates shows no sign of effects on the pre-treatment outcome.

Identifying Assumption III: Parallel Trends

The third assumption to address is the parallel trends assumption that requires outcomes to evolve parallel absent any treatments. In our dynamic setting, the parallel trends assumption must hold for all combinations of periods and groups (Roth et al., 2022), and there is no formal way to test this assumption (Lechner, 2010). Clearly, all operators follow different paths in running their businesses with differing marketing, pricing and vertical acquisition strategies. Therefore, operators that invest more in lift infrastructure might diverge in outcomes from those without investments. We state three reasons why we still expect parallel trends to hold in our setup.

First, trends are, on average, parallel before new lifts are built (we find no pretrends in the results in Section 2.5.2). Second, the public support of lift investments as well as no evidence of revenue-induced investments (on average) shows that not only successful operators can invest, but also those with high local public support or high public financial dependency (i.e., selection into treatment is mitigated through the large public involvement). Third, innovative pricing strategies influence outcomes (Lütolf et al., 2020; Wallimann, 2022) but, as we discuss in the following, do not violate parallel trends.

We argue prices only matter after 2016 because there was virtually no price competition beforehand. Before the Saas Fee price shock at the end of 2016 (Wallimann, 2022), prices reflected the size, comfort and attraction of a ski area (Alessandrini, 2013; Falk, 2008; Malasevska & Haugom, 2018). Price changes were thus directly linked to new lift openings.[24] We estimate the model in Equation 2.3 without ski areas that implemented substantial season-pass discounts or dynamic pricing in Appendix B.3.6 and show that the results are not sensitive to the inclusion of these observations. Therefore, we conclude that price competition does not drive our results and are confident that parallel trends are satisfied.

Identifying Assumption IV: Stable Unit Treatment Value Assumption

The fourth assumption is the Stable Unit Treatment Value Assumption (SUTVA). It requires no treatment interactions between the ski areas (Lechner, 2010). For example, suppose one operator invests in a lift and attracts customers from neighboring ski areas. In that case, those neighbors' demand will be lower than their potential demand in a world without this investment. Therefore, evidence of business stealing directly violates SUTVA. We show in Section 2.5.3 that neighboring ski lift investments do not affect ski area outcomes on average. However, when we distinguish neighboring investments by whether a new lift expands the ski area (extensive margin) or only increases the capacity within the area (intensive margin), we find business-stealing effects from ski area expansions. In this specification, the effect of own ski lift investments is, as expected, lower compared to the estimates without neighboring interference (see Butts, 2023, that shows how treatment effects are upward biased when negative spatial spillovers occur). Nonetheless, the bias is minimal and thus indicates that the SUTVA violation does not alter the results in a significant way.

Identifying Assumption V: Treatment Homogeneity

In our main specification in Equation 2.3, we get unbiased estimates when we assume treatment homogeneity across different years (Schmidheiny & Siegloch, 2023). However, recent advances in the econometric literature have pointed out that event study designs produce biased estimates when treatments are heterogeneous across time (Callaway &

[24]Absent any investment, the prices remain constant and ski area operators that neither invest nor change prices are therefore a valid control group. When areas change prices unrelated to investments but have at the same time systematically a higher or lower likelihood to invest, parallel trends are violated.

Sant'Anna, 2021; de Chaisemartin & D'Haultfœuille, 2020, 2023; Sun & Abraham, 2021). To our knowledge, only de Chaisemartin and D'Haultfœuille (2023) examine treatment heterogeneity with multiple events in the same unit (see Roth et al., 2022, for an overview of recent advances on the literature of treatment heterogeneity in TWFE models) and we accordingly run their estimator. Additionally, we follow Siegloch et al. (2022) by cutting our sample to units that have only been once or never treated (from 2009 to 2018) and run the estimator of Sun and Abraham (2021). See Appendix B.3.7 for the results with these two estimators. As the differences in the estimates are small compared to the baseline estimate, we conclude that our main results are not driven by treatment effect heterogeneity across time.

However, the sample cut produces a selection bias towards small ski areas, leading to larger point estimates than in the main specification.[25] Treatment effects may thus not be homogeneous across ski area sizes. A new lift installation could have a much broader effect on demand when only three lifts are in place compared to a ski area with twenty lifts. One way to examine effects across ski area size is by defining the treatment variable as relative treatment intensity. An investment is then formulated as the relative capacity change from one year to the next. Again, the results do not differ qualitatively but show that the relative effects of a single lift investment are likely larger for smaller ski areas and vice versa. See Appendix B.3.8 for results on this.

2.5 Results

2.5.1 Natural Snow Dependency

In Table 2.3, we show Ordinary Least Squares (OLS) estimates of the specification in Equation 2.1. Increasing the number of consecutive days with a natural snow coverage of above 30cm by one day leads on average to 0.16% higher skier demand all else equal

[25]The remaining sample contains 30 ski areas with an average of 6.3 lifts with a capacity of 6,992 persons per hour. These values are substantially lower than in the main sample (10.8 lifts with a capacity of 12,727 persons per hour).

(column 1).[26] As a typical year-to-year change in natural snow days within a ski area is 25 days (= within ski area standard deviation), skiing demand varies by 4% from one year to the next due to the natural snow conditions on average.

Table 2.3: The effect of natural snow coverage and weather on ski demand

Dependent variable:	Log winter first entries	Log winter transportation revenue
	(1)	(2)
Snow days	0.0016***	0.0012**
	(0.0003)	(0.0004)
Weather index	−0.0004	−0.0019
	(0.0023)	(0.0021)
Intercept	6.1481***	9.9608***
	(0.0983)	(0.0924)
Year fixed effects	Yes	Yes
Ski area fixed effects	Yes	Yes
N	581	581
R^2	0.9911	0.9934

Table Notes: The Table shows OLS estimates of the model in Equation 2.1. Column (1) shows estimates with the log of winter first entries as the outcome. Column (2) shows estimates with the log of winter transportation revenue as the outcome. Snow days are the consecutive days with natural snow cover above 30cm and the weather index is a weighted average of favorable skiing weather with high weights for high season days and low weights for low season days. The weather index variable is scaled from 0 to 100. Standard errors are in parentheses and clustered at the ski area level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

In column 2, Table 2.3, we show OLS estimates from the model in Equation 2.1 using winter transportation revenue as the outcome and find qualitatively the same results as with demand. We find that an increase of one day in natural snow days leads, on average, to a 0.12% increase in winter transportation revenue.

[26]This estimate and all of the following results are computed in exact percentages. Formally, for the coefficient on the snow days $\hat{\delta}$ and the change in snow days $\Delta S = 1$, we get $\%\Delta Y = exp(\hat{\delta} \cdot \Delta S) - 1$.

To differentiate the effect of snow days across the quartiles of artificial snowmaking capabilities, we estimate the model in Equation 2.2 and recover partial effects for each group g.[27] The group estimates are depicted in Figure 2.4. Each point depicts the effect of natural snow days on outcomes across the four groups between the quartiles indicated by $q1$ to $q4$. The first point (from left) shows the effect of the reference group and the other three points show the partial effect for each group g. For example, the point between q1 and q2 in panel (a) shows that an increase of one day in natural snow days leads, on average, to 0.17% more first entries for ski areas with a snowmaking capability between the first and second quartile. The effect of natural snow days becomes statistically insignificant for the ski areas around the third quartile. Thus, variations in natural snow days still positively affect more than half of the sampled ski areas.

Panel (b) in Figure 2.4 with revenues as the outcome shows similar results. Therefore, we conclude that only ski areas above the third quartile in snowmaking capability show independence of variations in days with natural snow cover. Nonetheless, ski areas above the median in snowmaking capabilities can reduce the demand dependency to approximately a third compared to those below the median (from the four groups, we get an average effect of 0.06% above vs. 0.19% below the median). Considering again how much natural snow days vary from year to year, the above median groups' demand varies on average by 1.4%, whereas the below median groups' demand varies by 4.8% due to natural snow conditions.

Notice that the coefficients on the weather are not significant in Table 2.3 as well as in the two regressions in Figure 2.4 (and the corresponding coefficient table in Appendix B.2.1). Thus, the weather conditions do not affect seasonal ski area outcomes, all else being equal.

[27] The partial effect is the partial derivative of the expected value of Equation 2.2 with respect to the snowmaking variable. Formally, $\frac{\partial E[\ln Y_{it}|S_{it},W_{it},D_g]}{\partial S_{it}} = \delta_0 + \delta_g D_g$. Therefore, $\hat{\delta_0} + \hat{\delta_1}$ is the respective partial effect for group $g = 1$.

Figure 2.4: Effect of natural snow days on winter outcomes across snowmaking capability

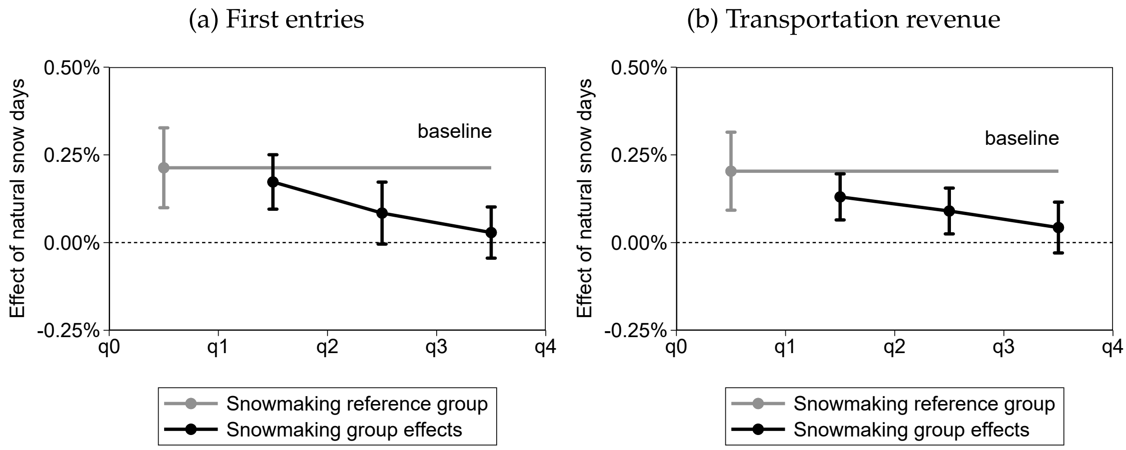

Figure Notes: Each point depicts group estimates of the model in Equation 2.2 across snowmaking capability groups split at quartiles. In particular, the first point from left (grey) depicts the point estimate of consecutive snow days for the reference group (below the first quartile) and the other points (purple) depict the partial effects of consecutive snow days for ski areas between the respective quartiles in the horizontal axis. For example, the point between $q2$ and $q3$ depicts the effect of natural snow days for the group that has a snowmaking capability between the second and third quartile (i.e. $\hat{\delta_0} + \hat{\delta_2} D_2$ with $D_2 = \mathbb{1}\left[snowmaking \in (q2, q3]\right]$). Panel (a) shows the estimates with the log of winter first entries as the outcome and panel (b) the estimates with the log of winter transportation revenue as the outcome. The bars show 95% confidence intervals and standard errors are clustered at the ski area level. The coefficient table with point estimates and standard errors is in Appendix B.2.1.

2.5.2 Lift Investments

Figure 2.5 depicts the results from the model in Equation 2.3. Panel (a) shows that in the winter after construction, demand increases on average by 4.1% for each built lift. There is no pretrend visible and a joint F-test of the three leads is statistically not distinguishable from zero at the 5% confidence level. At the same time, the effect drops to 2.0% for the next four winters and is no longer statistically significantly different from zero at the 5% confidence level.

In panel (b) of Figure 2.5, we depict that a lift opening translates to a 1.9% higher transportation revenue in the winter of the opening with no statistical significance at the 5% level and drops to zero in the fifth winter after the investment. Although the point estimate on revenue is considerably smaller than the effect on demand, we infer that ski

Figure 2.5: Effect of new ski lifts on first entries and transportation revenue

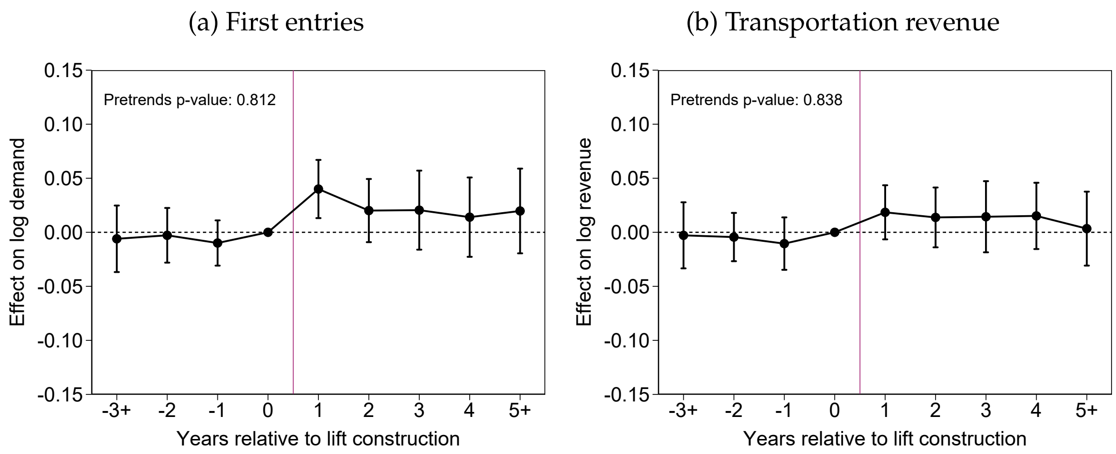

Figure Notes: Both panels show estimates of the model in Equation 2.3 across time. Period 0 indicates the winter before the lift construction (which is in the same year) and period 1 indicates the winter of the lift opening. Panel (a) shows the estimates with the log of winter first entries as the outcome using the unbalanced demand sample and panel (b) the estimates with the log of winter transportation revenue as the outcome using the unbalanced revenue sample. The bars signify 95% confidence intervals and standard errors are clustered at the ski area level. Endpoints are binned and indicated by a plus. The p-values of the joint F-tests for pretrends are indicated in the plots. The coefficient table with point estimates and standard errors is in Appendix B.2.2.

areas increase their transportation revenues after a lift investment.[28]

When we estimate the model in Equation 2.3 using the decomposition into daytrippers and overnighters, we find that the demand effect is entirely driven by daytrippers. To see this, consider the estimates in Figure 2.6. A new lift opening increases the number of daytrippers, on average, by 6.2% in the short term but has virtually no effect on the number of overnight stays in the access municipalities of the ski areas. Considering the large confidence intervals in panel (a), we estimate that the actual effect on the daytrippers is roughly the same as on the overall demand.

As the lift investments mainly affect the skiing demand from daytrippers, we continue in the next section to investigate whether and by how much these short-term demand shifts happen at the expense of neighboring ski areas.

[28]Notice that this effect is between 2.5% and 3.1% and significantly above zero on a 5% level in sensitivity checks using other samples. See Appendix B.3.5 for these results and coefficient tables.

Figure 2.6: Effect of new ski lifts on first entries by guest type

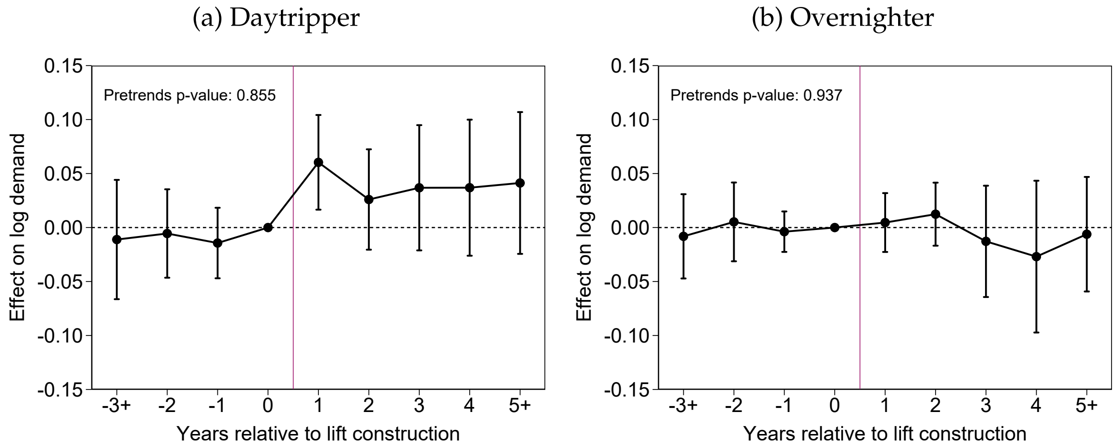

Figure Notes: Both panels show estimates of the model in Equation 2.3 across time. Period 0 indicates the winter before the lift construction (which is in the same year) and period 1 indicates the winter of the lift opening. Panel (a) shows the estimates with the log of winter first entries from daytrippers as the outcome and panel (b) the estimates with the log of winter first entries from overnighters as the outcome. The bars signify 95% confidence intervals and standard errors are clustered at the ski area level. Endpoints are binned and indicated by a plus. The p-values of the joint F-tests for pretrends are indicated in the plots. The coefficient table with point estimates and standard errors is in Appendix B.2.2.

2.5.3 Neighboring Lift Investments

We estimate the specification in Equation 2.5 including neighboring ski lift investments distinguished by road distance rings of 25 kilometers. Figure 2.7 depicts the results. Panel (a) shows the point estimates and 95% confidence intervals of the first lags across the four rings using all neighboring ski lift investments. Similar to our previous results, a new lift increases the first entries on average by 4.1%, all else equal. Furthermore, on average, neighboring ski lift investments do not affect skiing demand across all road distances up to 100km.

Finally, we distinguish the neighboring investments by whether a new lift expands the ski area (extensive margin) or only increases the capacity within the area (intensive margin). We find that neighboring ski area expansions within 25km decrease skiing demand on average by 10.2%, all else equal. In contrast, we do not find any effect for intensive capacity increases as panel (b) in Figure 2.7 depicts. It also shows that expansions affect neighbors negatively up to 50km before the point estimate decays to almost zero in the

Figure 2.7: Effect of own and neighboring ski lifts on first entries in the first winter

(a) Neighboring ski lift (b) Neighboring ski lift with or w/o expansion

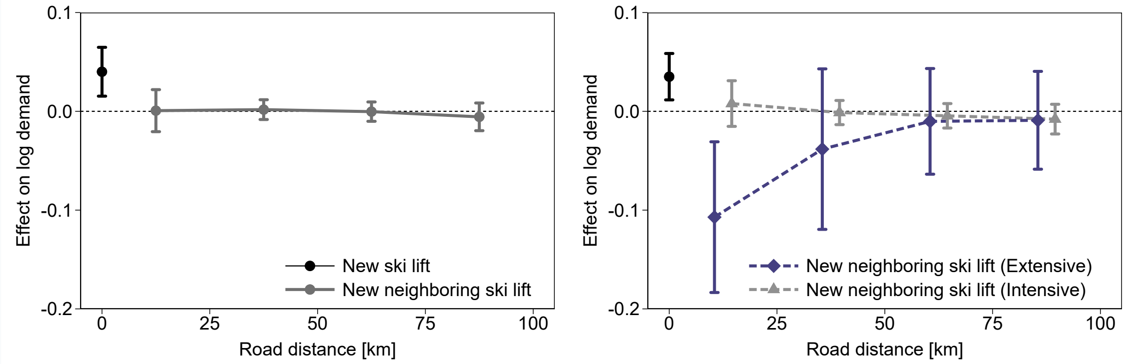

Figure Notes: The plots show point estimates and 95% confidence intervals of the first lags in the specification in Equation 2.5. The horizontal axis indicates the four road distance rings of 25 kilometers each. The road distances are calculated using the closest two access points between each ski area pair. Panel (a) depicts the estimates using all new neighboring ski lifts and panel (b) depicts the estimates where new ski lifts are distinguished by whether they expand a ski area or not. Endpoints are binned and the standard errors are clustered at the ski area level. The coefficient tables with point estimates and standard errors are in Appendix B.2.3.

ring between 50 and 75km.[29] The relatively large effect sizes of neighboring ski area expansions (-10.2%) compared to own ski lift investments (+4.1%) materialize due to two reasons. First, the average increase in own demand in the first winter season after an extensive ski area expansion is estimated to be 7.7% (see Appendix B.3.11). Second, extensive expansions occur in relatively large ski areas typically surrounded by smaller ski areas. The smaller relative effects in large areas compensate for the larger relative effects in small areas. Taking these point estimates to the absolute values of the treated ski areas and their neighbors, we find that the business stealing effects account for 56% of the absolute demand increase due to all ski area expansions. Business creation accounts for the other 44% of the demand increase.[30]

[29]Notice that we estimate the effects of neighboring ski area expansions relatively imprecise compared to those without expansions because we document only nine extensive ski lift investments between 2009 and 2018 in our main sample. In Appendix B.3.12, we address the concern of a parallel trends violation by a counterfactual exercise in which we shut the spatial competition among ski areas. By doing so, we find further evidence that the negative effects of neighboring ski area expansions are indeed driven by spatial competition.

[30]We take first the nine ski area expansions and calculate by how much the 7.7% effect increases the demand for the treated ski areas in absolute terms. Then, we compute the same absolute figure for the -10.2% decrease at the fourteen exposed neighbor-year cells and recover from both figures the estimate for the substitution effect.

Altogether, we find new ski lifts at the intensive margin induce new business from daytrippers, whereas they partially steal and partially create business in the case of investments at the extensive margin.

2.6 Discussion

In this section, we put our results into perspective by relating them with each other. First, we find that demand reacts, on average, more to standard deviation changes in natural snow days than to single ski lift investments (with accompanied infrastructure). Regarding revenues, a ski lift investment has approximately the same impact as a standard deviation change in natural snow days when ski areas have a relatively large snowmaking capability. For those with a relatively low snowmaking capability, the natural snow effect is twice as large as that of single ski lift investments. These comparisons imply that firms require relatively large and expensive infrastructure investments to earn revenues comparable to the yearly variation in revenues due to natural factors.

Moreover, the point estimates of the effects on the revenue are lower than the effects on demand in almost all results. We would, however, expect the exact opposite if ski lift investments allow operator firms to set higher prices and attract more daytrippers. Therefore, it further confirms that ski lift investments no longer go hand in hand with higher price levels.

Lastly, notice the small and insignificant coefficients on the weather index in all estimations across our results. It confirms the observation of Wegelin et al. (2022) that the weather has, on average, no effect on seasonal outcomes because skiers intertemporally substitute their consumption. This shows that capacity constraints at peak days are no financial risk for most ski area operators. As with skiers deterred by bad weather, skiers deterred by congestion ski on another, less congested day.

2.7 Conclusion

We find that (i) snowmaking investments lower the operator firm's dependency on natural snow variation, (ii) ski lift investments increase short-term demand and revenues from daytrippers and (iii) intensive ski lift investments create demand whereas extensive investments create and steal demand from neighboring ski areas.

Together with the ongoing divergence of ski area supply and demand (see Figure 2.1), our results show that investments in high-capacity lifts are a relatively ineffective means to retain demand and sustain revenues. Instead, it is crucial for decision-makers to carefully evaluate all costs of ski lift investments (including operation costs, connected snowmaking facilities and costs to neighboring ski areas) and whether a realistic demand expectation, pricing strategy and year-round use of such an investment justify its size and capacity. After all, most ski area operators do not primarily invest to raise immediate demand. But instead make use of innovative technologies to increase comfort, provide attractive slopes, increase summer use and allocate skiers efficiently across time and space. In combination, this should suffice to maintain operations and sustain the attractiveness of the ski area.

A limitation is that the sample is not representative in terms of ski area size and altitude. A broader data coverage would allow us to estimate the effects more precisely and draw additional conclusions for smaller ski areas. Related to this, our results are only externally valid to some extent. The public involvement, regulations, road infrastructure and topography are unique to Switzerland. This means that our identification strategy does not entirely translate to other contexts in how it is implemented here. Nevertheless, at least in the Alps, many aspects are similar and require only slight adjustments to establish a causal link between ski area investments and outcomes elsewhere. With the ongoing rise in global temperatures exacerbating ski lift supply while reducing skiing demand, such research remains relevant in the future.

Chapter 3

The Development of Ski Areas and Its Relation to the Alpine Economy in Switzerland

joint with Marcus Roller and Monika Bandi Tanner

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3.1 Introduction

Around 70% of the Swiss landscape is covered by mountains that historically exacerbated economic growth due to the complex topography and harsh climatic conditions. Consequently, the mountain villages and towns experienced a considerably lower population growth than low-altitude areas. Figure 3.1 depicts this by distinguishing the population development across altitudes. It shows that low-altitude municipalities quadrupled their population while less urbanized mid-altitudes grew only by 60% over the 170 years of observation. But why did the most remote high-altitude municipalities experience growth rates similar to those of low-altitude municipalities?

Figure 3.1: The Swiss population development across different altitudes

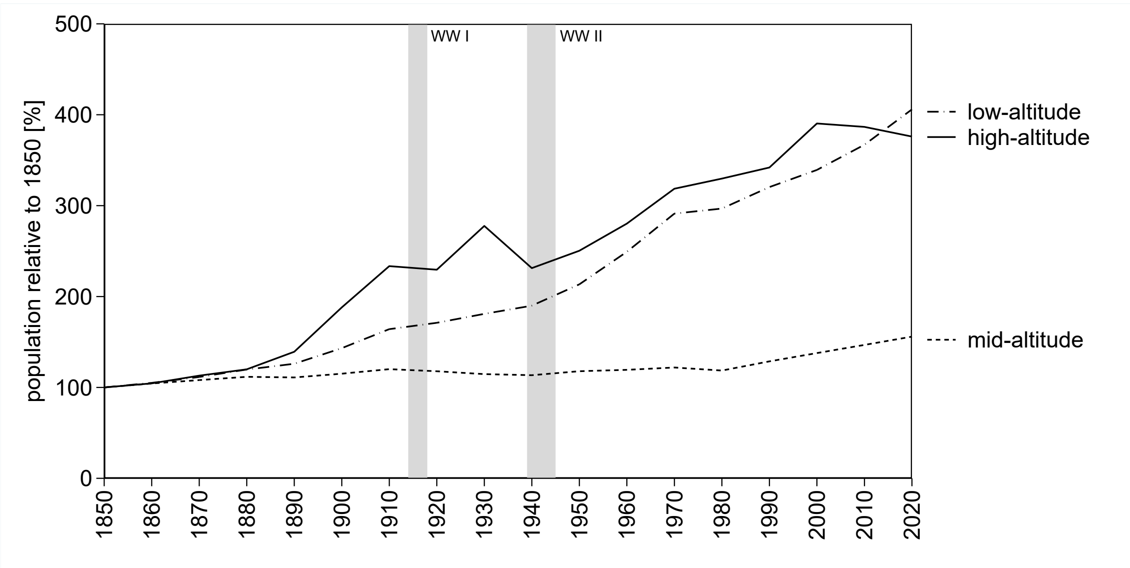


Figure Notes: The lines indicate aggregated population counts of Swiss municipalities below 750 m.a.s.l. (low-altitude), above 1500 m.a.s.l. (high-altitude) and at altitudes in between (mid-altitude) indexed to 100 in 1850.

We reckon the answer is tourism. Striking indications of tourism as a major driver of this growth are the simultaneous emergence of the first cableways[1] before World War I, the

[1] As the facilities described by the term "cableways" do not only transport skiers uphill, we call them cableways and not ski lifts (in contrast to Chapter 2). These include all surface lifts (such as t-bar and platter lifts), aerial cableways (such as chairlifts, gondolas, cablecars, funitels, funitors and hybrid lifts), cable railways, funiculars and, in some instances, racket railways.

sharp population declines at high altitudes during the two world wars and the subsequent opening of ski areas in the aftermath of World War II.[2] Accordingly, we find that Alpine skiing tourism emerged in two periods with the help of historical accounts and cableways data (Bärtschi, 2015; Gross, 2023; Tissot, 2022). First, during the pioneering period between 1890 and 1940, innovative engineers competed to create the most effective and secure way of transporting tourists close to the famous mountain peaks. At the time, skiing helped merely to operate the first racket railroads, funiculars and aerial cable cars in winter. After the Second World War, immense economic growth and the depoliticization, individualization and commercialization of leisure (Bandi Tanner & Müller, 2021) led to a nationwide skiing boom that drastically changed the primary purpose of cableways. During this second period between 1940 and 1980, therefore, the widespread opening of most ski areas took place.

In this paper, we focus on the second period, the ski area access period. In particular, we tackle the question of how municipalities that gained access to a ski area during this period developed economically relative to comparable alpine municipalities that did not gain access to ski areas.

We link data from all ski lifts ever built in Switzerland aggregated to ski area access points to municipal-level data of population, employment, taxable income and federal tax revenues from the Federal Statistical Office (FSO) and the Federal Tax Administration (FTA). To ensure comparability, we retain a sample of Alpine municipalities that gained ski area access between 1940 and 1982 and a set of Alpine municipalities without such access. We then use a Difference-in-Differences (DiD) strategy to study the development of these municipalities and find that access municipalities have a 16% larger population on average and enable substantially more employment in tourism-related service sectors. In the long run, by 2015, employment in the accommodation sector is almost twice that of the municipalities without ski area access, the gastronomy sector is 45% larger and the retail sector 35%. Contrarily, the less labor-productive agriculture sector is 40% lower.

[2]While the two wars waged in Europe, Swiss tourism development was disrupted by recessions, decreasing incomes, appreciating exchange rates, bureaucratic hurdles to enter the country, increasing public transportation prices and unforeseeable behavior of tourists (Tissot, 2022).

Furthermore, we find that the rise of tourism-related services translates into 41% higher taxable incomes at access municipalities persisting until today. After accounting for population growth and special cases (mostly foreign second home owners that pay federal taxes at the municipality of the second home), the residual income change is still at 15%. We argue that these changes originate primarily from individuals through (i) additional job opportunities that complement alpine farming and construction work and (ii) higher labor productivity across and within sectors. The former channel is consistent with formerly poor farmers and artisans finding work at better-paid service jobs in winter by substituting or complementing their previous jobs. Regarding labor productivity, we combine our sectoral employment estimates with productivity estimates from Rütter and Rütter-Fischbacher (2016) and find that the employment composition channel accounts for 2.9% of the residual change. Moreover, it is likely that agglomeration forces (i.e., having a larger population and, for example, larger hotels) led to more productive firms in access municipalities compared to firms of the same sector in municipalities without access.

The extension of the population and the higher employment rates led to substantial tax revenues for the municipal government. We find, on average, 66% higher federal tax revenues and 44% per resident. As the federal tax is a relatively constant share of cantonal and municipal taxes, equally sized gains can be expected for the local tax revenues.[3]

We contribute to several strands of the literature. The first strand deals with typical winter destinations' difficulty in adapting to climate change and the long-term consequences that they face. In particular, warming temperatures due to climate change threaten the natural snow reliability of ski areas (Elsasser & Bürki, 2002; Gonseth, 2013; Gössling et al., 2012; Koenig & Abegg, 1997; Marty et al., 2017; Scott & Gössling, 2022; Steiger et al., 2015) and, with them, sales of tourism-related service industries (Lohmann & Crasselt, 2012; Wallimann, 2022). To understand the adverse effects of so-called Lost Ski Area Projects (LSAP) (Schuck & Heise, 2020) and the declining tourism on the local economy,

[3]The Swiss pay income taxes to three federal tiers: The federal taxes levied by the Swiss Confederation, the cantonal taxes by the cantons and the commune taxes by the municipalities.

it is crucial to understand the positive impact of emerging ski areas in the first place. Our work contributes to both sides of the story.

Related to these challenges, we contribute to the debate on the effectiveness and efficiency of public involvement in ski areas. Most ski areas are either through subsidized funds or ownership supported by the public (Derungs et al., 2019; Lengwiler & Bumann, 2018; Schuck & Heise, 2020). Accordingly, municipal governments might use their additional tax revenues from the increased economic activity to fund expensive skiing infrastructure replacements. For example, Derungs et al. (2019) find that financial involvement in tourism infrastructure correlates with the financial capacity of municipalities in the canton of Grisons. We contribute here by showing that ski area access municipalities generate larger municipal tax revenues and that the financial flows between ski areas and municipal governments go both ways. However, as research shows, the path dependence arising from these tax revenue and investment cycles is not necessarily a threat to economic growth once the natural advantage is lost (Bleakley & Lin, 2012).[4]

Finally, we contribute to the literature on the emergence of tourism and its socio-economic impact. During the emergence of ski areas, the operator firm employs workers and the access municipalities require accommodations to host the expected tourist inflows (Wallimann, 2022). Because tourists consume more than skiing, demand for complementary products and services such as ski schools, equipment rentals and sales rise (Lohmann & Crasselt, 2012). Research in various other contexts stresses that the emergence of tourism fostered economic growth (Favero & Malisan, 2021; Nocito et al., 2021; Pigeassou, 1997). Nocito et al. (2021) find that a television series boosted tourism in the municipalities used for filming. A 10% increase in total tourist expenditure translates into 4.7% more municipal income, 11.5% more firms and 10.1% more workers in tourism-related services. Favero and Malisan (2021) show how the Italian city Matera profited

[4]Bleakley and Lin (2012) document the ongoing importance of historical portage sites in the US, although their initial use has become obsolete. Municipalities with ski area access have larger populations, as in Bleakley and Lin (2012), and might thus perform better than those without access even after losing such access.

from the 2019 selection to the European Cultural Capital beyond tourism-related services. Moreover, they find substantial positive effects for cultural, infrastructure-related and real estate employees. Faber and Gaubert (2019), studying the long-term economic consequences of tourism in Mexico, find additionally positive economic spillovers of touristic activities to the unrelated manufacturing sector. Our work confirms tourism-led growth but, in contrast to Faber and Gaubert (2019) and Favero and Malisan (2021), only to sectors directly related to tourism.

Furthermore, our documented shift from agriculture to services while bypassing rises in manufacturing is, interestingly, a common pattern in many developing economies such as India (T. Fan et al., 2022). Strengthening consumer-based service industries is seen as a viable alternative to fighting poverty instead of relying on capital-intensive manufacturing (Blake et al., 2008; Croes, 2014; Faber & Gaubert, 2019; T. Fan et al., 2022; Spenceley & Meyer, 2012). In our context, however, the emergence of a manufacturing sector was rather constrained by the lack of space and accessibility than the lack of financial capital. This might be the very reason why we find no local spillovers to the manufacturing sector but an increasing dispersion of population, income and tax revenue across space.

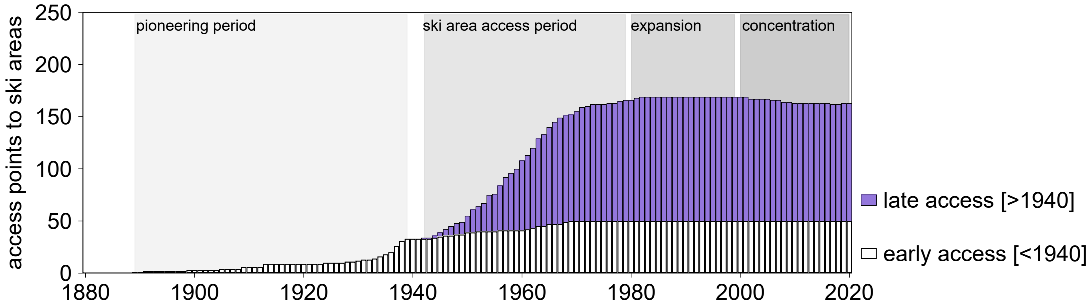
The paper continues as follows: Section 3.2 provides the history of ski area development. Section 3.3 describes the sample, various data sources and summary statistics. Section 3.4 leads through the methods. We present the results in Section 3.5 and conclude in Section 3.6.

3.2 History of Ski Area Development

The history of ski areas in Switzerland goes back to the 18th century. Thus, we split the history into four development periods based on historical accounts of Bärtschi (2015), Büchel and Kyburz (2020), Schuck and Heise (2020), and Tissot (2022). These are the pioneering period (1890-1940), the ski area access period (1940-1980), the expansion period (1980-2000) and the concentration period (2000-2020). Figure 3.2 depicts ski area growth across the four periods by showing the number of access points to ski areas distinguished by the time the municipalities gained access in panel (a) and by showing the aggregated capacities and number of lifts in panel (b).[5]

Figure 3.2: Development of ski areas

(a) Access points across access timing



(b) Aggregate capacities and number of cableways

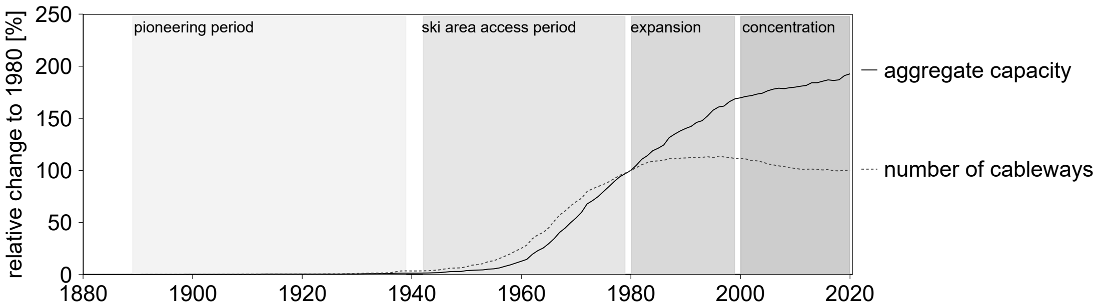


Figure Notes: The bars in panel (a) indicate Swiss ski area access point counts in municipalities with at least one access point before 1940 (white bars) and after 1940 (purple bars). The solid line in panel (b) shows the aggregate capacity of all lifts in all ski areas (measured as the number of persons lifted by 1 kilometer per hour) and the dotted line shows the overall number of cableways. Both are indexed to 100 in 1980. The two panels cover the last 140 years across four periods of ski area development.

Before the construction of cableways, the first documented tourism in a broader sense than some single travelers wandering to distant lands emerged in Switzerland around 1780-1830, when wealthy persons hoped to achieve fame by climbing the untouched peaks of the Alps. Back then, unsafe means of transportation, traffic routes, lodging, and international tensions hindered traveling. The emergence of the European and Swiss

[5] As our unit of interest is the municipality and ski areas can sometimes be accessed from multiple municipalities, having access to a ski area is the relevant measure to distinguish the municipalities. See Section 3.3.3 for further details.

railway network, the birth of the modern Swiss democracy and road improvements removed some of the objections to tourism after 1850 (Büchel & Kyburz, 2020; Tissot, 2022).

The first period of ski area development, the pioneering period, began in 1890 when large and prestigious tunnel and racket railway projects such as the Gotthard Tunnel or the Gornergrat-Bahn in Zermatt facilitated access to the Alps. During this period, skiing and other winter activities emerged and helped the seasonal hospitality industry capitalize on the winter season. This fostered investments into grand hotels in alpine municipalities that provided safe accommodation close to the appeal of the alpine peaks and could, at a later stage, when winter sports became more attractive, be run in summer and winter (Tissot, 2022). Up to 1940, less than 50 access points emerged in Switzerland that could be used for skiing (white bars in Figure 3.2). However, skiing or let alone tourism was often not their primary purpose. Instead, the goal was to meet military objectives, transport material for mining activities and provide transportation for residents (Bärtschi, 2015). The technical difficulties motivated innovative Swiss engineers to reach mountain tops with various lift systems such as racket railways, funiculars or cable cars. The latter ones were the majority until the 1930s. The dominance of winter sports in mountain areas started in 1934 when the first T-bar lift was opened in Davos but kicked off after the Second World War, establishing ski areas with all lift types that exist today (Bärtschi, 2015).

Consider panel (a) in Figure 3.2. It shows the total number of ski area access points at two municipality types. The white bars indicate access points that emerged in municipalities with a first access point during the pioneering period. The purple bars indicate those that emerged in municipalities during the next period, the ski area access period. Notice that some white-labeled points were accessed after 1940. These access points emerged in municipalities that already had access to another ski area before 1940.[6]

[6] A prominent example is the ski areas around Davos and Klosters. The first access to Schatzalp was built in 1899 (at first not a ski area), to Parsenn in 1931 and at Bolgen in 1934 (which was extended to the Jakobshorn in 1954). After 1940, three additional ski areas were built: In 1965 Madrisa, in 1969 Rinerhorn and in 1967 Pischa.

The ski area access period began after the Second World War. The economic boom years that followed amplified ongoing trends in individuals' recreational opportunities, such as a rising life expectancy, increasing wealth,[7] urbanization, commuting and car ownership, and reduced working hours[8] (Bandi Tanner & Müller, 2021). The rise in individual leisure opportunities was coupled with a surge in population.[9] Mass tourism emerged and with it a boom in skiing tourism, fueling investments in cableways that were now primarily intended to transport winter sports tourists uphill. The skiing infrastructure projects during this access period are the main focus of this paper. In panel (a) Figure 3.2, the newly developed ski area access points of the access period are depicted as purple bars. Approximately 100 new ski area access points were built between 1950 and 1970 alone and by 1980, the 191 ski areas[10] were offering 1,893 cableways that could lift 420K persons by one vertical kilometer per hour.

The third period from 1980 to 2000, called expansion, was marked by large investments within ski areas. By the first federal Land Use Planning Act ("Raumplanungskonzept" Federal Assembly of Switzerland, 1979) adopted in 1980 and the federal tourism concept ("Tourismuskonzept") from 1979, the construction of new ski areas from scratch was limited to some rare exceptions (Bandi Tanner & Müller, 2021; Krippendorf, 1983; Lendi, 2010). During this period, most cableways had to be renewed or were replaced by high-capacity lifts. Typically, surface lifts (like T-bars and platter lifts) were replaced by faster aerial lifts (like detachable chairlifts). Correspondingly, aggregate lift capacities increased by 69% within this period.[11] Consider again panel (b) in Figure 3.2 that shows how

[7] Aggregate incomes almost quadrupled and more than doubled per capita in real terms between 1947 and 1980. The tax base grew from 1.2 Million to 2.5 Million over the same period.

[8] Before the Second World War, Swiss workers usually worked 48 hours per week, which was reduced to 44 hours by 1971. On top of that, the 5-day week became established in 1960 (Degen, 2015).

[9] The Swiss population increased by more than 40% from 4.6 Million to 6.4 Million between 1947 and 1980. Population data for 1947 is imputed from municipality-level counts of 1941 and 1950 (see Appendix C.1.4).

[10] A ski area is defined as a connected cableway cluster of at least two cableways over time. See Section 3.3.3 for a detailed definition.

[11] Although the federal tourism concept did not intend large capacity increases, many operators and municipalities favored such enlargements because of the suggestive and non-binding nature of the federal tourism concept (Bandi Tanner & Müller, 2021; Krippendorf, 1983). The high-capacity investments during this period lead to high replacement costs today and reduce the ability of operators to finance replacements themselves (Bieger & Laesser, 2005; Derungs et al., 2019; Lengwiler & Bumann, 2018; Schuck & Heise, 2020)

aggregate lift capacities (as the number of persons that are lifted by 1 kilometer per hour) and the number of cableways evolved relative to 1980.

The last period, the concentration period, is characterized by stagnating demand (Seilbahnen Schweiz, 2018), a decline in the number of ski areas, but a 19% increase in aggregate lift capacities. We document nine lost ski area projects and three large mergers during this phase. The decline in Swiss ski areas is associated with several potential supply- or demand-side causes. On the supply side, climate change exposes ski areas to reductions in natural snow reliability (Elsasser & Bürki, 2002; Gonseth, 2013; Gössling et al., 2012; Koenig & Abegg, 1997; Marty et al., 2017; Scott & Gössling, 2022; Steiger et al., 2015) or operators were over-optimistic in their business cases but still found support by public funds (Schuck & Heise, 2020). On the demand side, exchange rate appreciation (Abrahamsen & Simmons-Süer, 2011; Plaz & Schmid, 2015), price reductions for air travel (Müller-Jentsch, 2017) and demographic challenges (Lütolf et al., 2020; Plaz & Schmid, 2015) all decrease skiing demand. Operators react by increasing competition over prices and infrastructure (Lütolf & Lengwiler, 2015; Lütolf et al., 2020; Wallimann, 2022) of which already large, higher-lying areas seem to gain the most (Schuck & Heise, 2020).

3.3 Data

3.3.1 General data sources

We are interested in the economic development of Swiss municipalities that gained access to a ski area between 1940 and 1982. Therefore, we combine municipality-level data on ski areas, geographical features, population, employment, tax revenue and income from various sources.

We use publicly available municipality data from the FSO and match it with alpine peaks from the Federal Office of Topography (swisstopo) and cableways data from the online platform *bergbahnen.org* (Gross, 2023). Municipality data covers municipality borders, the center coordinates and municipality mergers and splits back to 1960 (see Appendix C.1.1).

3.3.2 Sample

We restrict our sample based on geography to obtain one set of municipalities that gained access to a ski area and a comparable set that did not.

Figure 3.3 displays the sample by separating municipalities across three dimensions: The municipality centers' altitude, a peak measure cutoff and the timing of gaining access to a ski area. The peak measure indicates how many alpine peaks lie around the municipality centers. It is increasing in the altitude of the peaks, the proximity to the center in the 3-dimensional Euclidean distance and the number of peaks (see Appendix C.1.3 for an exact definition). Ultimately, this measure is a proxy of how deep a municipality lies in the Alps and, to some extent, how attractive the surrounding landscape is for skiing.

The white points in Figure 3.3 show all ski area access points in 1982 and the black lines indicate connected areas with access points in more than one municipality. The sample consists of municipalities indicated in purple and black. The former are municipalities that gained access to at least one ski area between 1940 and 1982. The latter are comparable Alpine municipalities that never had access to a ski area.

All other municipalities are excluded from the sample for either reason:

1. Municipalities labeled as "low-altitude" are in the Midlands, where the topography is too flat and the altitude is too low to build ski areas. Most of the largest Swiss cities and towns are located there.

2. Municipalities labeled as "low-altitude with peaks" are below 750 m.a.s.l. but are surrounded by peaks and sometimes even have access to ski areas. These are often

Figure 3.3: Municipality types and ski area access points in 1982

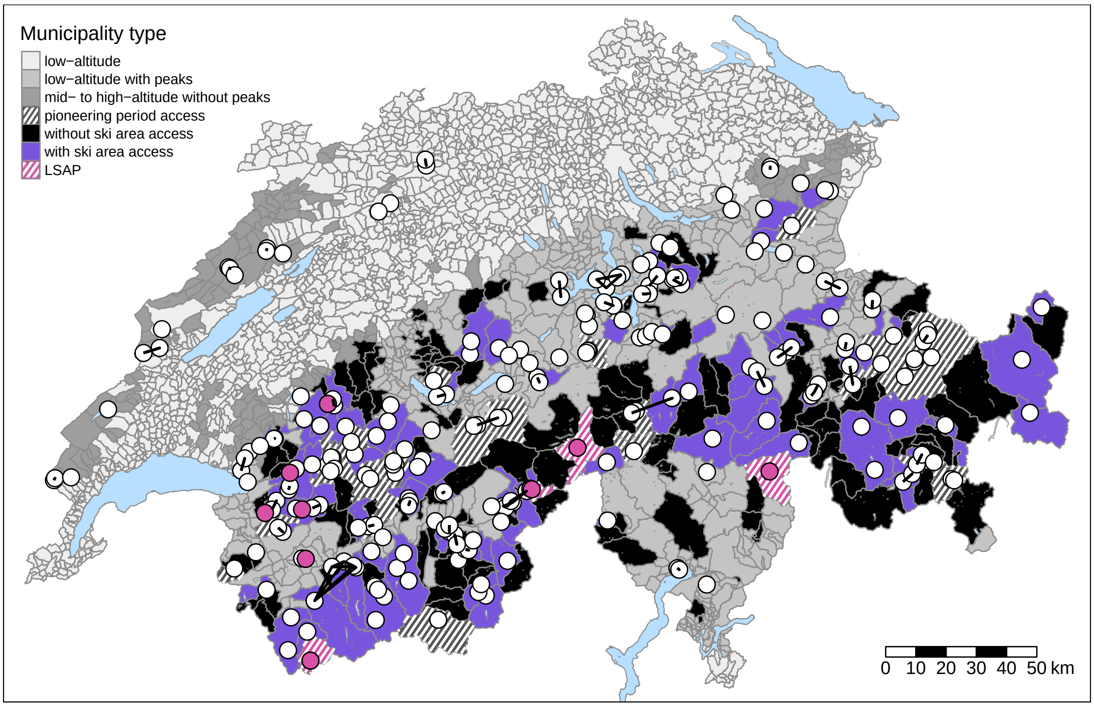


Figure Notes: The map indicates Swiss municipalities in 2021 jurisdictions separated into seven categories based on altitude and whether a municipality is surrounded by sufficient peaks to be added to our sample. Dark shades (black and purple) and hatched areas indicate mountainous municipalities above 750 meters above sea level with alpine peaks nearby (see Appendix C.1.3 for the exact definition of that measurement). Black areas are municipalities without access, purple areas are access municipalities. Grey-hatched areas are excluded due to their tourism investments before 1940 (indicated as pioneering period access). Pink-hatched areas are excluded because these municipalities are connected to (later) lost ski area projects (pink points). Points indicate ski area access points in 1982 and the black lines show ski area connections across municipality borders.

located on wide valley floors near large lakes or rivers and are well-connected to large agglomerations.[12]

3. Municipalities labeled as "mid- to high-altitude without peaks" are primarily found in the Jurassian mountains and are below the tree line. As with the "low-altitude with peaks" group, these municipalities are much more accessible and are topographically distant from the Alpine municipalities.

[12]For example, Lucerne or municipalities in the Rhone Valley. Both were historically well connected by highways and early railways (Büchel & Kyburz, 2020) and are, thus, topographically and economically very distant from the municipalities we intend to study.

4. We exclude grey-hatched municipalities labeled as "pioneering period access". These had access to cableways before the first ski areas emerged and could build a ski area around their existing infrastructure without much effort. Such a first-mover advantage makes them hardly comparable to municipalities that built ski areas from scratch.

5. We exclude pink-hatched municipalities connected to LSAP that were either unsustainable in their economic or climatic prospects (Schuck & Heise, 2020). Notice that this choice induces a survivorship bias. However, we are concerned with the policy implication of municipalities potentially losing their ski area access and not of municipalities gaining new access. Therefore, we restrict the sample to those municipalities exposed to such a possibility.[13]

Our resulting sample consists of 227 municipalities in the Alpine region that are above 750m, are surrounded by alpine peaks, have no first-wave access and are connected to ski areas in operation. Of those, 94 are in the access group (purple in Figure 3.3) and 133 in the group without access (black in Figure 3.3). Access municipalities gained access to at least one ski area during the ski area access period between 1940 and 1982.

3.3.3 Ski Area Access

We define a ski area as a cluster of cableways that consists, on average, of at least two lifts throughout its existence. The idea is to separate municipalities with small, often community-run village lifts from those that built ski areas to attract tourists. On top of that, lifts with a primary use other than winter sports are also excluded. These are excursion lifts and urban lifts.[14] Our remaining ski areas count to 190.

To aggregate these ski areas to our unit of interest, the municipalities, we define access

[13] Additionally, we remove Einsiedeln and Oberhünigen (due to missing observations) and the two Comunanza's Capriasca/Lugano (TI) and Cadenazzo/Monteceneri (TI) (not inhabited).

[14] Many large cities in Switzerland built funiculars to transport residents and commuters uphill—for example, the Marzilibahn in Bern or the Polybahn in Zurich.

points at which a ski area can be entered and allocate these geo-locations to the municipality borders of 2021. A ski area can sometimes be accessed from multiple municipalities, whereas some municipalities have access to more than one ski area. Thus, our primary treatment indicator, ski area access, is defined as having access to at least one ski area at a given time. Furthermore, we construct a capacity variable that captures all lift capacities that can be accessed from a single access point to that municipality. Further details on the definition and aggregation process can be found in Appendix C.1.2.

We document nine LSAP in our data.[15] From these lost projects, only three municipalities are entirely affected. Ernen, Obergoms and Bourg-Saint-Pierre. All other LSAP were accessed from municipalities connected to other ski areas or were built before 1940 (e.g., the first lift at Confin in San Bernardino was opened in 1939) and thus excluded anyway.

3.3.4 Geography

In addition to the municipality center altitude and the peak measure, we complement the municipality data with other geographical features:

1. The road distance to the next cantonal center is used as a proxy of economic accessibility. This measure is computed using the Here Application Programming Interface (API).[16]

2. Lakes attract residents and tourists (Leuba, 2019; Waltert et al., 2011). Therefore, we compute the road distance to the next lake to measure this attractiveness with the Here API.

3. Using a 3-dimensional shapefile from swisstopo, we measure developable land as the share of the suitable area over the whole municipality area. The suitable area is computed by identifying 158-by-158m cells with an average slope below 15 degrees

[15] These are: Bourg-Saint-Bernard, Confin, Ernergalen, Hungerberg, Isenau, Loutze, Monts Chevreuils, Schwyberg and Solacyre.

[16] We compute the road distances with the Stata command *georoute* (Weber & Péclat, 2017). Notice that road travel time has substantially changed over time through infrastructure investments. We argue that this affects the distances covered by roads less than the actual travel time and is thus a valid proxy of economic accessibility.

and within 200m in altitude of the municipality center. The idea is to proxy the size and space on the valley floor that can be used to develop buildings of any kind (historically, before the emergence of zoning laws). Details on how we construct this measurement are in Appendix C.1.3.

4. We construct additionally a measure of sunshine exposure of that developable land. For each 158-by-158m cell, we compute the sunshine exposure on a typical winter day (when the sun is relatively low) and calculate the mean sunshine exposure among all developable land cells in a municipality. More sunshine would facilitate some agricultural activities and is also considered attractive for housing (Leuba, 2019). Details on how we construct this measure are in Appendix C.1.3.

3.3.5 Population

The population data is from the FSO and includes Census (VZ), Population and Households Statistics (STATPOP) and Statistik des jährlichen Bevölkerungsstandes (ESPOP) data. All three sources represent essentially the same data for different periods with minor changes in data acquisition and, thus, structural breaks at the changes. VZ data is available for every decade between 1850 and 2000 except 1890 and 1940, where the data is available for 1888 and 1941, respectively. These years are imputed using a rule by Büchel and Kyburz (2020). Additionally, the population counts in 1947 and 1975 are imputed to link them to income data. ESPOP data is from 1981 to 2010 and STATPOP from 2011 to today. The ESPOP data was harmonized with the VZ data at each decade. Further inconsistencies appear in 2011 from the change of ESPOP to STATPOP. The imputation and a complete description of the data sources are in Appendix C.1.4. The municipalities Kandersteg and Icogne are merged with their neighbors Kandergrund and Lens in all estimates going further back than 1910, as these two municipality pairs were split from their neighbors between 1900 and 1910.

3.3.6 Economic Activity

We use employment, tax revenue and income data as economic activity variables. In addition, we complement the data with value-added estimates by Rütter and Rütter-Fischbacher (2016) to explore how sectoral labor productivity differences affect incomes.

Employment data is available from the FSO statistic Statistik der Unternehmensstruktur (STATENT) on the 6-digit International Standard Industrial Classification (ISIC) level between 2011 and 2017. Within this short period, no substantial structural changes occurred (Bandi Tanner et al., 2021). For that reason, we neglect the time variation in that data. Moreover, to match the results with 2015 Gross Domestic Product (GDP) estimates, we use STATENT data only from that specific year.

The tax revenue and income data are gathered from publicly available municipality-level federal tax records between 1947 and 2017 from the FTA. The data from 1959 to 1972, 1987 to 1988 and 1997 to 2002 is incomplete. Due to these gaps and the availability of GDP estimates in 2015, we mainly use data from 1980 and 2015[17] and build differences to 1947, the oldest data available.[18][19] Furthermore, we deflated all income data to 1947 CHF using a historical consumer price index from the FSO to sustain comparability over time.

A limitation of the federal tax data is that it contains only income from the taxpayers. Generally, these are taxable incomes that surpass the minimum threshold of the federal tax of individuals. These taxes are mostly collected from individuals who pay their federal income taxes at the municipality of legal domicile, which is normally the residence municipality at the end of the year. On top of that, the data contains so-called special cases. These contain primarily taxable incomes from foreign individuals economically "bound" to Switzerland but with legal domicile outside of Switzerland, including those that generate income from owning a second home (Federal Assembly of Switzerland,

[17] Year-to-year variation in economic activity is negligible at the very long time-horizons we study here.

[18] We digitized the data between 1947 and 1958 and connected it to already digitized data from 1975 onward. See Appendix C.1.6 for details of this process.

[19] Notice that six municipalities in our sample already gained access to a ski area before 1947. These are Ormont-Dessus (1942), Château-d'Oex (1944), Flims and Tujetsch (1945), Beatenberg and Leukerbad (1946).

1990; Federal Tax Administration, 2023).[20] We gathered the number of special cases in 1980 from the same data. However, we have no information about the incomes of individuals exempt from the tax (due to very low incomes) and from individuals who are taxed at the source (these are typically foreign seasonal workers). Increases in the number of taxpayers (without special cases) originate from either new residents moving to a municipality or more individuals surpassing the minimum federal tax threshold. Therefore, changes in that variable may reflect changes in individual incomes.

3.3.7 Summary Statistics

Summary statistics of the data for the whole sample, the access municipalities (AC) and the municipalities without access (NAC) are displayed in Table 3.1.

The municipalities with and without access are very similar in geographical features, except that the average access municipality covers a larger area (at municipality borders in 2021), lies at a higher altitude and has less developable land at its disposal. The latter two are likely interrelated as valleys become narrower the higher their altitude. All other geographic measures are close to being indistinguishable.

Notice how the access status of a municipality points to large differences in population and economic activity, regardless of the year of measurement.

The population distribution is right-skewed, with a few large and many small municipalities such that the standard deviation exceeds the mean. The access municipalities already had, on average, 50% more permanent residents in 1850 and grew faster than those without access.[21] Moreover, the number of taxpayers was, on average, already 60% greater in 1947. This suggests that larger municipalities, in terms of permanent residents,

[20]Special cases also include taxpayers whose income substantially changed within the bi-annual tax period, residents with foreign income, married persons who died within the period and persons who receive capital settlements instead of recurring benefits e.g. from pension funds. (see Federal Assembly of Switzerland, 1990; Federal Tax Administration, 2023, for further details).

[21]The population data is aggregated to 2021 jurisdictions. Access municipalities might have gone through more mergers over time and appear larger through that. Looking at municipalities that underwent no jurisdictional changes since 1960 reveals that access municipalities remained 30% larger in 1850 than municipalities without access.

Table 3.1: Summary statistics of the sample

	All municipalities ($n = 227$)					AC ($n = 94$)	NAC ($n = 133$)	
Variable	Year	Mean	SD	Min	Max	Mean	Mean	Diff
Geography								
Altitude [masl]	-	1,105	275	751	1,955	1,179	1,053	126***
Area [km^2]	-	57.84	64.38	1.17	438.75	73.43	46.82	26.61***
Distance to cantonal center [km]	-	49.19	26.77	4.75	137.76	51.91	47.28	4.63
Peak measure [$\frac{\#}{m^2} \cdot 1M$]	-	3.29	1.85	0.70	8.00	3.45	3.18	0.28
Lake distance [km]	-	14.19	8.58	0.01	43.00	14.36	14.07	0.30
Developable land measure [%]	-	16.55	24.98	0.00	99.51	9.12	21.80	-12.68***
Sunshine exposure of dev. land [%]	-	42.46	10.42	8.61	81.45	42.67	42.30	0.37
Population								
Permanent Residents	1850	871	909	0	5,693	1,052	743	309***
	1940	947	894	74	5,070	1,213	758	455***
	1980	933	917	30	5,779	1,253	707	546***
	2015	1,162	1,265	31	9,948	1,596	856	740***
Number of taxpayers	1947	148	152	3	1,043	183	123	60***
	1980	378	413	13	3,192	557	252	306***
	2015	553	674	20	6,467	813	369	444***
Economic activity								
Employed [FTE]	2015	308	430	4	4,138	492	178	315***
Federal tax revenue [1947 1,000 CHF]	1947	6	9	0	84	8	5	3***
	1980	61	81	1	567	91	41	50***
	2015	157	378	1	5,050	243	96	147***
Federal tax revenue per resident [1947 CHF]	1947	6	5	0	34	6	6	0
	1980	61	44	13	341	72	54	18***
	2015	114	120	14	957	136	99	37***
Taxable income [1947 1,000 CHF]	1947	622	715	9	5,662	783	508	275***
	1980	3,183	3,391	98	22,109	4,433	2,300	2,133***
	2015	6,375	8,465	180	89,471	9,007	4,514	4,493***
Income per taxpayer [1947 CHF]	1947	4,064	1,799	2,455	29,709	4,218	3,956	262***
	1980	8,437	1,477	3,819	12,367	8,098	8,677	-579***
	2015	11,324	2,109	5,851	22,715	10,964	11,578	-614***

Table Notes: The table shows summary statistics of geographic, demographic and economic data in our sample for all municipalities, access municipalities (AC) (that gained access to at least one ski area between 1940 and 1982) and municipalities without access (NAC). The last column (Diff) indicates the differences in means of municipalities with and without access. The stars indicate the statistical significance of the difference from a two-sided t-test.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

area and number of taxpayers, provided a more suitable environment to establish ski areas.

The distributions of the economic activity measures are also right-skewed, where the municipalities consist of many small jurisdictions and a few very large. The employment differences between municipalities with and without access are substantial and, most notably, greater than the differences in permanent residents. This indicates a higher employment rate in access municipalities when measured in Full-Time Equivalents (FTE).

Looking at the tax base, it is striking how little it was in 1947. Only 1 out of 8 residents was liable to pay federal income taxes. Therefore, the municipalities generated only 6 CHF federal income tax revenue per resident on average. By 2015, per capita incomes more than doubled, the number of taxpayers increased to 50% of the population and tax revenues are more than 20 times higher in real terms (in per capita and overall terms).

3.4 Method

3.4.1 Empirical Strategy

To study the development of municipalities connected to ski areas, we use a two-by-two DiD strategy:

$$\ln y_{jt} = \alpha_t + \beta D_{jt} + \gamma_j + \varepsilon_{jt} \tag{3.1}$$

where $\ln y_{jt}$ is the logarithm of the outcome (population, income or tax revenue) in municipality j at time t. D_{jt} is a ski area access indicator. It equals 0 for all municipalities in the baseline period (t_0). It equals 1 for the second period (t_1) for those municipalities that gain access to a skiing area. Municipalities that never had access to a ski area indicate $D_{jt} = 0$ at both t. α_t is a year fixed effect, γ_j a municipality fixed effect and ε_{jt} is the error term.

We estimate β in Equation 3.1, the association of ski area access to the outcome in period t, in first differences. This cancels time subscripts and allows a simple implementation and interpretation as a cross-sectional estimation using Ordinary Least Squares (OLS). In particular, we estimate:

$$\Delta \ln y_j = \Delta\alpha + \beta D_j + \epsilon_j, \tag{3.2}$$

where $\Delta \ln y_j = \ln y_{j,t_1} - \ln y_{j,t_0}$ is the difference of the outcome between the two periods, $\Delta\alpha = \alpha_{t_1} - \alpha_{t_0}$ is the constant, $D_j = \Delta D_{jt} = D_{j,t_1} - D_{j,t_0}$ is the access indicator that equals 1 if municipality j has ever access to at least one ski area in the ski access period (in which almost all ski areas in our sample were built, see Figure 3.2) and 0 otherwise. The municipality fixed effect γ_j cancels and ϵ_j is the error term.

For estimating the employment effects of which data is only available for one year, we adjust the model of Equation 3.1) to

$$y_j = \mu + \delta D_j + \nu_j, \tag{3.3}$$

where μ is the constant, δ is the coefficient of interest that recovers the association of ski area access to the outcome y_j and ν_j is the error term. This model has no time difference that cancels time-constant characteristics across municipalities. Hence, the coefficient δ recovers differences in averages between municipalities with and without access.

Because ski areas do not appear randomly across space and we are not able to exploit quasi-experimental variation, the OLS estimates cannot be interpreted causally. However, as long as we can rule out reverse causality, the direction of the association is credible. In the next section, we argue against reverse causality and show in which direction the size of the OLS estimates are likely biased.

3.4.2 Exogeneity Violations

Although we cannot identify variation that allows a causal interpretation of estimates from the models of Eqautions 3.2 and 3.3, we first argue why investments in ski areas cause population, income, and tax revenue growth and not the other way around. Then, we show in what direction the OLS estimates are most likely biased.

Looking at the history of emerging tourism after the Second World War, we assume that local stakeholders seized the opportunity and invested in ski area construction. Presumably, tourism-related services were then established to meet the increasing demand. It is well documented how a surge in tourism demand causes increasing economic activities (see e.g. Faber & Gaubert, 2019; Favero & Malisan, 2021; Nocito et al., 2021). At the same time, we rule out that a ski area was built as a consequence of an expected *ex-post* surge in population or an expected *ex-post* increase in financial means.

This would imply that individuals move to a municipality and raise local tax revenues before stakeholders build a ski area. We argue that such a series of events is implausible as individuals have no incentive to move to a relatively poor and rural municipality without new job offerings. Therefore, individuals move to a municipality after the decision to invest in a ski area has been made.[22] Moreover, this is plausible even if those municipalities tend to be larger and wealthier *ex-ante*. Instead of implying reverse causality, such a selection could be driven by differences in *ex-ante* growth rates which leads to a bias in OLS.[23]

Considering the permanent residents before the ski area access in Table 3.1, we see that a municipality about to be accessed was, on average, home to 42% more permanent residents in 1850 and 60% more permanent residents in 1940 compared to a municipality that was never accessed. This suggests that municipalities with an *ex-ante* larger population growth were more likely to be accessed by a ski area. Furthermore, differences in growth rates of other outcomes cannot be ruled out because we have no information prior to 1947. Altogether, it seems likely that access municipalities were on a positive economic growth path before the access. Not yet-accessed municipalities with large economic potential facilitate investing in a ski area. As changes in economic potential are not only positively correlated to investing in a ski area but clearly to the outcomes themselves,

[22]Notice that we explicitly exclude municipalities with access from the pioneering period where tourism emerged before the construction of the ski areas.

[23]Notice that we take care of time-constant *ex-ante* level differences by canceling the municipality fixed effects γ_j through the difference in Equation 3.2. However, OLS is biased if those level differences are not stable over time.

selection leads to upward-biased estimates in the models of Equations 3.2) and 3.3 for all observed outcomes.

A second concern is spillovers to neighboring municipalities. This refers to the problem when the effects disperse further in space than the access municipality's own jurisdiction and contaminate the municipalities without access.[24] We exploit road distance rings between municipality centers and ski area access points in Appendix C.2.2 to show that capacity changes in ski areas affect outcomes within 2km before 1980 but affect outcomes only above 2km thereafter. At the same time, all variation from capacity changes within 2km originates almost exclusively from access municipalities (i.e., almost all access points with road distances below 2km lie within the access municipalities' borders). Thus, we argue that spatial spillovers mainly appear after 1980. Presumably, a supply constraint in housing units (likely induced by the first federal Land Use Planning Act)[25] pushed residents increasingly to settle in neighboring municipalities because a commute to their working location became more attractive as rents and house prices rose.

Such spillover effects lead to downward biased estimates of all outcomes measured at the residence location of individuals.[26] These are population, income and tax revenue. Because employment is measured at the firm location, spillovers are only a concern regarding mobile tasks. Essentially, if a firm located in one jurisdiction can perform its task or value creation in another jurisdiction, for instance, in the construction sector. Notice that tourism-related services are mainly bound to their location.

Finally, there is no time difference in the cross-sectional model in Equation 3.3 that cancels unobserved individual characteristics across municipalities. One way to address this is to balance geographic covariates in municipalities with and without access using propensity scores. However, as we select the sample based on geographic features such

[24]In the causal inference literature known as the stable unit treatment value assumption (e.g. Lechner, 2010)

[25]The act was adopted on January 1st 1980 (Federal Assembly of Switzerland, 1979). The act set the framework for cantonal and municipal policies. These led to restricted housing construction (Lendi, 2010) and possibly to increased competition among permanent residents with second home owners and seasonal workers in tourist municipalities.

[26]See Butts (2023) on how positive spatial spillovers to the control group attenuate treatment effects to zero in DiD setups.

as altitude and the peak measure, the exogeneity assumption is violated for these covariates.[27] Most other geographic covariates are quite well balanced (as reported in Table 3.1) and, therefore, using simple averages identified from Equation 3.3 is more tractable here. The results from the inverse propensity score weighting (IPW) are in Appendix C.2.8 and yield quantitatively similar but less precise estimates as in the main specification.

3.5 Results

3.5.1 Population

In this section, we look at population changes in municipalities with ski area access. For this, we exploit data on permanent residents who live in a municipality at a given time. Table 3.2 shows point estimates of the model in Equation 3.2 at three different periods in columns (1) to (3) and an estimate of an additional difference in column (4).

The main result is indicated in column (2). By 1980, the population was, on average, 16% (the point estimate of 0.153 shown in Table 3.2 means a by 16% higher population expressed in exact percentages)[28] larger in access municipalities.[29]

However, access municipalities' growth exceeded that of municipalities without access already before the ski area access period and thus indicates a positively biased estimate. Consider column (1) in Table 3.2: By 1940, the population was, on average, already 6% larger in access municipalities. Taking another difference between the ski area access period (1940-1980) and the period before the access (1900-1940) allows us to mitigate this violation and recover a more accurate estimate. In particular, we take the point estimate from column (2), subtract the point estimate from column (1) and test whether this

[27]The altitude of the municipality center and the peak measure are post-access covariates in the sense that these measures serve as pre-conditions for building a ski area. Therefore, local stakeholders could anticipate the construction of a ski area by these alone, which invokes further endogeneity (Lechner, 2010).

[28]Henceforth, we express all point estimates as exact percentages. Exact percentage changes are obtained by $e^{\hat{\beta}} - 1 = e^{\ln y^1 - \ln y^0} - 1 = e^{\ln y^1 / y^0} - 1 = \frac{y^1 - y^0}{y^0} = \%\Delta y$ where superscripts 1 and 0 of outcomes indicate municipalities with and without access, respectively.

[29]Notice that municipalities without access were actually shrinking between 1940 and 1980 whereas access municipalities were able to maintain their population (see Table 3.1).

Table 3.2: The association of ski area access with population

Dependent variable:	Log population			Log population
Time difference $[t_1 - t_0]$:	$[1940 - 1900]$	$[1980 - 1940]$	$[2020 - 1980]$	$[(1980 - 1940) - (1940 - 1900)]$
	(1)	(2)	(3)	(4)
Ski area access	$0.060^{\dagger}$	0.153^{***}	0.044	$0.092^{\dagger}$
	(0.034)	(0.046)	(0.042)	(0.049)
Intercept	0.046^{*}	-0.120^{***}	0.154^{***}	-0.166^{***}
	(0.020)	(0.028)	(0.033)	(0.028)
N units with access	94	94	94	94
N units w/o access	131	131	131	131
N overall	225	225	225	225
R^2	0.091	0.075	0.215	0.130

Table Notes: The table indicates OLS estimates of the model in Equation 3.2. In particular, the average association of access to a ski area between 1940 and 1982 with the population from $t_0 = 1900$ to $t_1 = 1940$ in column (1), from $t_0 = 1940$ to $t_1 = 1980$ in column (2), from $t_0 = 1980$ to $t_1 = 2020$ in column (3) and the change in population from the period of 1940 to 1980 compared to the period of 1900 to 1940 in column (4). The intercepts are equivalent to the population changes of the municipalities without ski area access. Standard errors are in parentheses and clustered at the municipality level.
† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

difference is statistically different from zero.[30] The resulting estimate reveals that the population change at access municipalities is 10% at a 10% statistical significance level. This effect rests on the assumption that the diverging population trend before the ski area access period would have remained constant in the absence of ski area access. It directly reduces the exogeneity violation invoked through a positive pre-trend in the population. It is thus a more credible estimate of what can be attributed to ski area access up to 1980. The positive bias in the DiD estimate increases the coefficient by 60%.

Looking at the expansion and concentration period (1980-2020) in column (3) shows no significant population effects for the period after the access period. Hence, the population differences leveled off after 1980 when municipalities gained no additional ski area access points. This aligns with the result that the population effects dispersed outward

[30] In practice, we estimate a Difference-in-differnce-in-differences specification. Formally, $\Delta\Delta \ln y_j \equiv \Delta \ln y_{j,post} - \Delta \ln y_{j,pre} = \mu + \theta D_j + \zeta_j$, where $\Delta \ln y_{j,post}$ and $\Delta \ln y_{j,pre}$ correspond to Equation 3.2 for the two time periods during and before the ski area access period, respectively. θ is the coefficient of interest, μ is the constant and ζ_j is the error term.

from access municipalities after 1980 (see discussion in Section 3.4.2 and results in Appendix C.2.2). Presumably, the first Land Use Planning Act (Federal Assembly of Switzerland, 1979) adopted in 1980 restricted the housing supply while the ongoing increase in demand fuelled competition among permanent residents, second home owners[31] and seasonal workers for ever scarcer housing units. The increased competition for affordable housing is likely a direct consequence of the tourism expansion and the overall population growth that comes with it. As a result, the ongoing ski area growth still attracts permanent residents, but the effects disperse in equal measure to access and neighboring municipalities after 1980.

Among other things, people were attracted to ski area access municipalities because they provided new employment opportunities. That is why we look next at labor market outcomes.

3.5.2 Employment

So far, we observe that the access municipalities raised their population during the ski area access period. To pin down in what sectors people work, we look at employment shares. As data is only available for the most recent period, we interpret the following labor market shifts as long-term equilibrium from three decades after the construction of the last ski areas.[32]

The results of the employment shares are in Table 3.3. It presents OLS estimates of the model of Equation 3.3 using STATENT data across 2-digit ISIC industries in 2015. Column (1) shows that the share of full-time equivalents in access municipalities is, on average, 6.7 percentage points higher in the accommodation sector compared to municipalities without access with a share of 7.7%. Hence, access municipalities employ almost

[31]We find that the share of second home units among all housing units is 38% higher in ski area access municipalities than in municipalities without access by 2021 (i.e., the share of second home units is 55% and 40% in access and non-access municipalities, respectively) using publicly available data from the Federal Office for Spatial Development (ARE) (2023).

[32]We show that the number of hotels, hotel beds and rooms remained constant since 1995 using hotel supply data of the FSO. Thus, we are confident that the presented labor market shifts not only appeared in the last thirty years but throughout the ski area access period. See Appendix C.2.6 for details.

twice the share of FTE in the accommodation sector. In addition, the gastronomy and retail sectors indicated in columns (2) and (3) have, on average, a 45% and 35% higher share of FTE in access municipalities.

Table 3.3: The association of ski area access with employment shares in 2015

Dependent variable:	Accommodation [%]	Gastronomy [%]	Retail [%]	Agriculture [%]
	(1)	(2)	(3)	(4)
Ski area access	0.067***	0.025*	0.014*	−0.128***
	(0.017)	(0.009)	(0.006)	(0.025)
Intercept	0.077***	0.055***	0.039***	0.296***
	(0.010)	(0.006)	(0.005)	(0.019)
N units with access	94	94	94	94
N units w/o access	133	133	133	133
N overall	227	227	227	227
R^2	0.066	0.032	0.018	0.096

Table Notes: The table shows OLS estimates of the model in Equation 3.3. In particular, the average association of access to a ski area between 1940 and 1982 with the share of accommodation employment (1), the share of gastronomy employment (2), the share of retail employment (3) and the share of agriculture employment (4) of all employed persons in full-time equivalents in 2015. The intercepts are equivalent to the employment shares of the respective sector without ski area access. Standard errors are in parentheses and clustered at the municipality level.
† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The higher employment shares in these three sectors come at the expense of a reduced employment share in agriculture. The FTE employment share in access municipalities is, on average, 12.8 percentage points lower than in municipalities without access relative to an employment share of 29.6% (column (4) in Table 3.3). Therefore, the employment share in agriculture is reduced by 40% in access municipalities. Further, we find no other changes in employment shares of other sectors that are statistically different from zero (see Appendix C.2.9).

The labor market shifts associated with ski area access affect not only where residents are employed but also how much they earn. As labor productivity in tourism-related services is and was higher than in agriculture (Federal Statistical Office, 2016; Rütter & Rütter-Fischbacher, 2016), some of the profits are passed down to the workers. Therefore, a municipality's employment composition alone increases incomes because of differences in labor productivity across sectors. We use employment data and local GDP estimates of the Alpine area from Rütter and Rütter-Fischbacher (2016) to study this employment composition channel. Assuming constant within-sector labor productivity across municipalities, we find that the employment composition alone contributes, on average, 2.9% on differences in local GDP (see Appendix C.2.3 for details).

The overall association of ski area access with GDP might be larger since we expect within-sector productivity differences across municipalities and possible changes in labor volume. To incorporate the effects of these additional channels, we estimate changes in income using federal tax data.

3.5.3 Federal Tax Base

The federal tax data allows us to study the relation of ski area access to the taxable income generated in these municipalities. We estimate the association using the model in Equation 3.2 for the years between 1947 and 1980. The results are in Table 3.4. Column (1) shows the changes associated with ski area access in aggregate taxable income. On average, aggregate incomes are 41% higher in access municipalities by 1980. In column (2), we show that the number of federal taxpayers increased even more than the aggregate income. By 1980, 55% more persons pay taxes in access municipalities. Subtracting the special cases (mostly foreign second home owners, see Section 3.3.6) from all federal taxpayers in 1980, we get an estimate for the residential federal taxpayers (assuming little or no special cases in 1947) of 32% in column (3).

Because in access municipalities live 15% more permanent residents (column (4)) on average, the remaining association of 23%, 35% and 15% are the changes in aggregate taxable incomes and the number of federal taxpayers that cannot be explained by population

Table 3.4: The association of ski area access with the tax base in 1980

Dependent variable:	Log taxable income	Log number of federal taxpayers		Log permanent residents
	(1)	(2) All	(3) Residents only	(4)
Ski area access	0.342^{***}	0.439^{***}	0.280^{***}	0.136^{***}
	(0.084)	(0.086)	(0.070)	(0.042)
Intercept	1.538^{***}	0.755^{***}	0.564^{***}	-0.117^{***}
	(0.047)	(0.045)	(0.040)	(0.026)
N units with access	94	94	94	94
N units w/o access	133	133	133	133
N overall	227	227	227	227
R^2	0.888	0.719	0.657	0.079

Table Notes: The table shows OLS estimates of the model in Equation 3.2. In particular, the average association of access to a ski area between 1940 and 1982 with taxable income (1), the number of federal taxpayers (2) and the permanent residents (3). The baseline period is $t_0 = 1947$ and the second period is $t_1 = 1980$. Standard errors are in parentheses and clustered at the municipality level.
† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

growth.[33] Besides, at least another 2.9% of the difference is due to the labor composition across sectors (as shown in the previous section). In the following, we argue what may drive these residual associations after accounting for population growth and employment composition.

We explore two potential channels of the residual increase in the tax base: (i) Adjustments in labor volume at the intensive or extensive margin and (ii) changes in within-sector labor productivity differences across municipalities.

First, as a result of new job opportunities at ski areas, the labor volume might have increased at the extensive (more residents enter the labor force by finding employment) or intensive margin (the already employed work more hours and generate additional income). Comparing the employment rate across municipality types yields a relatively constant rate after the ski area access period (see Appendix C.2.7) and, therefore, suggests

[33] These figures are recovered by subtracting the coefficients of ski area access in column (4) from columns (1), (2), and (3) and calculating the exact percentage effect $e^{\hat{\beta}} - 1$. Notice that the association of ski area access with permanent residents is slightly smaller here than in Table 3.2 because the baseline period is at $t_0 = 1947$ instead of 1940.

no substantial adjustments at the extensive margin.

Unlike the extensive margin, changes at the intensive margin of labor volume are likely: In a survey from 1998, 64% of alpine farmers in Grisons and 51% in the Bernese Highlands state that they earn off-farm income from winter tourism (Behringer et al., 2000).[34] This suggests that alpine farming activities partly complement rather than substitute winter tourism in labor supply. Besides, the same could be true for other tasks obstructed by harsh winters in the mountains, such as craft work at construction sites. Hence, access to ski areas might have led to additional sources of income for local workers who were previously idle in winter. The additionally earned income would lift individuals' income above the minimum tax liability threshold and add them to the taxpayers.[35]

The second channel that increases individual income is raising labor productivity within sectors but across municipalities. Certainly, a bulk of the observed income differences across municipality types can be explained by agglomeration economies that enhance local productivity through a variety of channels (see, e.g. Davis & Dingel, 2019; Duranton & Puga, 2004; Glaeser, 2008). Looking at the accommodation sector supports the presence of agglomeration economies: By linking accommodation employment data to hotel supply data from the FSO, we find that by 2015, an average hotel contains 36% more rooms and employs 72% more FTE per room in access municipalities. Therefore, hotels can pay more employees per available room, which might be related to a higher occupancy rate and, possibly, economies of scale.[36] Furthermore, having twice the number of hotels in the access municipalities[37] might intensify horizontal competition or vertical product differentiation and, thereby, boost productivity (Barros & Alves, 2004; Zirulia, 2011).

[34]On top of that, land use data indicate that access municipalities allocate much more land to alpine farming than municipalities without access (see Appendix C.2.10).

[35]Because there are no changes from the taxpayers at the extensive margin, we can infer that the large changes in the number of residential federal taxpayers must stem from a higher proportion of the population surpassing the minimum threshold of the federal tax and through that, increasing the tax base sizeable. See Section 3.3.6.

[36]For a comprehensive overview of how hotels differ and are measurable in terms of productivity see Barros and Alves (2004).

[37]See Appenidx C.2.6 for details on how the number and size of hotels differ across municipalities.

The special cases reveal another interesting pattern. When looking at the mean differences between access and non-access municipalities, we find that access municipalities reported almost four times as many special cases as non-access municipalities in 1980. This confirms the high demand for second homes in access municipalities before the introduction of a federal law restricting foreigners from buying or building second homes (Federal Assembly of Switzerland, 1983).

When we look at how the tax base differences have evolved, we find that the three outcomes, taxable income, number of federal taxpayers and permanent residents, all remain at the level of 1980 (see Appendix C.2.4 for the results up to 2015, we have no information on special cases after 1980). As discussed above and at length in Appendix C.2.2, the effects disperse to neighboring municipalities due to a shortfall of housing supply after 1980 but remain positive.

Altogether, we find that residents in municipalities with access to ski areas generated substantially higher incomes in the aggregate than in municipalities without access. Naturally, the gains in the tax base translate into higher tax revenues. Therefore, access municipalities financially profit beyond having a larger and wealthier population. In the next section, we quantify these associations and discuss their implications for access municipalities.

3.5.4 Federal Tax Revenue

We use federal tax data to quantify further the associations of ski area access and tax revenues. Gains in federal taxes likely go hand in hand with similar changes in municipal and cantonal taxes[38] and serve, thus, as a valid proxy to measure overall changes to tax revenues.

[38] A regression of municipal tax multipliers on D_j and cantonal fixed effects for the year 2021 reveals that the municipal multiplier is, on average, 5 percentage points higher in access municipalities (significant at the 5% level). We have no information on municipal tax multipliers further back than 2010. Still, this result suggests that municipal tax revenues might be slightly higher in access municipalities than the federal tax revenues suggest.

The OLS estimates of the model in Equation 3.2 for the federal income tax revenue are in Table 3.5. Column (1) shows that federal tax revenues up to 1980 were, on average, 66% higher in access municipalities. Column (2) indicates that the federal tax revenues per resident were, on average, 44% higher in access municipalities by 1980. These substantial differences in tax revenues per resident further support the presence of individual income gains in access municipalities.

Table 3.5: The association of ski area access with federal tax revenues in 1980

Dependent variable:	Log federal tax revenue	Log federal tax revenue per resident
	(1)	(2)
Ski area access	0.516^{***}	0.380^{***}
	(0.115)	(0.102)
Intercept	2.173^{***}	2.291^{***}
	(0.065)	(0.058)
N units with access	94	94
N units w/o access	133	133
N overall	227	227
R^2	0.896	0.919

Table Notes: The table depicts OLS estimates of the model in Equation 3.2. In particular, the average association of access to a ski area between 1940 and 1982 with the federal tax revenues (1) and the federal tax revenues per resident (2). The baseline period is $t_0 = 1947$ and the second period is $t_1 = 1980$. Standard errors are in parentheses and clustered at the municipality level.
† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In line with the previous results, the tax revenue changes remain constant after 1980, suggesting that the ski area access period led to a one-time shift in tax revenues and did not induce a permanent faster growth path across municipalities (results across time are in Appendix C.2.5). However, as with the population and taxable incomes, we find that tax revenues disperse more in space after 1980 and, thus, affect access and non-access municipalities in equal measure (see the results in Appendix C.2.2).

Our results on tax revenues suggest that access municipalities became substantially wealthier during the ski area access period. Access municipalities collected more taxes through the faster population growth and substantial increases in tax revenues per resident.

3.6 Conclusions

We show in the present work that the gain of access to ski areas during the skiing boom between the Second World War and 1980 is, on average, associated with 16% more permanent residents and employment shifts from agriculture (-40%) to tourism-related service sectors such as accommodation (+90%), gastronomy (+45%) or retail (+35%). Gaining access to ski areas attracts residents and fosters structural changes in the economy. Access municipalities grew stronger until 1980 before increasing competition for constrained housing units among residents, second homeowners and seasonal workers led to increased population dispersion to neighboring municipalities. Although we have limited information on second homeowners and seasonal workers, our results point in that direction. Exploring the competition for housing, its spatial dispersion and prices, and the resulting conflicts between these groups is a relevant topic for future research.

Furthermore, we show that the structural changes in the labor market associated with ski area access go hand in hand with 41% higher taxable incomes on average. At the same time, the number of taxpayers extends by 55%. Accounting for population growth and special cases, the remaining residual rise in incomes emerges through two channels: First, for employed at occupations with weather-exposed tasks such as alpine farming or work at the construction site, ski area access enables additional employment in the winter season. This enhances labor volume at the intensive margin and raises individual incomes above the minimum tax liability threshold. Secondly, access municipalities offer more productive employment opportunities. Their employees work in more productive sectors and the productivity of tourism-related services is also likely higher due to economies of scale and agglomeration economies.

We cannot quantify the relative contribution of each association to the overall income changes and which sectors drive the within-sector productivity differences the most.

However, we argue that tourism-related services are certainly more productive using suggestive evidence from the hotel industry. It is conceivable that service industries unrelated to tourism also become more productive in municipalities connected to ski areas. Concentrating on such spillovers within the Swiss Alps, as discussed by Faber and Gaubert (2019), T. Fan et al. (2022), and Favero and Malisan (2021) in other contexts, is an interesting avenue for future research.

Finally, we find in access municipalities an average increase of 66% in overall tax revenues and a 44% increase in tax revenues per resident. This alleviates the provision of enhanced local public goods for the municipal government and, more interestingly, enables the ski area operators to negotiate public funds to maintain the costly skiing infrastructure. Surely, the presence of positive externalities of ski area access to local firms, employment and income can legitimize such an involvement (Lohmann & Crasselt, 2012). However, over time this leads to tight path dependencies between the local government and ski area operators (such local public financial involvement is documented in Derungs et al., 2019; Lengwiler & Bumann, 2018; Schuck & Heise, 2020). In light of climate change, this poses a challenge for municipal governments that face the decision to support their ski area further, even though natural snow reliability is no longer given. It is thus a viable path for future research to zoom in on more recent developments and evaluate the efficacy and efficiency of local public policies.

The main limitation of our work is the non-random nature of our data. This invokes potential biases that limit not the direction but the size of our estimates. Most estimates are upward biased because they are not solely attributable to the access to ski areas. Often, stakeholders in these municipalities decided to invest in a ski area precisely because the economic environment allowed them to do so. Taking an additional difference in population changes enabled us to lessen this selection bias. The point estimate remains sizable at 10% and is still 60% of the size of what we would have found if the data were restricted to a baseline period in 1940 instead of 1900. Considering these limitations, the sizes of our point estimates can, at best, be interpreted as upper bounds of causal effects and should, accordingly, be interpreted cautiously.

Appendix A

The Impact of Weather Forecasts on Skiing Demand

A.1 Weather and Forecast Data Processing

A.1.1 Pool of Weather and Forecast Variables

Next to the weather variables described in Section 1.3.2, I additionally considered the following variables: Daytime maximum and mean temperature [°C], wind chill temperature [°C][1], fresh snow accumulated [cm][2], 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].

[1]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 moisturize the snow and are 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)

[2]Snowfall is already measured in the precipitation variable. Thus, the solid precipitation is lagged one day into the future to represent the fresh snow that fell within the last 24 hours. Then, the precipitation variable depicts immediate snowfall or rain. Fresh snow is expected to affect demand differently than daily precipitation. Freeride-enthusiasts seek the former whereas the latter is generally considered as being bad conditions 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).

The forecast data covers additionally to the variables described in Section 1.3.3 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 and two weather variables (minimum temperature and precipitation) are in hourly values. Most other values are in daytime (6-18 UTC) or in daily granularity available (0-24 UTC). Not all hours matter for skiing as the ski areas normally operate between 8 a.m. and 4 p.m. Central European Time (CET). Therefore, the data is aggregated into the relevant hours, as shown in the next section.

A.1.2 Temporal Aggregation

All weather and forecast data from MeteoSwiss are specified in UTC. However, the pictograms and the published data users observe are specified in CET. In the winter months CET=UTC+1 whereas in the summer months CET=UTC+2. The time intervals used for aggregating weather and forecast data to daily observations are presented in Table A.1. 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[3] within the time interval of $6.00 - 18.00$ CET at the observed periods during the winter season. This means hourly and daily data are of the same quality.

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

[3] 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.

Table A.1: 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

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 (between 6-18 CET on most days) and then divided to receive the same percentage value for the forecast as in the measurement.

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 and the forecast values are available in hourly minimum (i.e., the minimum measured within an hour). The resulting daytime minimum temperature is then the lowest hourly value within the daytime hours for both variables.

A.1.3 Spatial Interpolation

To spatially join the chosen lift station with all weather stations within 30km, we use ArcGIS software to match geo-referenced data of our chosen lift stations and of all weather stations from Federal Office of Meteorology and Climatology (2023). 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

Burrough et al. (1998):

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

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 Burrough et al., 1998). Rearranged and evaluated for n weather stations in the vicinity of 30km yields

$$\omega_{A,t} = \frac{\frac{1}{d^p_{A,i}}}{\sum_{s=A}^{n} \frac{1}{d^p_{s,i}}} \tag{A.2}$$

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

$$\hat{w}_{it} = \sum_{s=A}^{n} w_{s,t} \cdot \omega_{s,t}. \tag{A.3}$$

A.1.4 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 skiers react to the weather, I set up the model

$$log(y_{ds}) = W_{ds}\beta + \alpha_d + o_{ds}\nu + \varepsilon_{ds}, \tag{A.4}$$

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 A.2, A.3 and A.4 for the three areas, respectively. The specification in column (1) uses the three main variables only. The one in column (2) adds season fixed effects and the one in 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 also enters the index in a quadratic way. 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.

Table A.2: 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

Table Notes: The table depicts OLS estimates of the model in Equation A.4 for area 1. 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 specified in the square brackets. The Easter dummy indicates the four Easter holidays (Good Friday to Easter Monday). Standard errors are in parentheses and clustered at the season day level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The relative relevance of weather variables is further investigated using Random Forest (RF). The idea is to find the key variables explaining skiing demand to create a weather

Table A.3: 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

Table Notes: The table depicts OLS estimates of the model in Equation A.4 for area 2. 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). Standard errors are in parentheses and clustered at the season day level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

and forecast index that proxies actual and expected skiing conditions in a single variable. First, I grow a RF on the model in Equation A.4 including the full set of available weather variables (described in Appendix A.1.1) in addition to the 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 a training set and the remaining data as a 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

Table A.4: 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

Table Notes: The table depicts OLS estimates of the model in Equation A.4 for area 3. 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). Standard errors are in parentheses and clustered at the season day level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

be shown to be equivalent to Leave-One-Out Cross Validation (LOOCV) (Hastie et al., 2009).

The OOB is also used to estimate variable importance. By randomly permuting a variable in the OOB sample, comparing the Mean-Squared Error (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., 2009). 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 computed 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 A.1 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 A.1: Variable importance measure of RF including all available predictors

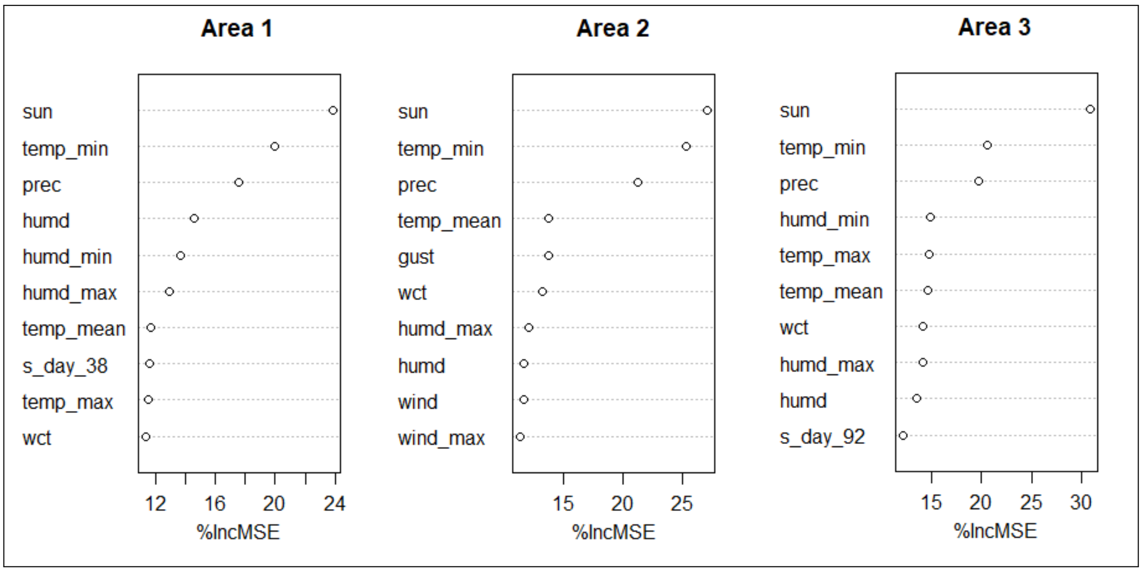


Figure Notes: Variable importance estimated by Random Forests for each area. The measure on the x-axis indicates by how much the MSE would increase, leaving the variable on the y-axis out of the Random Forest.

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 1.3.2. As the minimum temperature is inversely u-shaped to demand, I recover an estimate for the optimal temperature

$$\underline{temp}^* = -\frac{\hat{\beta}_{temp}}{2\hat{\beta}_{temp^2}} \tag{A.5}$$

using specification (7) as shown in Tables A.2, A.3 and A.4 for each area, respectively. The deviation from that optimum is then related to the lower partial temperature indices as shown in Equation 1.11.

A.2 Additional Theoretical Results

A.2.1 Asymmetric Effects Through Risk Aversion

The second channel that affects the symmetry of reactions to forecast errors is the degree of risk aversion. Using Equation 1.8 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 allows me to compare these distances formally.

$$u(v(a,g) - c^g) - u(v(a,g) - c^m) = \left(\frac{1-p_m}{p_m} - \frac{1-p_g}{p_g}\right) V_b \tag{A.6}$$

$$u(v(a,g) - c^m) - u(v(a,g) - c^b) = \left(\frac{1-p_b}{p_b} - \frac{1-p_m}{p_m}\right) V_b. \tag{A.7}$$

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

$$\underbrace{\frac{p_g - p_m}{p_g p_m} V_b}_{=c^m - c^g} < \underbrace{\frac{p_m - p_b}{p_m p_b} V_b}_{=c^b - c^m}. \tag{A.8}$$

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

$$c^{m,RA} - c^{g,RA} = (v - c^{g,RA}) - (v - c^{m,RA}) > u(v - c^{g,RA}) - u(v - c^{m,RA}) \tag{A.9}$$

and risk neutrality that

$$c^{m,RN} - c^{g,RN} = (v - c^{g,RN}) - (v - c^{m,RN}) = u(v - c^{g,RA}) - u(v - c^{m,RA}) \tag{A.10}$$

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 distances between c^b and c^g and the larger the differences between c^m and c^g. Comparing the differences in these distances yields

$$\left\{[c^{m,RA} - c^{g,RA}] - [c^{m,RN} - c^{g,RN}]\right\} - \left\{[c^{b,RA} - c^{g,RA}] - [c^{b,RN} - c^{g,RN}]\right\} \tag{A.11}$$

$$= (c^{m,RA} - c^{m,RN}) - (c^{b,RA} - c^{b,RN}) > 0 \tag{A.12}$$

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.

A.3 Additional Empirical Results

A.3.1 Demand Shares of Pass Validity Types and Age Groups

Figure A.2 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, 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 A.2: Shares in aggregate demand by validity types

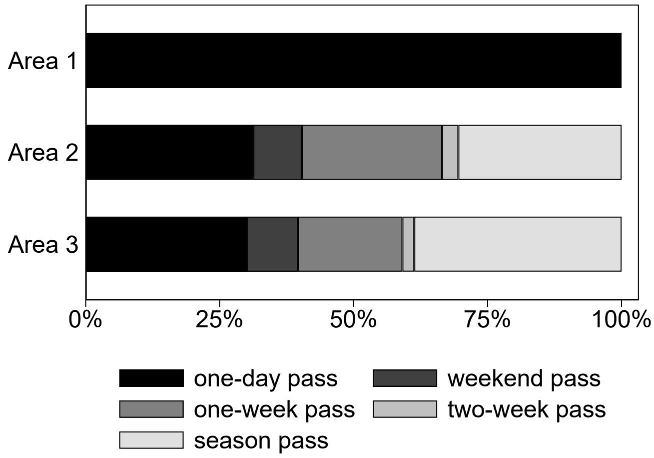


Figure Notes: The share of first entries generated by agents owning different pass validity type categories across the three areas is indicated. Pass validity types in area 1 are restricted to one-day passes.

Figure A.3: Shares in aggregate demand by age groups

(a) Shares in overall demand (b) Shares in one-day passes

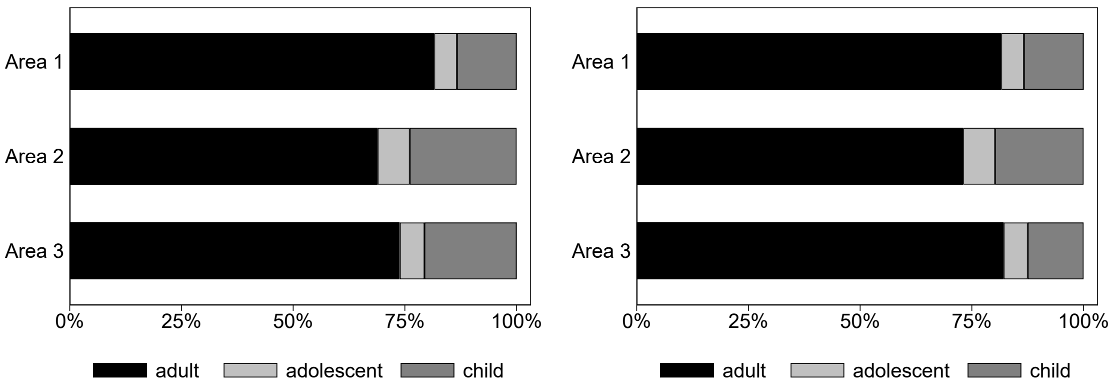


Figure Notes: Panel (a) indicates the share of first entries generated by agents of different age groups in overall demand across the three areas. Panel (b) indicates the share of first entries generated by agents of different age groups in one-day passes across the three areas.

Figure A.3 indicates the share in aggregate demand (panel (a)) and one-day pass owners (panel (b)), 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 defined by the ski areas.

A.3.2 Uneven Weather Probabilities across Switzerland

In this section, I show empirically that it is inherently more difficult for the forecaster to predict good than bad weather outcomes. Relating absolute forecast errors with weather percentiles in Figure A.4 for the three areas reveals precisely the expected pattern that bad weather situations are harder to predict than good weather situations. Forecasts at lower weather percentiles are more prone to errors in all three areas than at higher weather percentiles.

Figure A.4: Local polynomial smoothing of absolute forecast errors on weather percentiles

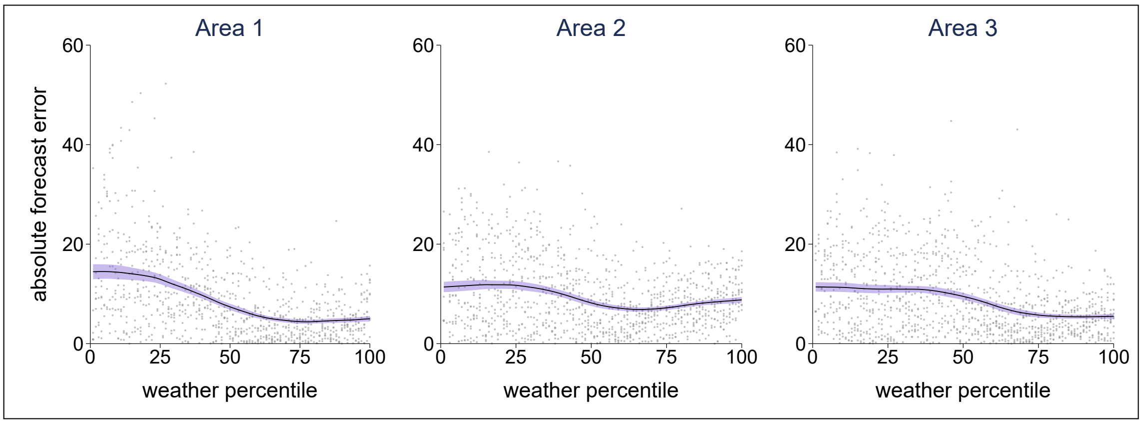


Figure Notes: The local polynomial smoothing applied here uses the kernel weighting of Epanechnikov, a bandwidth of 10 (arbitrary choice for illustrational purposes) and a degree of 0. See J. Fan and Gijbels, 2018 for a comprehensive work on the method applied here. Absolute forecast errors for horizon $h = 0$ are defined as $|f_0 - w|$ and weather percentiles are constructed from the weather index w (See Section 1.3.2).

Interestingly, area 1 lies furthest in the mountains and is simultaneously exposed to larger discrepancies in forecast errors across weather percentiles. This aligns with the intuition that it becomes more challenging to predict bad weather outcomes the further a place lies in the Alps.

Consequently, 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 Equation A.8. 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. Combined with risk-averse agents, I would argue that the shift 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 no longer as low. Consequently, potential skiers have difficulty 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 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 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.

In Figure A.4, 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 a pattern we observe all over the Swiss Alps. Figure A.5 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

$$|e_{dsj}^{d-0}| = w_{dsj}\beta + \gamma_j D_j + w_{dsj} \times D_j\delta + \varepsilon_{dsj} \tag{A.13}$$

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 $w_{dsj} \times D_j$ 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. Figure A.5 displays estimates at these geographical locations. 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 bad weather outcomes accurately 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 A.5: OLS estimates of absolute forecast errors on weather percentiles by ski areas

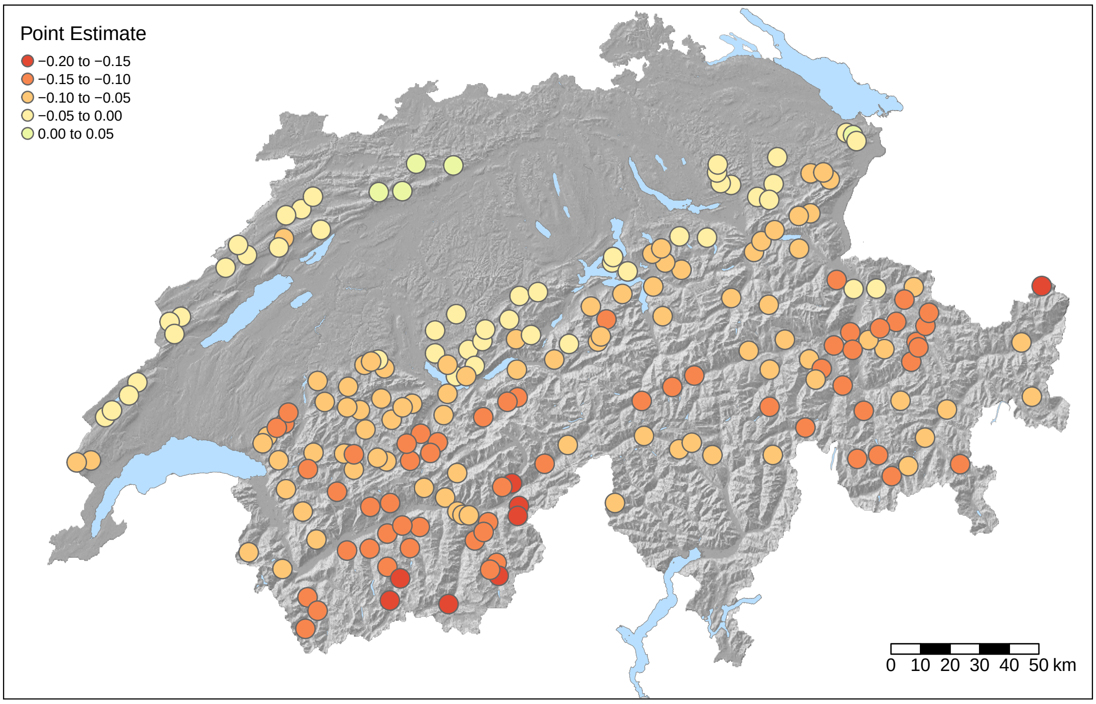


Figure Notes: The points indicate the geographic locations of two hundred major ski areas across Switzerland. The point's color shading from light yellow to red depicts the effect size of individual weather effects on forecast errors of the model in Equation A.13. A higher intensity of red is associated with a larger gap in the ability to accurately predict the weather in good relative to bad weather outcomes.

A.3.3 Effects of Partial Weather Indices

To give an idea how the partial weather indices of sunshine (Equation 1.9), precipitation (Equation 1.10), minimum temperature (Equation 1.11) and their respective forecast errors relate to the aggregate demand, I estimate

$$log(y_{ds}) = \widetilde{W}_{ds}\beta + \widetilde{E}_{ds}^{d-h}\delta + [\widetilde{E}_{ds}^{d-h} \times \widetilde{D}_{ds}]\lambda_0 + \alpha_d + o_{ds}\nu + \varepsilon_{ds}, \tag{A.14}$$

where $\widetilde{W}_{ds} = [\widetilde{sun}_{ds} \quad \widetilde{prec}_{ds} \quad \widetilde{temp}_{ds}]$ is a row-vector of partial weather indices defined by Equations 1.9, 1.10 and 1.11, $\widetilde{E}_{ds}^{d-h}$ 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 the model in Equation A.14 are presented in Table A.5. 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. Thus, weighting the weather index more towards precipitation leads to larger effects of pessimistic errors and weighting the index more towards sunshine leads to larger effects of optimistic errors. One possible explanation could be that a bad weather forecast's salient feature is precipitation, whereas a good forecast's salient feature is sunshine duration. Thus, when a forecast is framed around more or less precipitation, it is in the realm of bad weather occurrences.[4]

Table A.5: 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

Table Notes: The table depicts OLS estimates of the model in Equation A.14 for one-day pass owners in three areas. 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). Standard errors are in parentheses and clustered at the season day level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[4] For example, a forecast might be mixed because two days before the event, it indicates 5mm of precipitation and one day before 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.

Consider the counterfactual situations in Figure 1.2: The thresholds c^m and c^b are close because mixed forecasts in precipitation are 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 counterfactual. On the other hand, when the prevalent variable in a forecast is sunshine, then the forecast is in the realm of good weather occurrences.[5] 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.

A.3.4 Prediction Performance of the Weather Index

Using a one-dimensional weather index has the caveat that it potentially reduces the information of the three donor variables to predict skier demand. Such a loss could lead to biased estimates in all regressions using the index. I compare the accuracy in predicting skier demand of the weather index with the partial weather index and single weather variables using 10-fold Cross Validation (CV). The procedure randomly uses part of the data as training-set and the remaining data as test-set to compute the RMSE of the out-of-sample predictions. The 10-fold CV splits the sample in 10-folds and averages them over the 10 computed RMSE (Hastie et al., 2009). In other words, we use training data to compute a model to predict skier attendance in the test data and compare it to actual outcomes in the test data. The better the fit with reality, the better our model predicts skier outcomes.

The results in Table A.6 indicate the performance of a different model in each column. All are based on Equation A.4 where column (1) depicts a model using all eight weather variables (the same as in column (7) in Table A.2), column (2) a model using the three partial weather indices (Equations 1.9 to 1.11) and column (3) a model with the weather index (Equation 1.12). The performance measure depicts the share of the variation in

[5]For example, a forecast might be mixed because two days before the event it indicates 80% sunshine and one day before 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.

demand that each model correctly predicts. For example, the performance of the single variables model in area 1 is 0.424, meaning that roughly 42% of the variation in demand can be correctly predicted by the model. It is striking how little the performance changes across the three columns. Thus, we conclude that the one-dimensional weather index is as good at predicting skier attendance as the model with eight single weather variables and the model with the three key variables.

Furthermore, the lower prediction performance in ski area 2 is in line with the results from the main paper (Section 1.5): As the demand is less dependent on weather compared to the other areas, the performance of predicting skier outcomes with the weather is also worse.

Table A.6: Prediction performance of single weather variables, partial indices and the weather index

	(1) Single variables	(2) Partial indices	(3) Weather index
Area 1 out-of-sample fit ($1 - \frac{RMSE}{SD}$)	0.424	0.427	0.427
Area 2 out-of-sample fit ($1 - \frac{RMSE}{SD}$)	0.349	0.352	0.350
Area 3 out-of-sample fit ($1 - \frac{RMSE}{SD}$)	0.451	0.453	0.449

Table Notes: The table depicts a measure for the out-of-sample fit $1 - \frac{RMSE}{SD}$ (one minus the root-mean-squared error divided by the standard deviation of demand) recovered from 10-fold cross-validation across three models indicated by the columns and across three areas indicated by the rows. All estimates are OLS estimates of adaptations of Equation A.4 with Easter dummies and season day fixed effects. The sample consists of one-day passes only. In column (1) W_{ds} consists of all eight weather variables (the same as in column (7) in Table A.2), in column (2) it consists of the three partial weather indices (Equations 1.9 to 1.11) and in column (3) it consists of the uniformly weighted weather index (Equation 1.12).

A.3.5 Asymmetric Effects by Age

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[6]. Table A.7 shows that forecast reactions are dominated by pessimistic errors in all areas and in areas 2 and

[6]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.

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).[7]

[7]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 A.7: 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)	(1)	(2)	(3)	(1)	(2)	(3)
Weather effects									
Adults	0.027***	0.026***	0.026***	0.022***	0.022***	0.021***	0.032***	0.032***	0.032***
	(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***	0.017***	0.016***	0.014***	0.017***	0.017***	0.018***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Children	0.015***	0.017***	0.017***	0.017***	0.017***	0.015***	0.019***	0.020***	0.021***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Optimistic error effects									
Adults	0.003	0.005	0.004	0.016***	0.014***	0.009***	0.014***	0.014***	0.014***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Adolescents	−0.001	−0.004	−0.003	0.007	0.009	0.005	0.008*	0.009*	0.009*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.003)	(0.004)	(0.004)
Children	0.001	0.001	0.001	0.010*	0.008	0.003	0.009*	0.007	0.006
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Pessimistic error effects									
Adults	0.016***	0.018***	0.019***	0.011*	0.013***	0.009*	0.013***	0.011***	0.012***
	(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	0.026***	0.020***	0.015***	0.006	0.011***	0.012***
	(0.003)	(0.003)	(0.004)	(0.006)	(0.006)	(0.005)	(0.003)	(0.003)	(0.003)
Children	0.015***	0.012***	0.013***	0.014***	0.017***	0.013*	0.013***	0.011***	0.013***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)	(0.006)	(0.003)	(0.004)	(0.004)

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Dependent variable	Log demand, area 1			Log demand, area 2			Log demand, area 3		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Asymmetric effects									
Optimistic − Pessimistic, adults	−0.013	−0.013	−0.014*	0.005	0.001	0.001	0.001	0.004	0.002
	(0.007)	(0.007)	(0.007)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Optimistic − Pessimistic, adolescents	−0.005	−0.008	−0.008	−0.019*	−0.010	−0.010	0.002	−0.001	−0.003
	(0.006)	(0.006)	(0.006)	(0.009)	(0.009)	(0.008)	(0.005)	(0.006)	(0.005)
Optimistic − Pessimistic, children	−0.015	−0.011	−0.012	−0.005	−0.009	−0.010	−0.004	−0.005	−0.007
	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)	(0.009)	(0.006)	(0.007)	(0.007)
Controls									
Easter dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age category fixed effects	Yes	(Yes)	(Yes)	Yes	(Yes)	(Yes)	Yes	(Yes)	(Yes)
Season day fixed effects	Yes	(Yes)	(Yes)	Yes	(Yes)	(Yes)	Yes	(Yes)	(Yes)
Day-by-age fixed effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Season fixed effects	No	No	Yes	No	No	Yes	No	No	Yes
N	2,150	2,150	2,150	2,437	2,437	2,437	2,906	2,906	2,906
R^2	0.790	0.846	0.850	0.625	0.705	0.729	0.795	0.834	0.840

Table Notes: The table depicts OLS estimates of the model in Equation 1.18 for one-day pass owners in three areas. 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. The Easter dummy indicates the four Easter holidays (Good Friday to Easter Monday). Standard errors are in parentheses and clustered at the season day level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.3.6 Shares of Type A Agents by All Pass Validity Types

Table A.8 provides OLS results of all pass validity types of the model in Equation 1.16. It represents the same estimates as in Table 1.4 and recovers shares of type A agents also by Equation 1.17. 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 who expect to make a lot out of their passes and overtake some of the weather risks from ski area operators. Second, once they buy 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 discussed in Section 1.5), only weekend pass owners have significant shares in some specifications.

Table A.8: 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)	(1)	(2)	(3)
Gross weather effects						
One-day pass owners	0.022***	0.023***	0.021***	0.030***	0.030***	0.031***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Weekend pass owners	0.015***	0.014***	0.013***	0.014***	0.014***	0.014***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
One-week pass owners	0.009***	0.006***	0.005***	0.010***	0.007***	0.008***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Two-week pass owners	0.006***	0.007***	0.006***	0.006***	0.006***	0.007***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Season pass owners	0.016***	0.018***	0.017***	0.024***	0.026***	0.026***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
0-day error effects						
One-day pass owners	0.013***	0.015***	0.011***	0.011***	0.012***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Weekend pass owners	0.005*	0.004	−0.000	0.007***	0.008***	0.006***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
One-week pass owners	0.006*	0.005	0.000	0.008*	0.008***	0.006***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Two-week pass owners	0.012***	0.011***	0.007*	0.007***	0.008***	0.006***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Season pass owners	0.005***	0.007***	0.002	0.004	0.004	0.003
	(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***	0.353***	0.212***	0.247***	0.204***
	(0.099)	(0.107)	(0.093)	(0.055)	(0.057)	(0.052)
Weekend pass owners	0.218	0.172	−0.016	0.370*	0.379**	0.253*
	(0.112)	(0.120)	(0.090)	(0.144)	(0.140)	(0.109)
One-week pass owners	0.627	0.640	0.014	0.689	1.085	0.692
	(0.417)	(0.449)	(0.264)	(0.408)	(0.618)	(0.389)
Two-week pass owners	5.718	2.112	1.273	1.400	1.701	0.989
	(6.443)	(1.129)	(0.789)	(1.058)	(1.029)	(0.555)
Season pass owners	0.204*	0.233**	0.062	0.092	0.081	0.050
	(0.082)	(0.071)	(0.058)	(0.055)	(0.047)	(0.043)

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Dependent variable	Log demand, area 2			Log demand, area 3		
	(1)	(2)	(3)	(1)	(2)	(3)
Differences in shares						
One-day − Weekend	0.238	0.375**	0.369***	−0.158	−0.132	−0.048
	(0.122)	(0.131)	(0.107)	(0.126)	(0.120)	(0.094)
One-day − One-week	−0.170	−0.092	0.339	−0.477	−0.838	−0.487
	(0.431)	(0.424)	(0.251)	(0.416)	(0.605)	(0.380)
One-day − Two-week	−5.262	−1.564	−0.920	−1.188	−1.454	−0.785
	(6.428)	(1.104)	(0.772)	(1.049)	(1.016)	(0.545)
One-day − Season	0.253**	0.315***	0.292***	0.120**	0.166***	0.154***
	(0.087)	(0.086)	(0.074)	(0.044)	(0.043)	(0.038)
Controls						
Easter dummy	Yes	Yes	Yes	Yes	Yes	Yes
Pass-type fixed effects	Yes	(Yes)	(Yes)	Yes	(Yes)	(Yes)
Season day fixed effects	Yes	(Yes)	(Yes)	Yes	(Yes)	(Yes)
Day-by-pass fixed effects	No	Yes	Yes	No	Yes	Yes
Season fixed effects	No	No	Yes	No	No	Yes
N	4,829	4,829	4,829	5,370	5,370	5,370
R^2	0.593	0.735	0.757	0.726	0.841	0.847

Table Notes: The table depicts OLS estimates of the model in Equation 1.16 where the groups are separated by different pass validity categories using four specifications across two areas. 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 Equation 1.17 by a nonlinear combination of point estimates using the delta method. The Easter dummy indicates the four Easter holidays (Good Friday to Easter Monday). Standard errors are in parentheses and clustered at the season day level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.4 Robustness Using Pictograms

A.4.1 Data Processing to Weather and Forecast Classes

To create 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 MeteoSwiss 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 similarly. A recent representation is depicted in Figure A.6 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 A.6: A typical representation of a local weather forecast

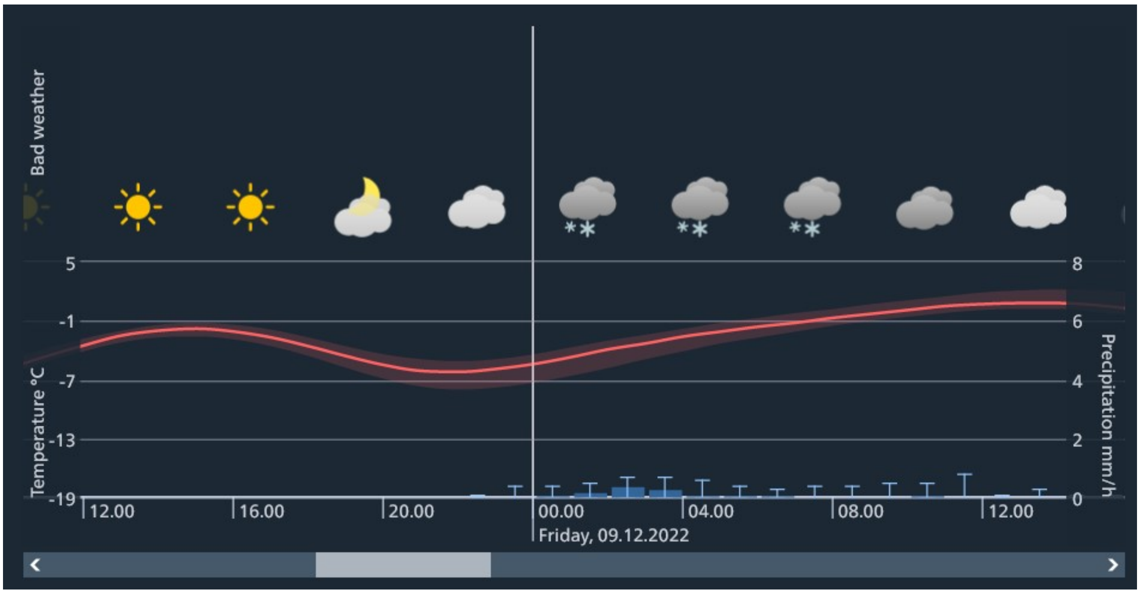

Figure Notes: A typical representation of a local weather forecast from https://www.meteoschweiz.admin.ch.

MeteoSwiss provided their exact decision node to recreate each of their 35 possible daytime pictograms[8] on an hourly basis and how each pictogram is aggregated to 3-hour, 6-hour or 12-hour aggregates. Please contact the author if these exact decision nodes are of interest as these are not meant to be published here.

My approach is to classify the weather and forecast variables on a certain day into four classes representing 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. Combined with the precipitation bars and disaggregated into 3-hour periods, a different weather outcome could be expected from the same temporally aggregated pictogram. For example, in an extreme case (which is very rare), a day with 80% relative sunshine duration with 2mm precipitation of snow over three hours (e.g., at the beginning or end of the day) may be aggregated to the same icon as a day with just 20% relative sunshine duration with 15mm precipitation of snow over eight hours (never exceeding 2mm per hour). MeteoSwiss has good reasons to aggregate these to the same pictogram as in both situations, the sun is shining and some snow is falling (and never strong), but users will see the difference between the two days by looking at the error bars and disaggregated 3-hour pictograms. Therefore, my 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*),[9] four precipitation intensity classes (*very weak*, *weak*, *moderate*, *strong*)[10] and three significant weather situations (*no significant*

[8]MeteoSwiss 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.

[9]MeteoSwiss 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%.

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

weather, *rain*, *snow*)[11] into account. In Table A.9 the classification into the four weather and forecast classes based on the MeteoSwiss 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.

Table A.9: Classification of pictograms into four weather/forecast classes

Opacity / Sig. weather	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 MeteoSwiss 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.

A.4.2 Empirical Model

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

$$\begin{aligned} log(y_{dsg}) =& W_{ds}\beta_0 + D_{ds}^{opt}\delta_0 + D_{ds}^{pes}\lambda_0 + \underline{\widetilde{temp}}_{ds}\eta \\ &+ \sum_{g=1}^{G} \left(D_g\delta_g + [D_g \times W_{ds}]\beta_g^w + [D_g \times D_{ds}^{opt}]\delta_g + [D_g \times D_{ds}^{pes}]\lambda_g \right) \\ &+ \alpha_d + o_{ds}\nu + \varepsilon_{dsg} \end{aligned} \tag{A.15}$$

where $W_{ds}\beta_0 = D_{ds}^2\beta_0^2 + D_{ds}^3\beta_0^3 + D_{ds}^4\beta_0^4$ for the four weather classes with class 1 as baseline category. D_{ds}^{opt} is a dummy that satisfies $\mathbb{1}[F_{ds} - W_{ds} > 0]$ meaning that forecasts predicted optimistic weather by at least one class. D_{ds}^{pes} is a dummy that satisfies $\mathbb{1}[F_{ds} - W_{ds} < 0]$ meaning that forecasts predicted pessimistic weather by at least one class. The group dummies D_g again indicate the heterogeneous groups in either pass

[11] MeteoSwiss 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*.

validity types or age and interactions with the weather classes, as well as with optimistic and pessimistic errors, which 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 implicitly reflect temperature differences. 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).

A.4.3 Results

Table A.10 shows the estimates of the model in Equation A.15 across three specifications per area for one-day pass owners in the aggregate. Therefore, these results represent the same estimates as Table 1.5 in Section 1.5. In contrast to the results using equally weighted indices, the error effects in area 1 are not asymmetric towards pessimistic errors but, on the contrary, asymmetric towards optimistic effects in area 2. The difference is that precipitation is weighted more heavily in the equally weighted indices than in the pictograms. Considering again Table A.5, 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 A.11 shows the estimates of the model in Equation A.15 across three specifications per area for one-day pass owners across age groups. Therefore, these results represent the same estimates as Table A.7 in Appendix A.3.5. Comparing the results of the two tables leads 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 small and slightly above the 5% significance threshold. Therefore, I do not confirm Proposition 3.

Table A.10: 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)

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dependent variable	log demand, area 1			log demand, area 2			log demand, area 3		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
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

Table Notes: The table depicts OLS estimates of the model in Equation A.15 for three specifications in three areas. 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. The linear combination of optimistic and pessimistic dummies tests asymmetric effects. The Easter dummy indicates the four Easter holidays (Good Friday to Easter Monday). Standard errors are in parentheses and clustered at the season day level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.11: 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)	(1)	(2)	(3)	(1)	(2)	(3)
Weather effects									
Class 2, adults	0.527***	0.524***	0.515***	0.499***	0.490***	0.451***	0.790***	0.767***	0.768***
	(0.088)	(0.091)	(0.090)	(0.080)	(0.083)	(0.079)	(0.069)	(0.076)	(0.073)
Class 2, adolescents	0.202*	0.261*	0.255*	0.352***	0.354***	0.284***	0.382***	0.392***	0.423***
	(0.095)	(0.106)	(0.104)	(0.100)	(0.103)	(0.083)	(0.091)	(0.093)	(0.096)
Class 2, children	0.343***	0.301*	0.292*	0.414***	0.452***	0.416***	0.474***	0.494***	0.514***
	(0.095)	(0.106)	(0.104)	(0.093)	(0.103)	(0.105)	(0.080)	(0.087)	(0.088)
Class 3, adults	1.001***	0.967***	0.962***	0.878***	0.895***	0.880***	1.248***	1.228***	1.220***
	(0.083)	(0.086)	(0.087)	(0.087)	(0.091)	(0.090)	(0.089)	(0.090)	(0.087)
Class 3, adolescents	0.437***	0.468***	0.472***	0.610***	0.591***	0.543***	0.568***	0.554***	0.573***
	(0.093)	(0.099)	(0.096)	(0.107)	(0.110)	(0.095)	(0.097)	(0.102)	(0.105)
Class 3, children	0.612***	0.617***	0.617***	0.685***	0.704***	0.682***	0.635***	0.696***	0.702***
	(0.089)	(0.098)	(0.096)	(0.107)	(0.114)	(0.119)	(0.105)	(0.106)	(0.108)
Class 4, adults	1.350***	1.352***	1.338***	1.001***	1.031***	0.990***	1.641***	1.643***	1.687***
	(0.083)	(0.088)	(0.089)	(0.078)	(0.084)	(0.080)	(0.070)	(0.070)	(0.069)
Class 4, adolescents	0.567***	0.611***	0.612***	0.721***	0.682***	0.627***	0.809***	0.854***	0.913***
	(0.100)	(0.108)	(0.109)	(0.103)	(0.094)	(0.080)	(0.076)	(0.080)	(0.084)
Class 4, children	0.825***	0.842***	0.834***	0.792***	0.807***	0.755***	1.027***	1.067***	1.120***
	(0.114)	(0.119)	(0.120)	(0.086)	(0.096)	(0.100)	(0.073)	(0.077)	(0.079)

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dependent variable	log demand, area 1			log demand, area 2			log demand, area 3		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Optimistic error effects									
Adults	0.317***	0.334***	0.342***	0.281***	0.303***	0.225***	0.319***	0.333***	0.324***
	(0.066)	(0.067)	(0.067)	(0.057)	(0.059)	(0.060)	(0.057)	(0.057)	(0.054)
Adolescents	0.117	0.096	0.103	0.191*	0.185	0.131	0.197***	0.251***	0.232***
	(0.072)	(0.074)	(0.074)	(0.078)	(0.092)	(0.075)	(0.063)	(0.070)	(0.070)
Children	0.204***	0.161*	0.168*	0.201***	0.171*	0.090	0.265***	0.206*	0.185*
	(0.070)	(0.072)	(0.071)	(0.068)	(0.068)	(0.075)	(0.080)	(0.082)	(0.084)
Pessimistic error effects									
Adults	−0.275*	−0.315***	−0.313*	0.025	0.026	−0.019	−0.330***	−0.296***	−0.319***
	(0.104)	(0.109)	(0.111)	(0.072)	(0.083)	(0.086)	(0.075)	(0.071)	(0.070)
Adolescents	−0.059	−0.091	−0.089	−0.076	−0.036	−0.050	−0.125	−0.166	−0.182*
	(0.114)	(0.120)	(0.122)	(0.139)	(0.145)	(0.108)	(0.075)	(0.085)	(0.087)
Children	−0.112	−0.117	−0.113	−0.058	−0.041	−0.077	−0.149	−0.183*	−0.206*
	(0.106)	(0.123)	(0.120)	(0.099)	(0.104)	(0.109)	(0.080)	(0.087)	(0.087)

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dependent variable	log demand, area 1			log demand, area 2			log demand, area 3		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Asymmetric effects									
Optimisitc + Pessimistic, adults	0.042	0.019	0.029	0.306***	0.330*	0.206	−0.010	0.038	0.005
	(0.146)	(0.151)	(0.154)	(0.106)	(0.120)	(0.123)	(0.106)	(0.099)	(0.097)
Optimisitc + Pessimistic, adolescents	0.059	0.005	0.013	0.115	0.149	0.081	0.073	0.085	0.050
	(0.149)	(0.157)	(0.159)	(0.185)	(0.206)	(0.157)	(0.107)	(0.122)	(0.123)
Optimisitc + Pessimistic, children	0.092	0.045	0.055	0.143	0.130	0.013	0.116	0.023	−0.021
	(0.148)	(0.164)	(0.159)	(0.131)	(0.135)	(0.149)	(0.132)	(0.140)	(0.141)
Controls									
Easter dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age category fixed effects	Yes	(Yes)	(Yes)	Yes	(Yes)	(Yes)	Yes	(Yes)	(Yes)
Season day fixed effects	Yes	(Yes)	(Yes)	Yes	(Yes)	(Yes)	Yes	(Yes)	(Yes)
Day-by-age fixed effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Season fixed effects	No	No	Yes	No	No	Yes	No	No	Yes
N	2,150	2,150	2,150	2,437	2,437	2,437	2,906	2,906	2,906
R^2	0.773	0.832	0.834	0.608	0.690	0.722	0.779	0.819	0.824

Table Notes: The table depicts OLS estimates of the model in Equation A.15 for four specifications in three areas. 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. The linear combination of optimistic and pessimistic dummies tests asymmetric effects. The Easter dummy indicates the four Easter holidays (Good Friday to Easter Monday). Standard errors are in parentheses and clustered at the season day level.

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

Appendix B

The Investment Competition among Swiss Ski Areas

B.1 Data Processing

B.1.1 Ski Lift Data

We use the dataset provided by *bergbahnen.org*, which consists of all ever-built cableway lifts grouped into pre-defined areas. We add missing observations, match this data to municipalities, identify access points, drop very small areas and excursion lifts and make some adjustments when areas have been merged over the years. The procedure of all these steps is described in Appendix C.1.2 which is part of the Appendix of Chapter 3.

We define a ski area as a cluster of ski lifts that consists, on average, of at least two lifts throughout its existence. That means we count the number of lifts per year and average this value across the existence of the cluster. All areas with an average ≥ 2 are retained. Doing this allows us to exclude urban lifts, excursion lifts and small community-run village lifts.

We distinguish the new ski lifts further by their use. The observations in the raw data indicate already whether the ski lift is a replacement of one or multiple shut lifts or whether it is built at new sites. The latter category can be further distinguished by ski lifts that expand the ski area's slopes and those built at new sites within the ski area's original boundaries.[1] This distinction is crucial from the guest's perspective: A new lift's site does not matter as much when built within the ski area as when it expands the ski area's slopes. Accordingly, we manually check each ski lift at a new site to see whether it actually expands the ski area. Notice that ski lifts connecting two ski areas also expand the original area by a whole second ski area and are thus also counted in this category.

Additionally, we impute missing capacity values. For this, we first define the construction cohort for each lift by taking its construction year and adding and subtracting five years. Then, we compute the average lift capacity of all lifts of the same lift type built within the same construction cohort of the missing lift. This average capacity is then used as an estimate of the missing capacity. Essentially, each lift with a missing capacity gets a capacity assigned that is typical for its construction period and lift type.

B.1.2 Between Ski Area Road Distance

We compute road distances between ski area access points using the Here API and the Stata command *georoute* (Weber & Péclat, 2017). To facilitate computation and limit requests, we first drop access points that lie within 500m in Euclidean distance of the previous access point. Therefore, we assume that very small changes in the location of access points do not affect the competition among areas. Then, we create all possible pairwise combinations of access points within one year and remove combinations of an access point to itself and in opposite directions. On top of that, we remove all combinations in years that have been computed in previous years.[2]

Now, we use only distances of access points from 2009 and keep them fixed until 2018. Such that small changes in access points do not mess with our road distance measures. By using road distances of 2023, we implicitly assume that road distances did not change between 2009 and 2023. The assumption is not far-fetched because we are primarily

[1] Lifts at new sites within the area might make it easier for guests to switch from one side of the area to the other or are so-called "trainer"-lifts that ski schools mainly use to teach beginners.

[2] As we can only compute road distances as of 2023, the road distance between two coordinates remains constant across years.

interested in having a measurement that allows us to differentiate between actual travel distances rather than Euclidean distances. Euclidean distances suffer the problem of not incorporating the presence of mountains and valleys that cannot be crossed at ease. Most roads in the mountains did not substantially change within these 15 years.

B.1.3 Ski Area Mergers

In two cases, ski areas have been linked by a new ski lift connection within the event window (between 2009 and 2018). These are Arosa-Lenzerheide, where the connection opened in January 2014, and Grimentz-Zinal, which built the connection in the summer of 2013 and opened it in the winter of 2013/2014.[3] We keep those areas separate but remove them as neighbors because investments are made in their own rather than in a neighboring area.

B.1.4 Firm Data

The firm data consists of yearly survey data of ski area operator firms conducted by SBS. It represents mostly figures from the annual reports of the individual firms. Because the data coverage and quality are rather poor or we are not allowed to match the data, we manually adjust data with annual reports found on the web. All reports used are listed in Table B.1. Because annual reports vary in their definition of, e.g., how to report investments, we concentrate on overall revenues, transportation revenues from summer and winter and first entries from summer and winter[4] of which we try to get the most comprehensive coverage. These are consistently reported across firms and show quite good

[3]The link between Andermatt and Sedrun was established in the summer of 2018 and falls out of our event window that ends in the winter of 2017/2018. However, these investments still show up as leads in our empirical model.

[4]In some cases, we fill gaps in first entries by the use of growth rates in lift use frequencies because only these data are available in these reports (assuming that the number of frequencies generated by a single guest does not change substantially across years). In even more rare cases, we only find frequencies in the annual reports. Then, we apply a simple rule of frequencies/6 equals the first entries. This rule was established at ski areas where both frequencies and first entries are available. Notice that we estimate only log changes in our empirical models. As long as the average frequency per first entry does not substantially change over the observed period, one variable is thus a valid proxy for the other.

initial coverage. Additionally, some operators entered their annual figures in rounded numbers to $1,000$. Thus, we round all revenue and first entry figures to $1,000$.

Table B.1: Annual reports and source

Ski area	Operator firm*	Online source**	Date accessed	Reporting years***
Aletschregion	Fiesch-Eggishorn AG	aletscharena.ch	2020-10-16	2012 – 2015
Aletschregion	Bettmeralp Bahnen AG	yumpu.com	2020-10-27	2013
Adelboden-Lenk	Bergbahnen Adelboden AG	adelboden-baag.ch	2020-09-29	2017
Andermatt-Sedrun	Andermatt Gotthard Sportbahnen AG	yumpu.com	2020-10-27	2012
Andermatt-Sedrun	Andermatt-Sedrun Sport AG	docplayer.org	2020-10-27	2015 – 2018
Anzère	Télé Anzère S.A.	anzere.ch	2020-10-22	2016 – 2019
Arosa-Lenzerheide	Arosa Bergbahnen AG.	yumpu.com	2023-08-08	2013
Arosa-Lenzerheide	Lenzerheide Bergbahnen AG.	rw-oberwallis.ch	2023-08-08	2013 – 2014
Axalp	Sportbahnen Axalp Windegg AG	axalp.ch	2023-07-24	2014
Belalp	Belalp Bahnen AG	belalp.ch	2020-10-16	2010 – 2018
Bellwald	Sportbahnen Bellwald Goms AG	docplayer.org	2023-07-24	2011
Bergün	Sportbahnen Bergün AG	docplayer.org	2023-07-24	2020
Braunwald	Sportbahnen Braunwald AG	braunwald.ch	2020-10-19	2018
Crans Montana	Crans Montana Aminona (CMA) AG	yumpu.com	2020-10-20	2011/2016
Davos Klosters	Davos Klosers Bergbahnen AG	davosklostersmountains.ch	2019-11-19	2019
Diavolezza	Diavolezza Lagalb AG	corvatsch-diavolezza.ch	2023-07-23	2017
Disentis	Bergbahnen Disentis AG	disentis.fun	2020-10-27	2017
Eischoll	Sportbahnen Eischoll Augstbordregion AG	docplayer.org	2023-07-23	2017 – 2019
Engelberg Titlis	Bergbahnen Engelberg-Trübsee-Titlis AG	titlis.ch	2020-10-29	2010 – 2019
Flims-Laax-Falera	Weisse Arena Gruppe	weissearena.com	2023-07-26	2018
Grimentz	Grimentz-Zinal SA	valdanniviers.ch	2020-10-27	2019
Grüsch-Danusa	Bergbahnen Grüsch-Danusa AG	sommer.gruesch-danusa.ch	2023-07-23	2017 – 2018
Gstaad	Bergbahnen Destination Gstaad AG	gstaad.ch	2020-10-30	2010 – 2018
Heidadorf Visperterminen	GIW	issuu.com	2023-07-24	2015
Hohsaas	Bergbahnen Hohsaas AG	yumpu.com	2020-10-22	2011
Klewenalp	Bergbahnen Beckenried-Emmetten AG	docplayer.org	2020-10-20	2017
Leysin	Télé Leysin – Col des Mosses – La Lécherette SA	docplayer.fr	2023-07-24	2018
Melchsee-Frutt	Korporation Kerns	melchsee-frutt.ch	2020-10-20	2010 – 2018
Meiringen Hasliberg	Bergbahnen Meiringen Hasliberg AG	meiringen-hasliberg.ch	2020-10-19	2010 – 2018
Moosalp	Moosalp Bergbahnen AG	moosalpregion.ch	2020-10-30	2011
Obersaxen Mundaun	Bergbahnen Obersaxeen AG	obersaxen-muncaun.ch	2019-11-27	2017
Portes du Soleil	Portes du Soleil Suisse SA	skipass-pds-ch.ch	2023-07-24	2020
Pizol	Pizolbahnen AG	pizol.com	2020-11-16	2011 – 2012
Rosswald	Rosswald Bahnen AG	rosswald-bahnen.ch	2023-07-24	2014 – 2017
Saas Fee	Saastal Bergbahnen AG	saas-fee.ch	2020-10-20	2010 – 2018
Samnaun	Bergbahnen Samnaun AG	docplayer.org	2023-07-26	2020
Sattel-Hochstuckli	Sattel-Hochstuckli AG	sattel-hochstuckli.ch	2019-11-19	2019
Schilthorn	Schilthornbahn AG Mürren	schilthorn.ch	2020-10-20	2009 – 2014
Sedrun	Sedrun Bergbahnen AG	docplayer.org	2020-10-27	2011/2016
Sörenberg	Bergbahnen Sörenberg AG	soerenberg.ch	2020-10-19	2018
Splügen Tambo	Bergbahnen Splügen-Tambo AG	spluegen.ch	2020-10-14	2017 – 2018
Stoos	Stoosbahnen AG	stoos.ch	2020-10-30	2009/2018
Torrent Leukerbad	My Leukerbad AG	leukerbad.ch	2020-10-28	2010/2012/2020
Tschiertschen	Bergbahnen Tschiertschen AG	tschiertschen.ch	2023-07-26	2017
Verbier	Téléverbier	verbier4vallees.ch	2020-10-25	2010 – 2018
Wengen-Männlichen	Luftseilbahn Wengen-Männlichen AG	maennlichen.ch	2020-09-29	2015/2018
Wildhaus	Bergbahnen Wildhaus AG	wildhaus.ch	2020-10-19	2011 – 2018
Zermatt	Zermatt Bergbahnen AG	matterhornparadise.ch	2019-08-20	2018

* We list the name of the operator firm at the year of the annual report. Names might have changed since.
** We list the link or website from which we retrieved the document at the accessed date. Links might no longer work. Contact the authors for specific documents.
*** The data retrieved from the reports is not necessarily the same as the reporting year. Some reports show past figures across several years.

B.1.5 Snowpack Data

Snow data are from an ongoing research project of the SLF and MeteoSwiss. In this project, researchers estimate snowpack data at a detailed spatial and temporal resolution using historical snow, precipitation and temperature measurements (see Michel et al., 2023, for details). They provided us with their most recent data, which has not yet been published. The data are modeled water equivalent of the snowpack in meters for each day from 1961 to 2021 in a spatial resolution of 1'000 x 1'000 meters.

Spatial Matching

We implemented the following steps to match the snowpack data to the ski areas. First, using the ski lift data (see Appendix B.1.1), we computed 2-dimensional centroids for each ski area in each year. The centroid is the mean of all lift stations' longitude and latitude values in each area-year cell. These data are then converted to the same coordinate-reference-system (CRS) CH1903+/LV95 used in the snowpack data.

Secondly, the gridded snowpack data are converted to the midpoints of each grid cell, such that each observation is assigned to a point in space. The grids follow the metric CRS CH1903+/LV95, where each cell follows multiples of $1,000$ meters. For example, the grid cell containing Zermatt's centroid in 1961 is from E $2,623,000$ to $2,624,000$ and from N $1,092,000$ to $1,093,000$. The midpoint of that cell is then simply E $2,623,500$ N $1,092,500$.

Third, the ski area centroids are matched to the closest grid midpoint in space. Each coordinate value (x_{at}, y_{at}) for each area a at year t is matched to the grid midpoints (x^m_{at}, y^m_{at}) by

$$x^m_{at} = x_{at} - (x_{at} \mod 1000) + 500 \tag{B.1}$$

$$y^m_{at} = y_{at} - (y_{at} \mod 1000) + 500. \tag{B.2}$$

Fourth, the identified grid midpoint could misrepresent the actual altitude of the ski area in some cases. For instance, when the ski area stretches across two sides of a valley, the assigned centroid might be at the bottom of the valley. To address this, we first match the grid midpoints to a 3-dimensional shapefile from swisstopo and extract the altitude of each ski area's grid midpoint. Then, we subtract the capacity-weighted average altitude from the identified altitude of the grid midpoint for each ski area. In 26 out of 186 ski areas, the difference between the two exceeds the absolute value of 200 meters and only 6 of those are actually in our main sample. For those 6 ski areas, we manually shift the grid midpoint to the closest midpoint in space within the absolute value of 200 meters from the capacity-weighted average altitude. Notice that a vertical difference of a maximum of 200 meters between the two is sufficiently accurate for our purpose because we use ski area fixed effects (by which we exploit only the within ski area variation in the snowpack) in the empirical implementation. Meaning that we exploit the changes over time in the snowpack at the grid midpoint. Level differences across the altitude do not matter as long as the changes in the snowpack at the grid midpoint are equal to the changes in the snowpack at the actual altitude of the ski area. With our method, the midpoints are randomly higher or lower and do, therefore, not affect our estimates in any substantial way.

Temporal Matching

After matching the daily snowpack data to the ski areas' centroids, data are aggregated to year-area cells. To achieve this, we assign first to each observation a dummy indicator that equals one when the snowpack exceeds 30cm and zero otherwise. For this, we use 120mm water equivalent as the threshold for a 30cm snowpack corresponding to a median snow density at 400kg/m^3 (Vorkauf et al., 2022). Next, we label all continuous periods between December 1st and April 30 with a snowpack larger than 30cm and keep only the longest period per year-area cell. Notice that observations in December are added to the succeeding year to align with the winter season and not the calendar year. Finally, the indicator is summed across each season, which yields the number of continuous days with a sufficient snowpack for skiing in a given year-area cell. An observation in 2010 corresponds then to the number of days with a snowpack above 30cm for the winter season 2009/2010 (the snowpack data evolves now parallel to the firm data in time).

B.1.6 Weather Index

To construct the weather index, we start at the daily weather index from Chapter 1, Section 1.3.4. We stay close to this definition, where relative sunshine duration, precipitation and minimum temperatures are first transformed to partial indices scaled from 0 to 100 (worst to best condition) and then further transformed into a weather index scaled from 0 to 100 that proxies skiing preferences. However, we refrain from using precipitation data in this Chapter as it correlates strongly with the snowpack of a ski area. As we want to control for weather conditions without snow conditions, we do not use precipitation data.

The following steps lead to the weather index used here:

1. We draw daily data on temperature and sunshine duration from 190 weather stations across Switzerland.
2. We spatially aggregate the data to the centroid of each ski area using inverse distance weighted averaging.
3. The partial index for temperature is built based on optimal skiing temperature and the partial index for sunshine duration is left as obtained from the raw data.
4. We take data from Chapter 1 and regress daily skiing demand on the three partial weather indices (scaled from 0 to 100) and daily fixed effects and recover weather weights from the coefficients of the partial indices and season day weights from the fixed effects (e.g., each last Sunday before Christmas receives the same weight).
5. The daily weather index is then a weighted index from the two partial indices, where sunshine receives a weight of 0.59 and temperature a weight of 0.41.
6. As in Chapter 1, we construct the daily weather index from the three weather variables for each day within a certain period at all ski areas.

7. We take the weighted average of the daily index across each season to construct the final weather index for each ski area in each season.

Next, we explain some details on this process.

Spatial Averaging

To spatially match the weather to the 186 ski areas, we apply inverse distance weighted averaging from weather stations within 50 kilometers of Euclidean distance. Thus, the closer a weather station is to the area centroid, the more weight its values receive. The inverse distance is additionally squared, such that a large distance to the weather station is penalized by the power of two (see e.g. Burrough et al., 1998). We pursue the same spatial averaging as in Appendix A.1.3, except that we use 50 instead of 30 kilometers as the cutoff for the weather station.

Partial Temperature Index

Daytime weather data back to 1960 is scarcely available. Thus, we construct our index using daily data (covering 24 hours and including the night). To adjust for this, we proxy the daytime minimum temperature by daily average temperatures. Temperature differences between daytime and night are higher when the sky is clear (warm days, very cold nights) instead of overcast. Thus, using daily minimum temperatures would largely underestimate the daytime minimum temperature on clear days. Average daily temperatures demean these differences.

Furthermore, we require a temperature that accounts for the fact that very cold and very warm temperatures are not favorable for skiing (see Chapter 1 and Malasevska et al., 2017a). That is, an optimal skiing temperature. We use estimates from Appendix A.1.4 (Tables A.2 to A.4) of each of the three areas to calculate optimal skiing temperatures (using Equation A.4). We find an optimal minimum temperature for the three areas of -3.3°C at 2,002 m.a.s.l., -6°C at 1,766 m.a.s.l. and -2.55°C at 1,283 m.a.s.l. Using the thumb rule of temperature gradients across altitudes,[5] we find optimal temperatures at the ski

[5]Because the temperature changes with altitude, elevation differences in weather stations and ski area centroids are adjusted by the thumb rule -6.5°C per 1,000m of altitude(International Organization for Standardization, 1975)

area centroids in the year 2010 are -3.16, -8.52 and -5.83°C for the three areas. From this we conclude that the optimal minimum temperature for skiing, regardless of the altitude, lies somewhere between -3.2 and -8.5°C. Thus, we slightly adjust the partial temperature index from Chapter 1 to

$$\widetilde{\underline{temp}_t} = \begin{cases} 100, & \text{if } \underline{temp}_t = [-3.2, -8.5] \\ 100 - (|-8.5 - \underline{temp}_t|) * 10, & \text{if } \underline{temp}_t < -8.5 \text{ and } |-8.5 - \underline{temp}_t| \leq 10 \\ 100 - (|-3.2 - \underline{temp}_t|) * 10, & \text{if } \underline{temp}_t > -3.2 \text{ and } |-3.2 - \underline{temp}_t| \leq 10 \\ 0, & \text{otherwise.} \end{cases} \tag{B.3}$$

The partial temperature index is at its maximum between -3.2 and -8.5°C, decreases by 10 points for every degree C deviating from the optimal temperature interval and cannot go below 0. Thus, we assume that temperatures below -18.5°C and above 6.8°C are very unfortunate conditions for skiing (too cold or too warm).

Partial Sunshine Index

As the relative sunshine duration is in its original data scaled from 0 (the sun shines 0% of the day) to 100 (the sun shines 100% of the day), we do not transform this variable any further.

Daily Weather Index

We regress daily demand skiing demand from ten seasons and three areas on the two partial indices (temperature and sunshine) and a partial index for precipitation (with data from Chapter 1 except with the two partial indices defined as above) to recover the relative importance of each partial weather index as well as season-day fixed effects. The coefficients of the regression are in Table B.2.

The daily weather index is then computed using

$$\tilde{W}_{idt} = \omega Sun_{idt} + (1 - \omega) Temp_{idt} \tag{B.4}$$

Table B.2: Regression of daily demand on partial weather indices and season-day fixed effects

Dependent variable:	Log daily demand
Partial index sunshine	0.0081***
	(0.0005)
Partial index precipitation	0.0115***
	(0.0009)
Partial index temperature	0.0057***
	(0.0010)
Intercept	3.1780***
	(0.1327)
Season-day fixed effects	Yes
Ski area fixed effects	Yes
Season fixed effects	Yes
Easter dummy	Yes
N	3,156
R^2	0.7757

Table Notes: The coefficient table corresponds depicts estimates of partial weather indices. Standard errors are in parentheses and clustered at the ski area level. For details on the empirical strategy and variables used, we refer to Chapter 1.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

where $\omega = 0.0081/(0.0057 + 0.0081) = 0.59$ is computed using the coefficients on the two respective partial indices in Table B.2.

Temporal Averaging

Instead of simply aggregating this weather index across each season, we first restrict the season to the high season between the last Saturday before Christmas and the first Sunday in March and then weight individual days in terms of their value within the season. For the latter, we use estimates of the season-day fixed effects in Table B.2. From this, we create seasonally weighted averages of the weather, where high-season days with good weather receive a substantially higher weight than season days with bad weather.

B.1.7 Remoteness Measure

To perform a decomposition of the ski area demand into overnighers and daytrippers (see Appendix B.1.8), we require a measure that allows us to differentiate ski areas in their potential share of daytrippers. We proxy this by the ski areas' remoteness to the agglomerations.

The population data of the agglomerations is drawn from Francelet et al. (2020) and connected to municipality centers from SwissTopo. For agglomerations labeled by two towns, we take the center of the larger town. Then, we compute the travel time from the access points in 2009 (at the beginning of our event window) to the municipality centers using the Here API.[6] Then we compute a gravity-based measure of the accessibility potential to daytrippers that is commonly used in the economic geography literature (see Gutiérrez et al., 2010, for an overview of studies that use such measures). The measure is defined as

$$daytrip_i = \sum_{j=1}^{J} \frac{pop_j}{\min t_{ij}} \tag{B.5}$$

where i is a ski area, j is an agglomeration center, pop indicates the population of the agglomeration in 2009[7] and t_{ij} indicates the travel time between access points and municipalities evaluated in 2023 with the assumption that travel times did not significantly change within the last 15 years. The measure is computed for two modes using travel time by car and travel time by public transportation (train and bus) and is then averaged across the two figures for each access point. When a ski area can be accessed by multiple access points, we always take the shortest travel time to that area.

[6] We compute the travel times with the Stata command *georoute* (Weber & Péclat, 2017).

[7] We impute the population from 2000 and 2018 by taking the yearly population growth rate $pgr_{00,18} = \left(\frac{pop_{18}}{pop_{00}}\right)^{1/18}$ between 2000 and 2018 and calculate the population in 2009 as $pop_{09} = pop_{00} \cdot (pgr_{00,18})^9$ thereby assuming a constant growth rate between 2000 and 2018.

Next, we take the inverse of the $daytrip_i$ measure and scale it between 0 and 1 by dividing it by its maximum value. Formally

$$rmte_i^h = \frac{1}{daytrip_i} \Big/ \max_{i \in n}(daytrip_i). \tag{B.6}$$

The more remote a ski area is, the less daytripper it receives and the more its demand should be composed of overnighters. Thus, for $rmte_i^h$, the most remote area receives a value of 1 in this measure. Particularly, the most remote ski area is assumed to receive 100% (in our case, the ski area of Samnaun) and the least remote ski area around 24% (in our case, the ski area at the Pilatus) of overnighters. As the assumption of zero daytrippers for Samnaun is quite strong, we adjust the measure by subtracting the minimum value (0.24) divided by two from the high baseline measure $rmte_i^h$ and compute additionally a low baseline measure $rmte_i^l$. Formally,

$$rmte_i^m = rmte_i^h - \left(\frac{\min_{i \in n}(rmte_i^h)}{2}\right) \tag{B.7}$$

$$rmte_i^l = rmte_i^h - \min_{i \in n}(rmte_i^h). \tag{B.8}$$

The summary statistics of the three remoteness measures are shown in Table B.3. The low baseline $rmte_i^l$ is used in the main text because it is the most reasonable measure and leads accordingly to the most precise estimates.[8] The other two measures are used in Appendix B.3.10.

B.1.8 Demand Decomposition

Demand at ski areas is separated into two groups: The overnighters and the daytrippers. We have data on the overall demand from first entries into a ski area (a count for each

[8]Two reasons speak for a rather high daytripper share compared to the overnighter share. First, in the demand decomposition (see Appendix B.1.8), all residents, second home owners and seasonal employees at the municipality count to the daytrippers. No matter where the ski area is located, these groups make up a substantial share, for example, because they have season passes. Secondly, in the case of ski areas close to large agglomerations, the overnighter's primary purpose is likely not skiing because their activity choice set is much larger. The assumption that a change in the overnighters translates one-to-one to changes in their skiing consumption certainly fails.

Table B.3: Summary statistics of the remoteness measures

Remoteness measures	N	Mean	SD	Min	Max
Low baseline ($rmte_i^l$)	581	0.33	0.14	0.00	0.76
Mid baseline ($rmte_i^m$)	581	0.45	0.14	0.12	0.88
High baseline ($rmte_i^h$)	581	0.57	0.14	0.24	1.00

Table Notes: The table shows summary statistics of the three remoteness measures.

person that enters a ski area once per day) and data on overnighters from the FSO. From the two available sources and the remoteness measure (that captures the daytripper potential for each area), we estimate the demand composition split by overnighters and daytrippers for each area.

First, we aggregate overnighters from adjoining municipalities to their respective ski area. For those ski areas with access points from multiple municipalities, overnighters are just summed up across those municipalities and assigned to that area. The first entries, on the contrary, are split between the municipalities proportionally to their overnight stays (this matters because, in very rare instances, ski areas have access to multiple municipalities that, in turn, have access to other ski areas as well). For those municipalities with access to multiple ski areas, we split the overnighters proportionally to the first entries (which might have been split beforehand because they have access to another area as well) and assign each ski area that proportional value.

To estimate the share of daytrippers, we start with the following decomposition:

$$D_{it} = A_{it} + B_{it} \tag{B.9}$$

where D_{it} is demand measured as first entries in area i at time t, A are the daytrippers and B are the overnighters. Our goal is to estimate the counts of A and B. As not all overnighters visit the ski area, B is also unknown. Assuming that changes in overnighters translate one-to-one to changes in skiing demand from overnighters helps us to find an estimate for B and A. Now notice that a change in demand, denoted as ΔD (omitting the subscript i for notational ease) from one year to the next is equal to

$$\underbrace{\frac{D_t - D_{t-1}}{D_{t-1}}}_{=\Delta D} = (1-\omega)\underbrace{\frac{A_t - A_{t-1}}{A_{t-1}}}_{=\Delta A_t} + \omega \underbrace{\frac{B_t - B_{t-1}}{B_{t-1}}}_{\Delta B_t} \tag{B.10}$$

where $\omega = \frac{B_{t-1}}{D_{t-1}}$ is the initial share of overnighters.[9] We set ω to be equal to the lower remoteness measure, i.e. $\hat{\omega} = rmte^l$ (see in Appendix B.1.7 how it is derived). We conduct sensitivity checks in all results depending on other evaluations of ω (see Appendix B.3.10). From the initial share ω, the change in overnighters ΔB_t and the observed changes in overall demand ΔD_t, we derive A_t and B_t for all ski areas with available demand data. Notice that these steps lead to a few observations that equal zero in either A_t or B_t. As we take the log of these values to estimate the effects, those observations drop out.

B.1.9 Data Example of the Event Window

[9]To see this, plug $B_t = D_t - A_t$ and $B_{t-1} = D_{t-1} - A_{t-1}$ into the right-hand side of Equation B.10 and rearrange until your left with $\frac{D_t - D_{t-1}}{D_{t-1}}$.

Table B.4: Data example of the event window with binned endpoints

t	$\ln Y_{it}$	$C_{i,t+3}$	$C_{i,t+2}$	$C_{i,t+1}$	$C_{i,t}$	$C_{i,t-1}$	$C_{i,t-2}$	$C_{i,t-3}$	$C_{i,t-4}$	$C_{i,t-5}$
2005		8	0	0	0	0	0	0	0	0
2006		8	0	0	0	0	0	0	0	0
2007		7	1	0	0	0	0	0	0	0
2008		4	3	1	0	0	0	0	0	0
2009	6.51	4	0	3	1	0	0	0	0	0
2010	6.48	4	0	0	3	1	0	0	0	0
2011	6.49	3	1	0	0	3	1	0	0	0
2012	6.19	3	0	1	0	0	3	1	0	0
2013	6.18	1	2	0	1	0	0	3	1	0
2014	6.15	1	0	2	0	1	0	0	3	1
2015	6.13	1	0	0	2	0	1	0	0	4
2016	6.08	1	0	0	0	2	0	1	0	4
2017	6.11	0	1	0	0	0	2	0	1	4
2018	6.12	0	0	1	0	0	0	2	0	5
2019		0	0	0	1	0	0	0	2	5
2020		0	0	0	0	1	0	0	0	7

B.2 Coefficient Tables

B.2.1 Natural Snow Dependency

Table B.5: Coefficient table of the natural snow dependency

Dependent variable:	Log demand	Log revenue
	(1)	(2)
Snow days	0.0021***	0.0020***
	(0.0006)	(0.0006)
Snow days x Group 1 $(q1, q2]$	−0.0004	−0.0007
	(0.0007)	(0.0007)
Snow days x Group 2 $(q2, q3]$	−0.0013*	−0.0011
	(0.0006)	(0.0006)
Snow days x Group 3 $(q3, q4]$	−0.0018**	−0.0016*
	(0.0006)	(0.0006)
Weather index	−0.0004	−0.0014
	(0.0023)	(0.0020)
Intercept	6.3357***	10.0425***
	(0.0925)	(0.0902)
Year fixed effects	Yes	Yes
Ski area fixed effects	Yes	Yes
N	545	545
R^2	0.9916	0.9945

Table Notes: The coefficient table corresponds to Figure 2.4. Standard errors are in parentheses and clustered at the ski area level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

B.2.2 Lift Investments

Table B.6: Coefficient table of the event study estimates

Dependent variable:	Log demand			Log revenue
	Overall	Daytripper	Overnighter	Overall
Year 3 before lift construction	−0.006	−0.011	−0.008	−0.003
	(0.015)	(0.028)	(0.020)	(0.015)
Year 2 before lift construction	−0.003	−0.006	0.005	−0.004
	(0.013)	(0.021)	(0.018)	(0.011)
Year 1 before lift construction	−0.010	−0.014	−0.004	−0.010
	(0.010)	(0.016)	(0.009)	(0.012)
Year 1 after lift construction	0.040**	0.060**	0.005	0.018
	(0.014)	(0.022)	(0.014)	(0.013)
Year 2 after lift construction	0.020	0.026	0.012	0.014
	(0.015)	(0.023)	(0.015)	(0.014)
Year 3 after lift construction	0.020	0.037	−0.013	0.014
	(0.018)	(0.029)	(0.026)	(0.017)
Year 4 after lift construction	0.014	0.037	−0.027	0.015
	(0.018)	(0.032)	(0.035)	(0.015)
Year 5 after lift construction	0.020	0.041	−0.006	0.003
	(0.020)	(0.033)	(0.027)	(0.017)
Snow days	0.002***	0.002***	0.001	0.001**
	(0.000)	(0.001)	(0.001)	(0.000)
Weather index	0.001	0.001	−0.003	−0.002
	(0.002)	(0.004)	(0.003)	(0.002)
Intercept	6.047***	5.476***	5.371***	9.912***
	(0.149)	(0.200)	(0.196)	(0.145)
Year fixed effects	Yes	Yes	Yes	Yes
Ski area fixed effects	Yes	Yes	Yes	Yes
N	581	581	572	581
R^2	0.991	0.972	0.985	0.994

Table Notes: The coefficient table corresponds to Figure 2.5 and Figure 2.6. Standard errors are in parentheses and clustered at the ski area level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

B.2.3 Neighboring Lift Investments

Table B.7: Coefficient table of the event study estimates across space

Dependent variable:	Log demand				
Road distance ring [km]:	0	$(0,25]$	$(25,50]$	$(50,75]$	$(75,100]$
Year 3 before lift construction	−0.013	−0.015	0.007	−0.008	−0.004
	(0.017)	(0.012)	(0.008)	(0.007)	(0.006)
Year 2 before lift construction	−0.009	−0.009	0.007	−0.001	0.007
	(0.014)	(0.010)	(0.007)	(0.007)	(0.006)
Year 1 before lift construction	−0.013	−0.009	0.008	−0.006	−0.006
	(0.012)	(0.012)	(0.007)	(0.007)	(0.006)
Year 1 after lift construction	0.040**	0.001	0.002	−0.000	−0.006
	(0.012)	(0.011)	(0.005)	(0.005)	(0.007)
Year 2 after lift construction	0.020	−0.000	0.009	−0.008	−0.001
	(0.013)	(0.012)	(0.007)	(0.006)	(0.010)
Year 3 after lift construction	0.015	−0.013	0.001	−0.009	−0.001
	(0.018)	(0.013)	(0.008)	(0.007)	(0.010)
Year 4 after lift construction	0.012	−0.024	−0.004	−0.011	−0.003
	(0.018)	(0.013)	(0.008)	(0.009)	(0.011)
Year 5 after lift construction	0.016	−0.009	−0.002	−0.010	−0.002
	(0.019)	(0.012)	(0.007)	(0.009)	(0.009)
Snow days	0.002***				
	(0.000)				
Weather index	0.001				
	(0.002)				
Intercept	6.479***				
	(0.529)				
Year fixed effects	Yes				
Ski area fixed effects	Yes				
N	581				
R^2	0.992				

Table Notes: The coefficient table corresponds to panel (a) in Figure 2.7. The estimates depicted in the figure are from the fourth row (Year 1 after lift construction). Standard errors are in parentheses and clustered at the ski area level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.8: Coefficient table of the event study estimates across space by lift type

Dependent variable:	Log demand								
Margin:	Ski lift	Neighboring ski lift, extensive				Neighboring ski lift, intensive			
Road distance ring [km]	0	$(0,25]$	$(25,50]$	$(50,75]$	$(75,100]$	$(0,25]$	$(25,50]$	$(50,75]$	$(75,100]$
Year 3 before lift construction	−0.024	−0.047	−0.044	−0.001	−0.021	−0.016	0.015	−0.014	−0.003
	(0.017)	(0.037)	(0.031)	(0.021)	(0.020)	(0.013)	(0.009)	(0.009)	(0.007)
Year 2 before lift construction	−0.017	−0.067	−0.047	0.016	0.004	−0.014	0.012	−0.013	0.005
	(0.016)	(0.041)	(0.041)	(0.024)	(0.017)	(0.012)	(0.007)	(0.007)	(0.006)
Year 1 before lift construction	−0.018	−0.016	−0.048	−0.013	−0.037	−0.010	0.012	−0.012	−0.006
	(0.014)	(0.022)	(0.030)	(0.019)	(0.020)	(0.013)	(0.008)	(0.008)	(0.007)
Year 1 after lift construction	0.035**	−0.107**	−0.038	−0.010	−0.009	0.008	−0.001	−0.005	−0.008
	(0.012)	(0.038)	(0.041)	(0.027)	(0.025)	(0.012)	(0.006)	(0.006)	(0.008)
Year 2 after lift construction	0.020	−0.080	−0.094*	−0.060*	−0.033	0.007	0.017	−0.007	−0.002
	(0.015)	(0.054)	(0.043)	(0.028)	(0.026)	(0.013)	(0.009)	(0.007)	(0.010)
Year 3 after lift construction	0.013	0.028	−0.048	−0.032	−0.031	−0.023	0.005	−0.011	−0.003
	(0.020)	(0.055)	(0.035)	(0.026)	(0.030)	(0.016)	(0.009)	(0.009)	(0.012)
Year 4 after lift construction	0.010	−0.029	−0.047	−0.034	−0.019	−0.030	0.003	−0.009	−0.003
	(0.019)	(0.047)	(0.039)	(0.030)	(0.036)	(0.017)	(0.010)	(0.011)	(0.012)
Year 5 after lift construction	0.015	−0.051	−0.048	−0.045	−0.019	−0.011	0.004	−0.012	−0.003
	(0.021)	(0.067)	(0.046)	(0.029)	(0.042)	(0.013)	(0.009)	(0.009)	(0.009)
Snow days	0.002***								
	(0.000)								
Weather index	0.002								
	(0.003)								
Intercept	6.701***								
	(0.627)								
Year fixed effects	Yes								
Ski area fixed effects	Yes								
N	581								
R^2	0.993								

Table Notes: The coefficient table corresponds to panel (b) in Figure 2.7. The estimates depicted in the figure are from the fourth row (Year 1 after lift construction). Standard errors are in parentheses and clustered at the ski area level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

B.3 Additional Empirical Results

B.3.1 Samples

In the following results, we use various samples for the sensitivity checks. Taking other samples is either on purpose to check whether a specific type of ski area drives the results (e.g., areas participating in price competition) or because we look at other time periods (e.g., by looking at whether snow conditions affect lift replacements historically), or because we use alternative estimators that cannot handle certain types of unbalancedness (e.g., the estimator of de Chaisemartin and D'Haultfœuille (2023) cannot cope with missing observations between time periods).

In Table B.9, we show the coverage of all samples used in the remainder and is analog to Table 2.1 in the main text. Additionally, the last column indicates in what Section of the Appendix each sample is used. The first and the second rows repeat all ski lift data and the main sample between 2009 and 2018. Rows (3) and (5) show the most comprehensive samples with the two outcomes (revenue and demand, respectively) without the restriction that each observation contains non-missing values of both variables (as in the main sample). These two samples are balanced in rows (4) and (6). This is achieved by removing the data at the first and (in the case of the demand sample) last year (due to the low coverage in those years) and then dropping all incomplete areas.

Table B.9: Data coverage of the samples

#	[Period] Sample	N	n	T	New	Ext	Int	Capc 2010 [%]	Appendix
(1)	[2009 – 2018] Overall	1,849	186	9.9	156	10	146	100	-
(2)	[2009 – 2018] Main sample	581	72	8.1	83	9	74	63.1	B.3.3, B.3.4, B.3.10, B.3.12
(3)	[2009 – 2018] Revenue unbalanced	739	83	8.9	112	9	103	74.4	B.3.5
(4)	[2010 – 2018] Revenue balanced	558	62	9.0	78	5	73	59.0	B.3.5, B.3.8
(5)	[2009 – 2018] Demand unbalanced	592	72	8.2	84	9	75	63.1	B.3.5
(6)	[2010 – 2018] Demand balanced	405	45	9.0	59	5	54	46.2	B.3.5, B.3.8
(7)	[2009 – 2018] No price	543	72	7.5	73	6	67	63.1	B.3.6
(8)	[2009 – 2018] Demand no m. treatments	299	38	7.9	17	0	17	18.6	B.3.7
(9)	[2009 – 2018] Demand no gaps	534	62	8.6	74	9	65	54.7	B.3.7
(10)	[2009 – 2018] No mergers	540	67	8.1	68	3	65	56.5	B.3.9

Table Notes: The table shows the number of observations (N), the number of panels (n) (= ski areas), the average time periods (T), the number of investments (Inv) distinguished by lifts that expand the ski area's terrain extensively (Ext) and those that affect the intensive margin of ski area supply (Int). The last two columns indicate the share of aggregate capacities that each sample covers from all Swiss ski areas in 2010 (Capc 2010) and in which Appendix the sample has been used.

In row (7), we exclude all ski areas participating in dynamic pricing and setting substantial price discounts for season passes or multiple area season passes. Rows (8) and (9) use samples that allow for heterogeneous treatment effects across time. We cut those samples only that much such that they fit the specific requirements of the two estimators used in

Appendix B.3.7. Lastly, row (10) shows the sample that excludes ski area mergers to make sure that the results are not driven by these three substantial ski area changes in our main sample.

B.3.2 Concession Status vs. Induced-Investment Effect

In this Section, we explore the possibility that lift investments are revenue- and or demand-driven. For this, we use ski lift data of all replacement lifts and their concession status linked to snowpack data back to 1960.

We estimate a linear probability model with OLS. In particular

$$y_{kit} = S'_{it-3}\beta + \delta z_{kit} + \alpha_i + \theta_t + \varepsilon_{kit}, \tag{B.11}$$

where y_{kit} is a binary outcome that is equal to 1 if a lift k is replaced at time t in area i and zero if a lift is still operating. S'_{it-3} are lagged snow conditions/cumulative lagged snow conditions up to three periods (as a proxy for winter first entries/ winter revenues) in area i, z_{kit} is the concession status that equals 1 if lift k is operating with an extended concession at time t in area i and zero otherwise, α_i is an area fixed effect and θ_t a time fixed effect.

Because of the strong assumption of estimating a binary outcome model with OLS, we additionally specify the model in Equation B.11 as logit. In particular, we estimate

$$Pr(y_{kit} = 1 | S'_{it-3}, z_{kit}, \alpha_i, \theta_t) = \frac{exp(S'_{it-3}\beta + \delta z_{kit} + \alpha_i + \theta_t)}{1 + exp(S'_{it-3}\beta + \delta z_{kit} + \alpha_i + \theta_t)} \tag{B.12}$$

where all variables and coefficients are defined as in Equation B.11.

In Table B.10, we find that past snow conditions have, on average, a very small and statistically insignificant effect on the probability that a ski lift is replaced in a given year. For example, column (7) shows that a one standard deviation increase in cumulative snow days of the past three seasons leads to a 0.2 percentage point increase in the probability of a lift replacement. Again, this small effect is statistically not distinguishable from zero. On the contrary, the results also show that a change in concession status from the original concession to an extended concession increases the chance of replacement by 3.3 percentage points on average.

Table B.11 shows the Pseudo Maximum Likelihood Estimates (PMLE) of the logit specification in Equation B.12. It shows quantitatively and qualitatively the same results as the linear probability model. That means ski area operators do, on average, not take past snow conditions and, hence, revenues into account when deciding to replace a lift or not. Therefore, we find no *induced-investment effect* on average.

Table B.10: The effect of past snow conditions on the probability of a lift replacement

Dependent variable:	Binary indicator of lift replacement						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Snow days	0.002	0.002	0.001	0.001			
	(0.003)	(0.003)	(0.003)	(0.003)			
Snow days (t-1)		−0.000	0.000	0.000			
		(0.003)	(0.003)	(0.003)			
Snow days (t-2)			−0.000	−0.003			
			(0.003)	(0.003)			
Snow days (t-3)				0.005			
				(0.003)			
Cumulative snow days (t-1)					0.001		
					(0.002)		
Cumulative snow days (t-2)						0.001	
						(0.003)	
Cumulative snow days (t-3)							0.002
							(0.002)
Concession status	0.033***	0.033***	0.033***	0.033***	0.033***	0.033***	0.033***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Intercept	0.044***	0.056***	0.073***	0.084***	0.056***	0.072***	0.082***
	(0.006)	(0.008)	(0.010)	(0.011)	(0.008)	(0.011)	(0.011)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ski area fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	24,676	24,513	24,351	24,194	24,513	24,351	24,194
R^2	0.067	0.068	0.064	0.065	0.068	0.064	0.065

Table Notes: It shows OLS estimates of the linear probability model in Equation B.11. Snow days are consecutive days with a sufficiently thick snowpack (>30cm) for skiing within a winter season. The parentheses next to the variable name indicate lagged variables. The cumulative snow days are the same variables except that all past values are summed to the snow days at t. All snow day variables are standardized to mean zero and standard deviation one. Concession status is a binary indicator that equals 1 when the ski lift operates with an extended concession and zero when the lift operates with the original concession. Standard errors are in parentheses and clustered at the ski area level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.11: The effect of past snow conditions on the probability of a lift replacement

Dependent variable:	Binary indicator of lift replacement						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Snow days	0.029	0.020	0.015	0.022			
	(0.073)	(0.082)	(0.082)	(0.083)			
Snow days (t-1)		0.005	0.028	0.019			
		(0.063)	(0.073)	(0.072)			
Snow days (t-2)			−0.027	−0.096			
			(0.066)	(0.073)			
Snow days (t-3)				0.116			
				(0.064)			
Cumulative snow days (t-1)					0.022		
					(0.073)		
Cumulative snow days (t-2)						0.012	
						(0.074)	
Cumulative snow days (t-3)							0.041
							(0.073)
Concession status	1.053***	1.052***	1.049***	1.043***	1.052***	1.050***	1.043***
	(0.097)	(0.097)	(0.097)	(0.098)	(0.097)	(0.097)	(0.098)
Intercept	−4.824***	−4.206***	−3.592***	−3.811***	−4.210***	−3.602***	−3.842***
	(0.821)	(0.759)	(0.770)	(1.061)	(0.761)	(0.777)	(1.077)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ski area fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	24,609	24,443	24,287	24,130	24,443	24,287	24,130
Pseudo R^2	0.116	0.114	0.114	0.114	0.114	0.114	0.114

Table Notes: It shows pseudo maximum likelihood estimates (PMLE) of the logit specification in Equation B.12. Snow days are consecutive days with a sufficiently thick snowpack (>30cm) for skiing within a winter season. The parentheses next to the variable name indicate lagged variables. The cumulative snow days are the same variables except that all past values are summed to the snow days at t. All snow day variables are standardized to mean zero and standard deviation one. Concession status is a binary indicator that equals 1 when the ski lift operates with an extended concession and zero when the lift operates with the original concession. Standard errors are in parentheses and clustered at the ski area level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B.3.3 Natural Snow Dependency With Lower Snow Density

As discussed in Section 2.3.4, we check the results on snowmaking assuming a lower snow density of 190kg/m^3 to ensure a snow reliable baselayer of 30cm. The results are shown in Figure B.1 and Table B.12. The effect sizes are larger but less precisely estimated than in our main results and the point estimates remain within the confidence intervals. We conclude that there is qualitatively no difference to our main results in Section 2.5.1.

Figure B.1: Estimates of natural snow dependency with a snow density of 190kg/m^3

(a) First entries (b) Transportation revenue

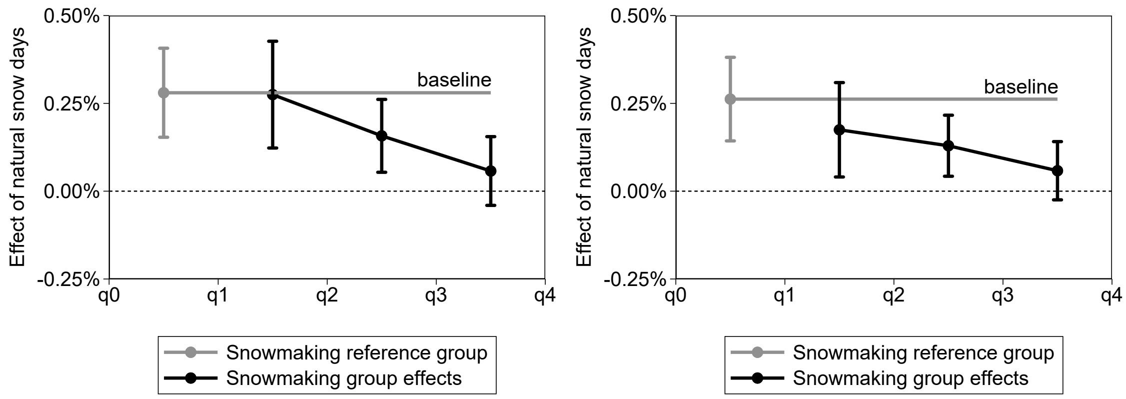


Figure Notes: Each point depicts group estimates of the model in Equation 2.2 across snowmaking capability groups split at quartiles. In particular, the first point from left (grey) depicts the point estimate of consecutive snow days for the reference group (below the first quartile) and the other points (black) depict the partial effects of consecutive snow days for ski areas between the respective quartiles in the horizontal axis. For example, the point between $q2$ and $q3$ depicts the effect of natural snow days for the group that has a snowmaking capability between the second and third quartile (i.e. $\hat{\delta}_0 + \hat{\delta}_2 D_2$ with $D_2 = \mathbb{1}\left[snowmaking \in (q2, q3]\right]$). Panel (a) shows the estimates with the log of winter first entries as the outcome and panel (b) the estimates with the log of winter transportation revenue as the outcome. The bars show 95% confidence intervals and standard errors are clustered at the ski area level. The coefficient table with point estimates and standard errors follows in Table B.12.

Table B.12: Coefficient table

Dependent variable:	Log demand	Log revenue
	(1)	(2)
Snow days	0.0028***	0.0026***
	(0.0006)	(0.0006)
Snow days x Group 1 $(q1, q2]$	−0.0001	−0.0009
	(0.0009)	(0.0009)
Snow days x Group 2 $(q2, q3]$	−0.0012	−0.0013
	(0.0007)	(0.0007)
Snow days x Group 3 $(q3, q4]$	−0.0022**	−0.0020**
	(0.0007)	(0.0007)
Weather index	−0.0003	−0.0015
	(0.0022)	(0.0020)
Intercept	6.2948***	10.0279***
	(0.1135)	(0.0988)
Year fixed effects	Yes	Yes
Ski area fixed effects	Yes	Yes
N	545	545
R^2	0.9920	0.9947

Table Notes: The coefficient table corresponds to Figure B.1. Standard errors are in parentheses and clustered at the ski area level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

B.3.4 Natural Snow Dependency Across Altitude

Similarly to the snowmaking capabilities, we estimate the model in Equation 2.2 using the capacity-weighted average altitude of a ski area in 2009 to form four groups across altitude. The groups are separated by the indicator $D_g = \mathbb{1}\left[altitude \in (q(g), q(g+1))\right]$. The estimates are depicted in Figure B.2, where each point again shows the effect of the natural snow days on outcomes across the groups. In panel (a), we show that a one standard deviation increase in natural snow (=25 days) leads to an average increase in demand of 5.5% for areas below the first quartile in altitude (reference group). The effect drops to 1.25% for the group between the third and fourth quartile. Panel (b) shows that altitude is not a relevant moderator of the effect of natural snow days on revenues. This might be due to the efficient use of snowmaking in lower-lying ski areas to ensure operations during the high season.

Figure B.2: Effect of natural snow days on winter outcomes across altitudes

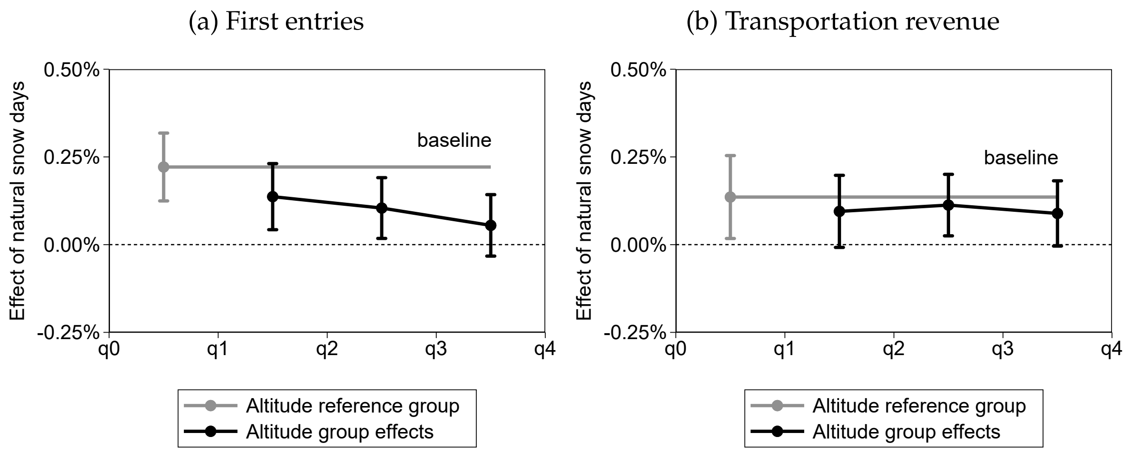


Figure Notes: Each point depicts group estimates of the model in Equation 2.2 across altitude groups split at quartiles. In particular, the grey point depicts the point estimate of consecutive snow days for the reference group (below the first quartile) and the black points depict the partial effects of consecutive snow days for ski areas between the respective quartiles in the horizontal axis. For example, the point between $q2$ and $q3$ depicts the effect of natural snow days for the group that lies at an average altitude between the second and third quartile (i.e. $\hat{\delta_0} + \hat{\delta_2} D_2$ with $D_2 = \mathbb{1}\left[altitude \in (q2, q3]\right]$). Panel (a) shows the estimates with the log of winter first entries as the outcome and panel (b) the estimates with the log of winter transportation revenue as the outcome. The bars signify 95% confidence intervals and standard errors are clustered at the ski area level. The coefficient table with point estimates and standard errors follows in Table B.13.

Table B.13: Coefficient table

Dependent variable:	Log demand	Log revenue
	(1)	(2)
Snow days	0.0022***	0.0014*
	(0.0005)	(0.0006)
Snow days x Group 1 $(q1, q2]$	−0.0008	−0.0004
	(0.0006)	(0.0007)
Snow days x Group 2 $(q2, q3]$	−0.0012	−0.0002
	(0.0006)	(0.0007)
Snow days x Group 3 $(q3, q4]$	−0.0017**	−0.0005
	(0.0006)	(0.0007)
Weather index	−0.0008	−0.0021
	(0.0023)	(0.0021)
Intercept	6.2505***	9.9751***
	(0.0934)	(0.0867)
Year fixed effects	Yes	Yes
Ski area fixed effects	Yes	Yes
N	581	581
R^2	0.9913	0.9935

Table Notes: The coefficient table corresponds to Figure B.2. Standard errors are in parentheses and clustered at the ski area level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

B.3.5 Balanced and Unbalanced Samples

To ensure that our results are not driven by the sample selection procedure described in Section 2.3.1, we draw four additional samples and run our main results from Section 2.5.2 with these samples. Figure B.3 shows that our results remain qualitatively and quantitatively the same as in Section 2.5.2 when the balanced instead of the unbalanced panels are used. Our results are thus not driven by sample selection.

Figure B.3: Construction of new lifts on winter outcomes using other samples

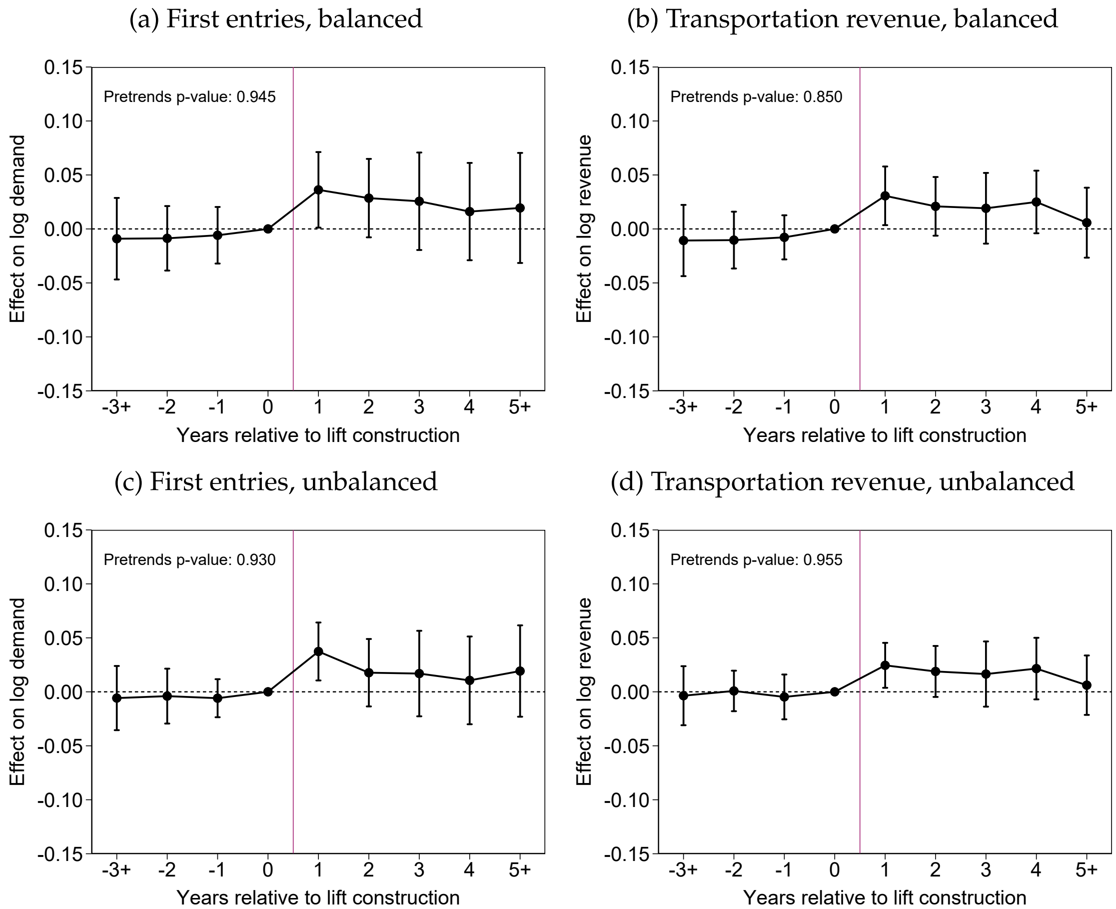


Figure Notes: All panels show estimates of the model in Equation 2.3 across time. Period 0 indicates the winter before the lift construction (which is in the same year) and period 1 indicates the winter of the lift opening. Panels (a) and (c) show the estimates with the log of winter first entries as the outcome using the balanced and unbalanced demand sample and panels (b) and (d) the estimates with the log of winter transportation revenue as the outcome using the balanced and the unbalanced revenue sample. The bars signify 95% confidence intervals and standard errors are clustered at the ski area level. Endpoints are binned and indicated by a plus. The p-values of the joint F-tests for pretrends are indicated in the plots. The coefficient table with point estimates and standard errors follows in Table B.14.

Table B.14: Event study estimates using other samples

Dependent variable:	Log demand		Log revenue	
	balanced	unbalanced	balanced	unbalanced
Year 3 before lift construction	−0.009	−0.006	−0.011	−0.004
	(0.019)	(0.015)	(0.016)	(0.014)
Year 2 before lift construction	−0.009	−0.004	−0.010	0.001
	(0.015)	(0.013)	(0.013)	(0.009)
Year 1 before lift construction	−0.006	−0.006	−0.008	−0.005
	(0.013)	(0.009)	(0.010)	(0.010)
Year 1 after lift construction	0.036*	0.037**	0.031*	0.025*
	(0.017)	(0.013)	(0.014)	(0.010)
Year 2 after lift construction	0.029	0.018	0.021	0.019
	(0.018)	(0.016)	(0.014)	(0.012)
Year 3 after lift construction	0.026	0.017	0.019	0.016
	(0.022)	(0.020)	(0.016)	(0.015)
Year 4 after lift construction	0.016	0.011	0.025	0.022
	(0.022)	(0.020)	(0.014)	(0.014)
Year 5 after lift construction	0.019	0.019	0.006	0.006
	(0.025)	(0.021)	(0.016)	(0.014)
Snow days	0.001***	0.002***	0.001**	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Weather index	−0.000	0.001	0.000	−0.001
	(0.003)	(0.003)	(0.003)	(0.002)
Intercept	6.088***	6.092***	9.835***	9.866***
	(0.176)	(0.149)	(0.148)	(0.146)
Year fixed effects	Yes	Yes	Yes	Yes
Ski area fixed effects	Yes	Yes	Yes	Yes
N	405	592	558	739
R^2	0.993	0.991	0.992	0.992

Table Notes: The coefficient table corresponds to Figure B.3. Standard errors are in parentheses and clustered at the ski area level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

B.3.6 Without Price Competition

We show in Table B.15 that our results remain qualitatively and quantitatively the same as in Section 2.5.1 when all ski area-year cells from operator firms known to have implemented new pricing strategies such as dynamic pricing or substantial discounts on season passes are removed.[10] Our results are thus not driven by price competition between ski areas.

Table B.15: Natural snow dependency without price competition

Dependent variable:	Log demand		Log revenue	
	(1)	(2)	(3)	(4)
Snow days	0.0017***	0.0022***	0.0012**	0.0021***
	(0.0004)	(0.0006)	(0.0004)	(0.0006)
Snow days x Group 1 $(q1, q2]$		−0.0005		−0.0008
		(0.0007)		(0.0007)
Snow days x Group 2 $(q2, q3]$		−0.0012		−0.0011
		(0.0007)		(0.0007)
Snow days x Group 3 $(q3, q4]$		−0.0019**		−0.0017*
		(0.0007)		(0.0007)
Weather index	−0.0001	−0.0001	−0.0016	−0.0010
	(0.0024)	(0.0024)	(0.0023)	(0.0022)
Intercept	6.1200***	6.3233***	9.9390***	10.0271***
	(0.1022)	(0.0973)	(0.1005)	(0.0969)
Year fixed effects	Yes	Yes	Yes	Yes
Ski area fixed effects	Yes	Yes	Yes	Yes
N	543	509	543	509
R^2	0.9910	0.9916	0.9931	0.9943

Table Notes: The table provides estimates of the model in Equations 2.1 and 2.2 using the sample without price competition. Standard errors are in parentheses and clustered at the ski area level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

[10]These are Flims-Laax-Falera after 2012 and Davos after 2013 (Knupfer, 2015). Arosa-Lenzerheide, Andermatt-Sedrun (Lütolf et al., 2020) and Saas Fee after 2016 (Wallimann, 2022). Additionally, all magic pass areas after 2017. In particular: Anzère, Les Bugnenets-Savagnières, Charmey, Château-D'Oex, Crans-Montana, Crêts-du-Puy, Grimentz-Zinal, Glacier 3000, Jaun, La Berra, Les Diablerets, Les Paccots, Les Marécottes, Leysin, Les Mosses, La Lécherette, Mayen de Conthey, Moléson, Ovronnaz, Nax, Rathvel, Schwarzsee, St-Luc/Chandolin, Tramelan, Vercorin, Villars-Gryon (magicpass.ch, 2017)

We show in Figure B.4 that our results remain qualitatively and quantitatively the same as in Section 2.5.2 when all ski area-year cells from operator firms known to have implemented new pricing strategies such as dynamic pricing or substantial discounts on season passes. Our results are thus not driven by price competition between ski areas.

Figure B.4: Construction of new lifts on winter outcomes without price competition

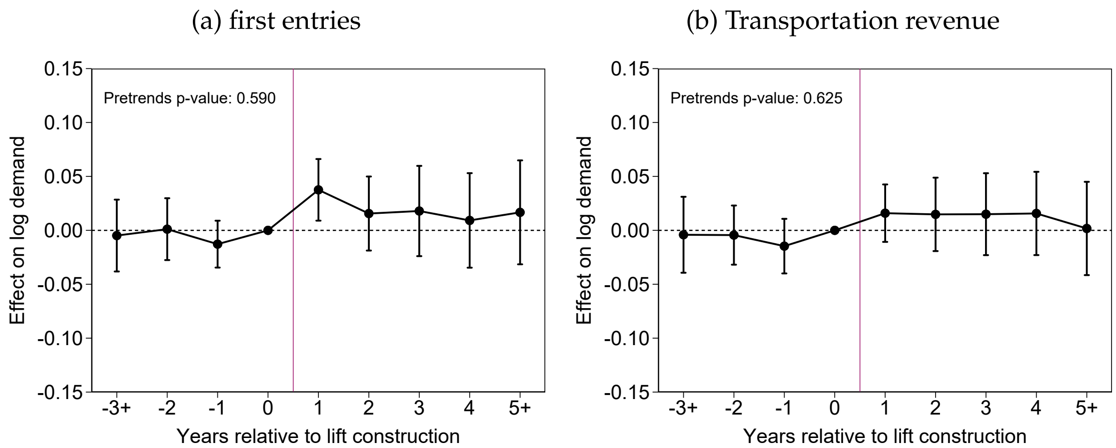


Figure Notes: Both panels show estimates of the model in Equation 2.3 across time. Period 0 indicates the winter before the lift construction (which is in the same year) and period 1 indicates the winter of the lift opening. Panel (a) shows the estimates with the log of winter first entries as the outcome using the unbalanced demand sample and panel (b) the estimates with the log of winter transportation revenue as the outcome using the unbalanced revenue sample. Both samples are cleared of observations of area-year combinations that are known to have a competitive pricing strategy. The bars signify 95% confidence intervals and standard errors are clustered at the ski area level. Endpoints are binned and indicated by a plus. The p-values of the joint F-tests for pretrends are indicated in the plots. The coefficient table with point estimates and standard errors follows in Table B.16.

Table B.16: Event study estimates without price competition

Dependent variable:	Log demand	Log revenue
Year 3 before lift construction	−0.005	−0.004
	(0.017)	(0.018)
Year 2 before lift construction	0.001	−0.004
	(0.014)	(0.014)
Year 1 before lift construction	−0.013	−0.015
	(0.011)	(0.013)
Year 1 after lift construction	0.038*	0.016
	(0.014)	(0.013)
Year 2 after lift construction	0.016	0.015
	(0.017)	(0.017)
Year 3 after lift construction	0.018	0.015
	(0.021)	(0.019)
Year 4 after lift construction	0.009	0.016
	(0.022)	(0.019)
Year 5 after lift construction	0.017	0.002
	(0.024)	(0.022)
Snow days	0.002***	0.001**
	(0.000)	(0.000)
Weather index	0.000	−0.002
	(0.002)	(0.002)
Intercept	6.044***	9.904***
	(0.161)	(0.159)
Year fixed effects	Yes	Yes
Ski area fixed effects	Yes	Yes
N	543	543
R^2	0.991	0.993

Table Notes: The coefficient table corresponds to Figure B.4. Standard errors are in parentheses and clustered at the ski area level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

B.3.7 Treatment Effect Heterogeneity Across Time

In Figure B.5, we show that the effects across different estimators that account for treatment heterogeneity across time are similar in sign and size. Notice that each of the estimators uses different control groups. The estimator by Sun and Abraham (2021) uses never-treated units as the control group, whereas the estimator by de Chaisemartin and D'Haultfœuille (2023) uses never-treated and not-yet treated units as the control group.

Figure B.5: Effects on first entries with treatment heterogeneity across time

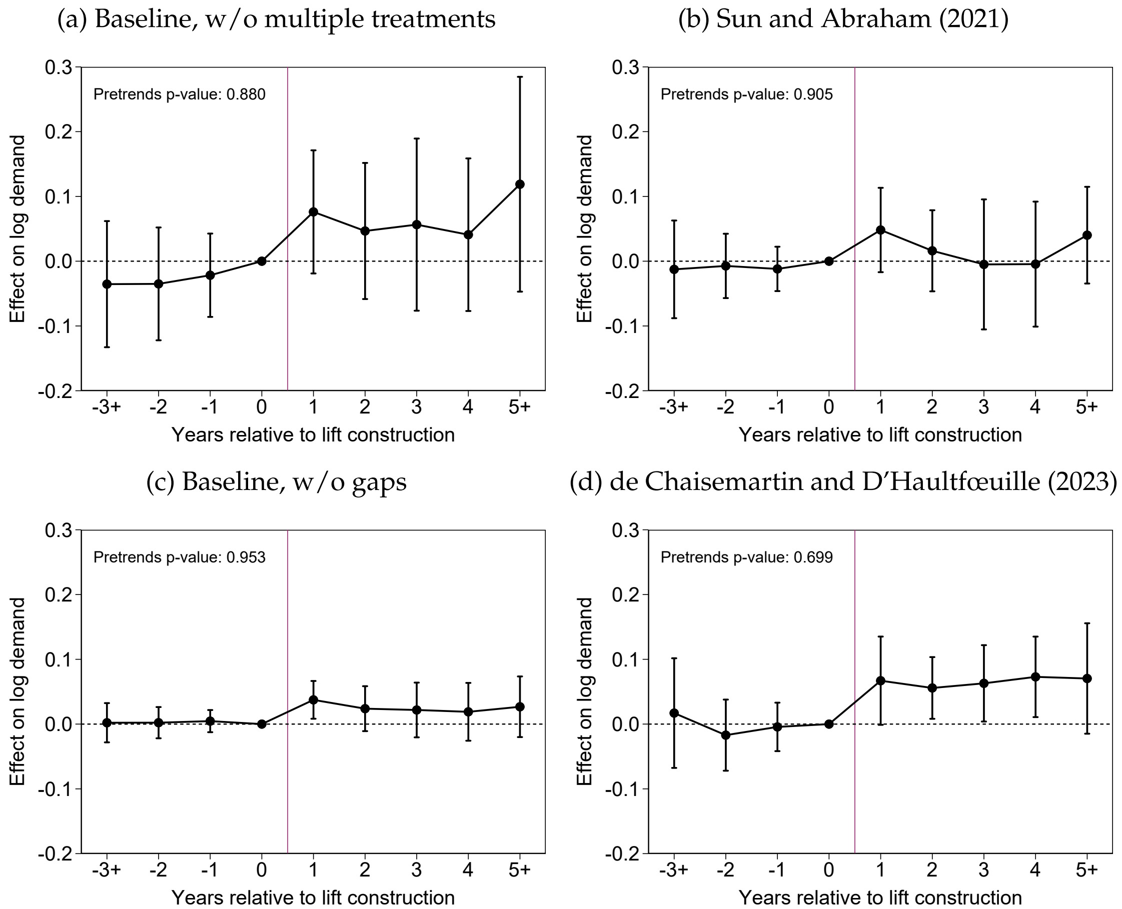


Figure Notes: The figure plots the coefficients and 95% confidence intervals of three estimators. The baseline estimates use the model in Equation 2.3 with the samples as stated in the title and described in Appendix B.3.1. The estimator in panel (b) from Sun and Abraham (2021) is implemented with the Stata command *eventstudyinteract* and also uses the sample w/o multiple treatments. The estimator in panel (d) from de Chaisemartin and D'Haultfœuille (2023) is implemented with the Stata command *did_multiplegt_dyn* and uses the sample w/o gaps. Period 0 indicates the winter before the lift construction (in the same year) and period 1 indicates the winter of the lift opening. The standard errors are clustered at the ski area level. Endpoints are binned in the baseline and the estimator from Sun and Abraham (2021) and are indicated by a plus. The coefficient table with point estimates and standard errors follows in Table B.17.

Table B.17: Event study estimates with treatment heterogeneity across time

Dependent variable:	Log demand			
	(a)	(b)	(c)	(d)
Year 3 before lift construction	−0.035	−0.013	0.002	0.017
	(0.048)	(0.038)	(0.015)	(0.043)
Year 2 before lift construction	−0.035	−0.007	0.002	−0.017
	(0.043)	(0.025)	(0.012)	(0.028)
Year 1 before lift construction	−0.022	−0.012	0.005	−0.004
	(0.032)	(0.017)	(0.009)	(0.019)
Year 1 after lift construction	0.076	0.048	0.037*	0.067
	(0.047)	(0.033)	(0.015)	(0.035)
Year 2 after lift construction	0.047	0.016	0.024	0.056*
	(0.052)	(0.032)	(0.017)	(0.024)
Year 3 after lift construction	0.056	−0.005	0.022	0.063
	(0.066)	(0.051)	(0.021)	(0.030)
Year 4 after lift construction	0.041	−0.005	0.019	0.073
	(0.058)	(0.049)	(0.022)	(0.032)
Year 5 after lift construction	0.119	0.040	0.027	0.070
	(0.082)	(0.038)	(0.023)	(0.043)
Snow days	0.002***	0.002**	0.001***	–
	(0.001)	(0.001)	(0.000)	
Weather index	0.006	0.008	−0.000	–
	(0.004)	(0.005)	(0.003)	
Intercept	3.814***	3.856***	6.116***	–
	(0.204)	(0.245)	(0.167)	
Year fixed effects	Yes	Yes	Yes	Yes
Ski area fixed effects	Yes	Yes	Yes	Yes
N	298	298	534	534
R^2	0.988	0.990	0.992	–

Table Notes: The coefficient table corresponds to Figure B.5. Standard errors are in parentheses and clustered at the ski area level. The Stata command *did_multiplegt_dyn* used in column (d) does not allow to recover coefficients on the intercept and covariates and generates no r-squared. These four cells in column (d) are thus marked by a −.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

B.3.8 Treatment Effect Heterogeneity Across Ski Area Size

In Figure B.6 we show that a 10% capacity increase leads on average to a 3.6% increase in winter first entries and a 6.3% change in transportation revenues. The effect remains constant after that. Notice that the treatment here is $c_{it} = \ln(capc_{it}) - \ln(capc_{it-1})$ in the model in Equation 2.3 and that the interpretation is not as well defined as just looking at new lift investments due to the following two reasons:

First, it includes cases with negative capacity changes. This complicates the interpretation because most negative capacity changes might not have a diminishing effect on demand. For example, some lifts are closed because a new lift is much larger and replaces the access to more slopes than just the lift at the same spot. Redundant lifts are removed and overall capacity decreases even though all slopes now have more comfortable access.

Second, capacity data is not as complete as lift data. The imputation of the missing data is an estimation by itself and does, therefore, not always represent reality (see Appendix B.1.1 for the imputation of missing capacities).

Third, when looking at Figure B.6, a parallel trend violation seems apparent even though the pretrends p-values are not statistically significant. Considering these reasons, we are cautious in interpreting too much at that end.

We nevertheless reckon that the percentage effects from our main results are likely larger when the baseline lift endowment is small and vice versa because point estimates are quite larger once we remove large ski areas from the sample as in Appendix B.3.7 or Appendix B.3.11.

Figure B.6: Ski area capacity changes on winter outcomes

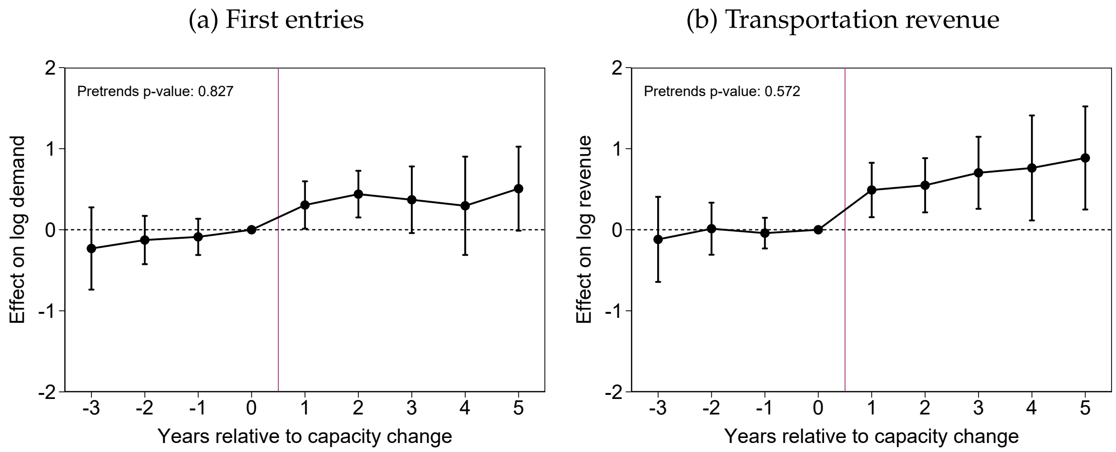


Figure Notes: Both panels show estimates of the model in Equation 2.3 across time. Period 0 indicates the winter before a capacity change (which is in the same year) and period 1 indicates the winter where the change unfolds. Panel (a) shows the estimates with the log of winter first entries as the outcome using the balanced demand sample and panel (b) the estimates with the log of winter transportation revenue as the outcome using the balanced revenue sample. The bars signify 95% confidence intervals and standard errors are clustered at the ski area level. Endpoints are binned and indicated by a plus. The p-values of the joint F-tests for pretrends are indicated in the plots. The coefficient table with point estimates and standard errors follows in Table B.18.

Table B.18: Event study estimates using capacity changes

Dependent variable:	Log demand	Log revenue
Year 3 before lift construction	−0.231	−0.119
	(0.252)	(0.262)
Year 2 before lift construction	−0.127	0.013
	(0.148)	(0.160)
Year 1 before lift construction	−0.088	−0.042
	(0.111)	(0.095)
Year 1 after lift construction	0.305*	0.490**
	(0.145)	(0.168)
Year 2 after lift construction	0.439**	0.548**
	(0.143)	(0.167)
Year 3 after lift construction	0.370	0.702**
	(0.204)	(0.222)
Year 4 after lift construction	0.295	0.762*
	(0.301)	(0.324)
Year 5 after lift construction	0.507	0.886**
	(0.257)	(0.318)
Snow days	0.001***	0.001**
	(0.000)	(0.000)
Weather index	−0.000	0.000
	(0.002)	(0.002)
Intercept	6.170***	9.826***
	(0.083)	(0.092)
Year fixed effects	Yes	Yes
Ski area fixed effects	Yes	Yes
N	405	549
R^2	0.993	0.993

Table Notes: The coefficient table corresponds to Figure B.6. Standard errors are in parentheses and clustered at the ski area level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

B.3.9 Without Mergers

We show in Figure B.7 that our results remain qualitatively and quantitatively the same as in Section 2.5.2 when all observations from ski areas known to have been linked over the observed period are removed.[11] Our results are thus not particularly driven by mergers between ski areas.

Figure B.7: Construction of new lifts on winter outcomes without ski area mergers

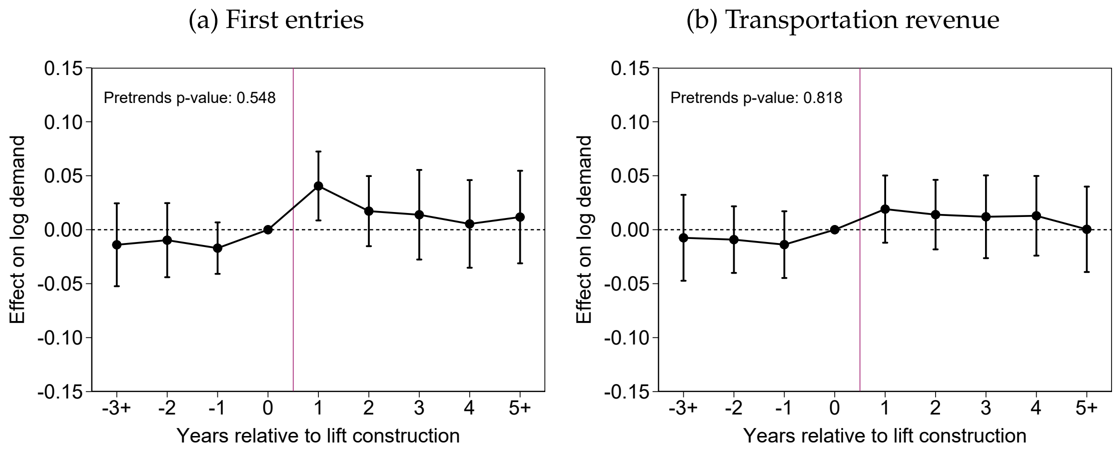


Figure Notes: Both panels show estimates of the model in Equation 2.3 across time. Period 0 indicates the winter before the lift construction (which is in the same year) and period 1 indicates the winter of the lift opening. Panel (a) shows the estimates with the log of winter first entries as the outcome using the unbalanced demand sample and panel (b) the estimates with the log of winter transportation revenue as the outcome using the unbalanced revenue sample. Both samples are cleared of observations of ski areas that were linked between 2010 and 2018. The bars signify 95% confidence intervals and standard errors are clustered at the ski area level. Endpoints are binned and indicated by a plus. The p-values of the joint F-tests for pretrends are indicated in the plots. The coefficient table with point estimates and standard errors follows in Table B.19.

[11] Arosa-Lenzerheide, Andermatt-Sedrun and Grimentz-Zinal

Table B.19: Event study estimates without mergers

Dependent variable:	Log demand	Log revenue
Year 3 before lift construction	−0.014	−0.008
	(0.019)	(0.020)
Year 2 before lift construction	−0.010	−0.009
	(0.017)	(0.015)
Year 1 before lift construction	−0.017	−0.014
	(0.012)	(0.015)
Year 1 after lift construction	0.040*	0.019
	(0.016)	(0.016)
Year 2 after lift construction	0.017	0.014
	(0.016)	(0.016)
Year 3 after lift construction	0.014	0.012
	(0.021)	(0.019)
Year 4 after lift construction	0.005	0.013
	(0.020)	(0.018)
Year 5 after lift construction	0.012	0.000
	(0.021)	(0.020)
Snow days	0.002***	0.001**
	(0.000)	(0.000)
Weather index	0.000	−0.002
	(0.002)	(0.002)
Intercept	6.091***	9.938***
	(0.159)	(0.161)
Year fixed effects	Yes	Yes
Ski area fixed effects	Yes	Yes
N	540	540
R^2	0.991	0.993

Table Notes: The coefficient table corresponds to Figure B.7. Standard errors are in parentheses and clustered at the ski area level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

B.3.10 Varying Remoteness Measure

In the following section, we apply two other remoteness measures (see Appendix B.1.7) on the specification in Equation 2.3. In Figure B.8, we show that changing the remoteness measure's baseline neither quantitatively nor qualitatively alters our main results. Only in terms of precision, the low baseline in the remoteness measure from the main text performs better than the mid or high baseline.

Figure B.8: Construction of new lifts on winter outcomes using other samples

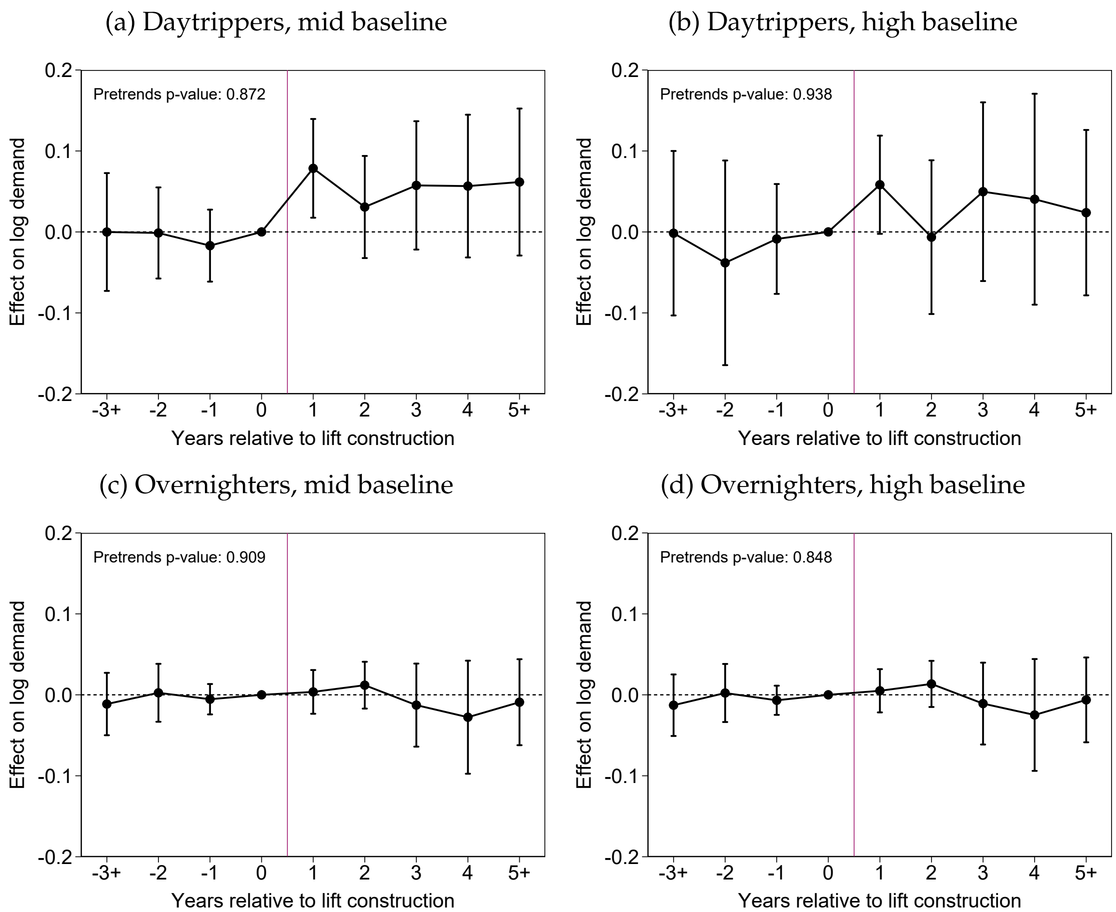


Figure Notes: All panels show estimates of the model in Equation 2.3 across time. Period 0 indicates the winter before the lift construction (which is in the same year) and period 1 indicates the winter of the lift opening. Panels (a) and (b) show the estimates with the log of winter first entries from daytrippers as the outcome distinguished by the low and high baseline in the remoteness measure and panels (b) and (d) the estimates with the log of winter first entries from overnighters as the outcome distinguished by the low and high baseline in the remoteness measure. The bars signify 95% confidence intervals and standard errors are clustered at the ski area level. Endpoints are binned and indicated by a plus. The p-values of the joint F-tests for pretrends are indicated in the plots. The coefficient table with point estimates and standard errors follows in Table B.20.

Table B.20: Event study estimates using other samples

Dependent variable:	Log daytripper demand		Log overnighter demand	
	(a) mid	(b) high	(c) mid	(d) high
Year 3 before lift construction	−0.000	−0.002	−0.011	−0.013
	(0.036)	(0.051)	(0.019)	(0.019)
Year 2 before lift construction	−0.001	−0.038	0.002	0.002
	(0.028)	(0.063)	(0.018)	(0.018)
Year 1 before lift construction	−0.017	−0.009	−0.005	−0.007
	(0.022)	(0.034)	(0.009)	(0.009)
Year 1 after lift construction	0.079*	0.058	0.004	0.005
	(0.031)	(0.030)	(0.014)	(0.013)
Year 2 after lift construction	0.031	−0.006	0.012	0.013
	(0.032)	(0.048)	(0.014)	(0.014)
Year 3 after lift construction	0.057	0.050	−0.013	−0.011
	(0.040)	(0.055)	(0.026)	(0.025)
Year 4 after lift construction	0.057	0.040	−0.028	−0.025
	(0.044)	(0.065)	(0.035)	(0.035)
Year 5 after lift construction	0.062	0.024	−0.009	−0.006
	(0.046)	(0.051)	(0.027)	(0.026)
Snow days	0.002*	0.003**	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Weather index	0.002	−0.002	−0.003	−0.003
	(0.005)	(0.008)	(0.003)	(0.003)
Intercept	5.144***	4.874***	5.684***	5.918***
	(0.268)	(0.361)	(0.195)	(0.195)
Year fixed effects	Yes	Yes	Yes	Yes
Ski area fixed effects	Yes	Yes	Yes	Yes
N	579	570	581	581
R^2	0.954	0.921	0.985	0.985

Table Notes: The coefficient table corresponds to Figure B.8. Standard errors are in parentheses and clustered at the ski area level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

B.3.11 Extensive vs. Intensive Ski Lift Investments

We adjust the model in Equation 2.3 slightly by separating the binned variables $C_{i,t-k}$ into new ski lifts that expand the ski area's terrain extensively ($C^{ext}_{i,t-k}$) and new ski lifts without such an expansion ($C^{int}_{i,t-k}$). This yields:

$$\ln Y_{it} = \alpha_i + \sum_{k=-3}^{5} \left(\beta_k^{ext} C^{ext}_{i,t-k} + \beta_k^{int} C^{int}_{i,t-k}\right) + \delta S_{it} + \eta W_{it} + \theta_t + \varepsilon_{it}, \tag{B.13}$$

where all coefficients and variables are defined as in the model in Equation 2.3. The results are depicted in Figure B.9 and in Table B.21. The extensive investments are quite imprecisely estimated because there were only nine extensive investments during the observation window. However, the coefficient of the first lag is much more accurately estimated at around 7.7% on average, all else equal. Although the data varies strongly from year to year, the change in demand after a lift investment is very similar across the few ski areas affected.

Figure B.9: Effect of new ski lifts on first entries across lift types

(a) Extensive investments (b) Intensive investments

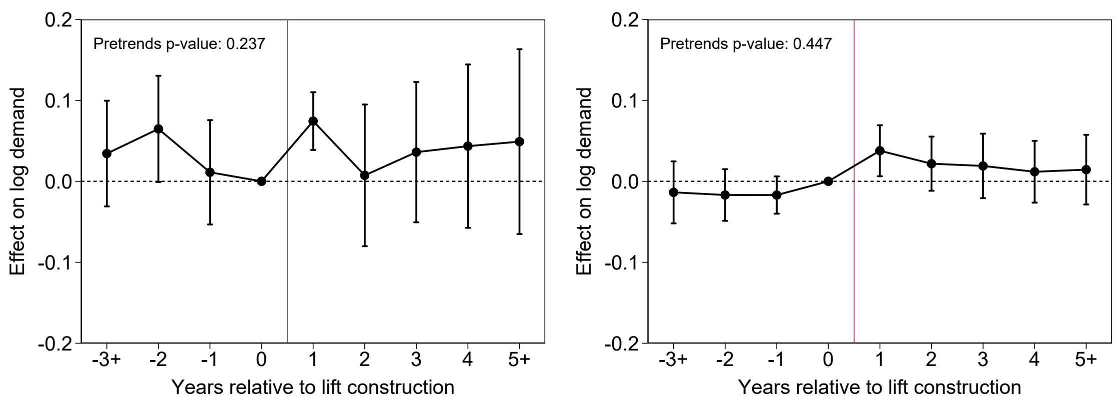


Figure Notes: Both panels show estimates of specification (B.13) across time. Period 0 indicates the winter before the lift construction (which is in the same year) and period 1 indicates the winter of the lift opening. Panel (a) shows the point estimates of the extensive investments and panel (b) the point estimates of the intensive investments using the main sample. The bars signify 95% confidence intervals and standard errors are clustered at the ski area level. Endpoints are binned and indicated by a plus. The p-values of the joint F-tests for pretrends are indicated in the plots. The coefficient table with point estimates and standard errors follows in Table B.21.

Table B.21: Coefficient table of the event study estimates by lift type

Dependent variable:	Log demand	
	(a) extensive	(b) intensive
Year 3 before lift construction	0.034	−0.014
	(0.033)	(0.019)
Year 2 before lift construction	0.065	−0.017
	(0.033)	(0.016)
Year 1 before lift construction	0.011	−0.017
	(0.032)	(0.012)
Year 1 after lift construction	0.074***	0.038*
	(0.018)	(0.016)
Year 2 after lift construction	0.007	0.022
	(0.044)	(0.017)
Year 3 after lift construction	0.036	0.019
	(0.043)	(0.020)
Year 4 after lift construction	0.043	0.012
	(0.051)	(0.019)
Year 5 after lift construction	0.049	0.014
	(0.057)	(0.022)
Snow days	0.002***	
	(0.000)	
Weather index	0.001	
	(0.002)	
Intercept	6.049***	
	(0.150)	
Year fixed effects	Yes	
Ski area fixed effects	Yes	
N	581	
R^2	0.991	

Table Notes: The coefficient table corresponds to Figure B.9. Standard errors are in parentheses and clustered at the ski area level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

B.3.12 Evidence of Spatial Competition

We show that a neighboring extensive ski lift investment within 25km affects demand negatively in Section 2.5.3. This section addresses the concern that a parallel trend violation may drive this result. As we observe only nine extensive investments within the observation window of the outcome, the ski areas within the 25 kilometers of these investments may have differing trends from those expanding and those further away. Compared to ski lift replacements, ski area expansions happened only at relatively large ski areas with relatively good business prospects.

To see how much the effects are driven by spatial competition, we conduct a counterfactual exercise where we switch off the business stealing channel by shuffling all ski areas across locations. For this, we randomly assign each of the 186 ski areas to one of the 186 locations and compute road distance rings across these random neighbors using road distances.[12] After this procedure, we estimate the model in Equation 2.5 and recover the point estimates. As random neighbors are not (or at least much less) affected by business stealing, a new lift installment from a fake neighbor should no longer affect its demand. Therefore, the spatial competition among neighboring ski areas is purged. Scholars in economic geography typically perform such counterfactual exercises. See, for instance, section 6.1 in Dauth et al. (2022).

We perform 100 repetitions of the random shuffling and find that without the spatial competition, the demand effect of the first lag (i.e., in the winter of the lift opening) revolves around zero. This is depicted by the histogram of the coefficients (of the first lag) from the random shuffling in panels (b) to (d) in Figure B.10. In other words, if the effect were completely induced by business creation, we would estimate a zero effect on demand when a neighbor invests in a ski area expansion. We find a clear sign of business stealing for ski area expansions within 25 kilometers: In a one-sided test with the Null being that

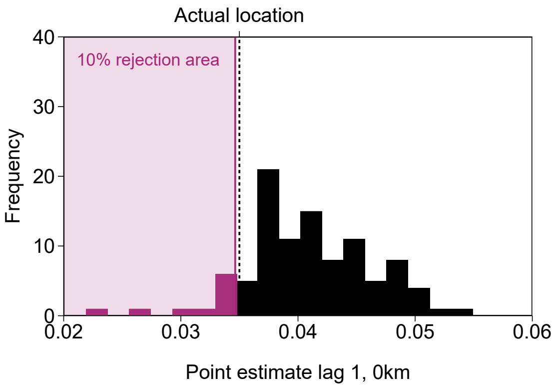
[12] In practice, we take all characteristics of the 186 ski areas (i.e., outcomes, investments, weather, and snow conditions) and randomly shuffle them across the 186 locations of the ski areas (=coordinates). Then, using the road distances between two locations (=coordinates), we generate the set of binned event variables $\tilde{C}_{ir,t-k}$ that equal one when a random neighbor within the road distance rings r expand their ski area $k \in [-3, ..., 5]$ years ago as in Equation 2.5.

the effect is equal or greater than zero (meaning that there is no business stealing), we reject the Null at the 10% level because only 7 out of 100 repetitions are further away from zero than our estimate. This is depicted in panel (b) in Figure B.10: The vertical dashed line shows the point estimate with the actual location compared to the distribution from the random shuffling and the 10% rejection area. The point estimate with the actual location lies within the rejection area. We thus conclude that this estimate is driven by spatial competition. However, when we look at panels (c) and (d), we find no statistical significance of business stealing for road distances between 25 and 75 kilometers on a 10% level.

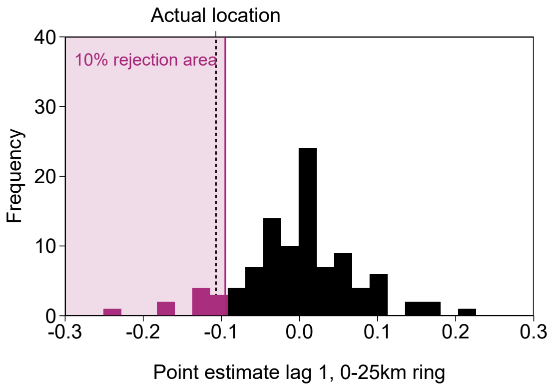
Panel (a) in Figure B.10 shows that the point estimate of own ski lift investments is lower than without spatial competition (albeit not statistically significant). This is in line with the SUTVA violation induced through the business stealing: Once we account for the negative spatial spillovers that ski lift investments have, the positive bias in treatment effects from own ski lift investments is reduced (Butts, 2023).

Figure B.10: Histogram of coefficients when location is random versus actual location

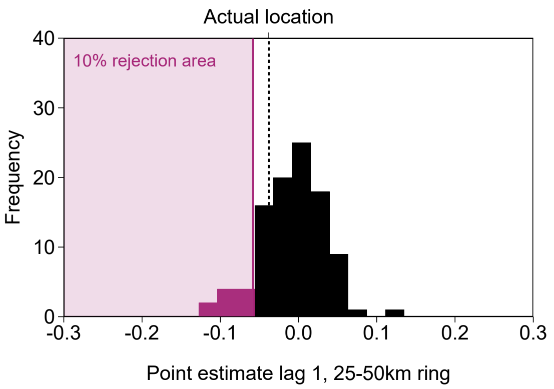
(a) New ski lift, 0km



(b) Neighboring expansion, 0-25km



(c) Neighboring expansion, 25-50km



(d) Neighboring expansion, 50-75km

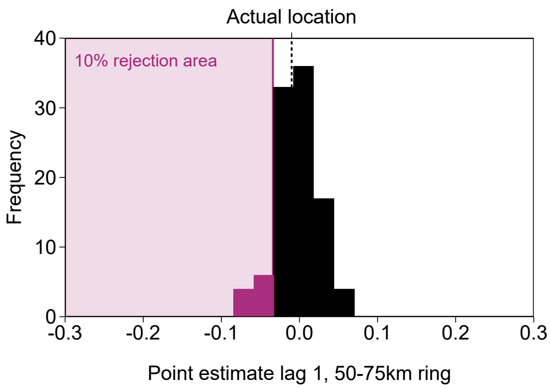


Figure Notes: The bars show the distribution of point estimates of the first lag of the model in Equation 2.5 using random locations (as described in the text) versus the point estimate of the same estimation using the real locations (vertical dashed line) corresponding to the fourth row in Table B.8. In panels (b) to (d), we find evidence of business stealing if the estimate of the actual location lies within the shaded 10% rejection area, meaning that the Null of no business stealing is rejected at the 10% level.

Appendix C

The Development of Ski Areas and Its Relation to the Alpine Economy in Switzerland

C.1 Data Processing

C.1.1 Municipality Data

The data covers municipality borders, the center coordinates that remained arguably at the same spot over the past 170 years[1] and the complete list of all municipality mergers and separations between 1960 and 2021. We aggregate all data to the 2021 jurisdictions because, in the past, most municipalities were merged rather than separated. Historical data based on old jurisdiction is easily merged to the 2021 borders. However, recent data cannot be split into the historical jurisdictions from 1960.

[1] In the data description, it is noted that the center was often manually chosen at the church or the central village square.

C.1.2 Ski Area Data

We use the dataset provided by *bergbahnen.org*, which consists of all ever-built cableway lifts grouped into pre-defined areas. The goal is to match these data with Swiss municipalities as they exist at the beginning of 2021. First, we want these data grouped at municipality-area-year cells and later at municipality-year cells to match all other data.

Cableway data consists of roughly 500 areas that require matching to the adjoining municipalities, our unit of interest. The following steps have been implemented to match ski areas to municipalities coherently. A year in the data is always considered the initial operation year of a lift. For example, a lift built in the summer of 2013 operates normally from the winter of 2013/14 onwards.

First, we manually add missing lifts or data. For example, all racket railways are missing even though they were crucial to the emergence of ski areas, especially in the early 20th century. Second, we detect access lifts from which ski areas are entered. Some areas have multiple access lifts from separate municipalities and others are connected to more than one ski area. Third, we define ski areas from the cableways clusters and drop all clusters not in our definition. Fourth, we adapt ski area mergers manually. That is, we split areas in those years where they are considered one area (as defined by *bergbahnen.org*) when they were two areas. Or, we merge areas considered to be two areas (as defined by *bergbahnen.org*) when they are one area for the years in question.

Missing Data

Some lift observations have missings in z-coordinates. They are recovered by matching the 2-dimensional latitude-longitude coordinates to a 3-dimensional shapefile of Switzerland from the swisstopo.

The *bergbahnen.org* data does not cover rack railways. Thus, I use information from historical accounts (Bärtschi, 2015; Frey & Schiedt, n.d.-b) and wikipedia to add missing railway stations that were explicitly linked to winter sports. Note that access points are defined at the train station of the last municipality before the mountaintop. For example, the train from Blonay to Pleiades starts actually in Montreux. But because the distance from Montreux to Blonay can be seen as road or train distance to that train station, we only count Blonay, the last municipality, before reaching the top. When two municipalities from opposing mountainsides reach the top with different trains, both are counted as access points (e.g., Rigi).

Table C.1: Racket railways in Switzerland that are connected to a ski area

Name	Source & Info	Access points	Coordinates (lat/lon)	Operates in Winter since
Wengernalpbahn	Bärtschi (2015) de.wikipedia.org	Wengen Grindelwald	46.60507/7.92087 46.62456/8.03266	1909
Gornergratbahn	Bärtschi (2015) de.wikipedia.org	Zermatt	46.02381/7.74929	1928
Furka-Oberalp-Bahn	Bärtschi (2015) de.wikipedia.org	Sedrun Andermatt	46.68112/8.76960 46.63696/8.59331	1945
Blonay - Les Pléiades	Frey and Schiedt (n.d.-b) fr.wikipedia.org	Blonay	46.46584/6.89578	1954
Rochers de Naye	Bärtschi (2015) de.wikipedia.org	Glion	46.43192/6.92420	1957
Bex-Villars-Bretaye	Frey and Schiedt (n.d.-a) de.wikipedia.org	Villars	46.29580/7.05652	1937
Rigi	Bärtschi (2015) rigi.ch	Vitznau Arth	47.00901/8.48274 47.04895/8.54968	1905

Detection of Access Lifts

First, the data are cleaned and expanded to the operation years of each lift to get lift-area-year cells. Next, access points of the areas are searched. These points are crucial: Access points should be matched to municipalities in some form of spatial aggregation (e.g., inverse distance weighting) such that investments in the lift capacity of an area connected to that access can be considered a treatment to the surrounding municipality. Some lifts might not lie in the municipality that has access to these lifts. Thus, allocating the areas to their corresponding municipalities via access points is crucial.

To calculate the access points to the municipalities, we first match all valley stations to municipality polygons of 2021 jurisdictions from the FSO. Then, we create three potential indicators of area access for each valley station of all lifts:

1. All valley stations that lie at a maximum 500m above or below the municipality center (the center where the lift lies)
2. The lowest-lying valley station within each area-year cell
3. The lowest-lying valley station within each area-municipality-year cell

The second indicator is considered always an area entry. We require the third indicator because an area might have access to more than one municipality. Yet, the third indicator is not always necessarily a true access point. It could be that a municipality contains a lift on top of a mountain within its borders but does not have direct access to that area. Thus, a true access point must also satisfy the first indicator.

Finally, an access point is defined as the lowest-lying station for each area in each year (indicator 2) or it is at the same time the lowest-lying station for each area-municipality-year cell (indicator 3) and is not too far from the municipality center in vertical distance (indicator 2).

Access lifts from multiple municipalities to an area

The goal is to aggregate the data into year-municipality cells. Thus, if an area is accessed by more than one municipality, we duplicate the observations of the lifts in each year-municipality-area cell such that when we collapse to the area level (instead of the lift level) of that cell, both municipalities have access to the same summed up lift characteristics (such as capacities and numbers of lifts) in the same year. In practice, we expand all lift observations of an area on the number of access points, allocate all lift duplicates to a new access point municipality and collapse the data again by year-municipality-area cells.

This procedure leads to the intended cells at the area level because there is only one access point per year-municipality-area cell (as defined above). An area accessed by two municipalities is then aggregated into two observations with the same characteristics per year. When only one access point to the area initially exists, only one observation exists in the data.

Multiple access lifts in one municipality to multiple areas
As we collapse the data to year-municipality-area cells, a municipality with access to, for instance, two areas mechanically has two observations per year. One for each area. This gives a relatively simple solution when data are later collapsed into year-municipality cells. The area characteristics (such as capacities and the number of lifts) are summed across areas to the municipalities.

Ski Area Definition

We define a ski area as a cluster of cableways consisting, on average, of at least two lifts throughout its existence. That means we count the number of lifts per year and average this value across the existence of the cluster. All areas with an average ≥ 2 are kept in the data, the rest is dropped. Doing this allows us to exclude urban cableways, excursion lifts and small community-run village lifts.

Ski Area Mergers

In some minor instances, ski areas merged over the years. In such a year, a municipality might suddenly get access to twice the lift capacity. We keep the areas at their historical access. Thus, a not yet merged area shows up as two before the merge and has an additional area ID. As soon as they merge they will show up as one individual area with one of the succeeding area's IDs.

C.1.3 Geographical Data

Peak Measure

Using swisstopo data of map names allows us to identify alpine peaks. All main peaks and alpine peaks (called "Hauptgipfel" and "Alpiner Gipfel" in the swisstopo-3D-Names) are first cleaned from duplicates (some peaks appear in two or more languages).

The peaks are then assigned to the municipalities in a gravity-based measure that weighs their altitude and closeness to the peak (see Gutiérrez et al., 2010, Chapter 2.2 for a list of literature that uses such measures in the transportation literature). The altitude mass is calculated by simply dividing each peak by the altitude of the lowest peak (=1,607 meters above sea level) to get altitude mass m_p^{alt}. Then, a mass of one is assigned to the smallest peak and a mass above one to all higher peaks proportionally to their altitude.

In the next step, we link each peak ($P = 2,954$) to all municipalities ($J = 2,175$) and calculate the three-dimensional Euclidean distance [in meters] of each peak to all municipality centers. From this we divide each peak's mass by the inverse squared distance and sum those values up for each municipality:

$$peak_j = \sum_{p=1}^{P} \frac{m_p^a}{(d_{pj}^{E3})^2} \tag{C.1}$$

where *peak* is the final measure, j is a municipality, p is an individual peak, d_{pj}^{E3} the three-dimensional Euclidean distance between peak coordinates $p^{\otimes}$ and municipality center coordinates $j^{\otimes}$. We use a squared inverse distance weight to overweight short distances compared to long distances. The reason for this is twofold.

First, the closer one gets to a peak, the harder and slower it gets to reach the top[2]. Thus, being able to start an expedition (in the 19th century) or reach the peak by cableways (in

[2]Take the access to the Matterhorn as an example where the journey starts in the large Rhone valley of Wallis with flat terrain where moving through the valley goes unhindered. After that, one enters the narrower Matter valley that becomes narrower and more difficult the closer one gets to Zermatt. After passing through Zermatt, the hike begins and the closer one gets to the top, the more it becomes a challenging climb.

more recent times) is simpler the closer one can lodge overnight (in the 3-dimensional distance).

Second, Switzerland is relatively small, so we would overweight central municipalities to border municipalities when distances were weighted inversely linear. Additionally, the measure is scaled up by 1,000,000 for a simple interpretation. The peak measure has the following intuition: A peak measure of 1 means that there is exactly one peak with an altitude of 1,607m and a 1km distance to the municipality center. A peak measure of 2 could mean that there is one high peak of exactly 3214m altitude at 1km distance, two low peaks at 1km distance, two high peaks at $\sqrt{2km}$ distance and so on.

Developable Land Measure

To construct the developable land measure, we first aggregate the shapefile from swisstopo to a resolution of 158-by-158m to facilitate computation. Then, we remove all pixels with an average slope above 15 degrees and an altitude above 2000 m.a.s.l. because this terrain is either too steep or too high (no municipality centers in Switzerland lie above 1900 m.a.s.l.) for large-scale construction of housing or industrial buildings.

Next, we match the data with municipality polygons from swisstopo and remove all pixels on lakes. On top of that, we remove pixels that are further than 200m in altitude apart from the municipality center. In the 19th century, developing land far from the municipality center (without good roads and barely any racket railways/cableways) would greatly complicate things.

Finally, we compute all pixels that fulfill the above conditions, count them, and divide them by the total number of pixels within a municipality's jurisdiction. The resulting measure is then the share of developable land within each municipality.

Sunshine Exposure of Developable Land

For this measure, we take the same pixels with a resolution of 158-by-158m from the developable land measure and compute the exposure to the sun on a winter day. For each pixel the sun exposure is computed using the rayshader package in R (Morgan-Wall, 2023) with a sunshine angle of 195.03° (sunshine from south-south-west) and sunshine altitude of 18.53 which is where the sun lies at the winter solstice on 21st December at 13.25 p.m.[3] in Andermatt (pretty much the center of the Swiss Alps).

The sunshine exposure is a variable scaled between 0 (no exposure) and 1 (maximum exposure) assigned to each developable land pixel on the map. Then, we take the average of all pixel values within a municipality to get the average sunshine exposure of the developable land.

C.1.4 Population Data

Data Sources

The FSO describes the three data sources as follows (rough translation from information gathered at Federal Statistical Office, 2023a, 2023c, 2023e).

ESPOP
ESPOP was a statistic based on the statistics of natural population movements (BEVNAT), the statistics of the foreign resident population (PETRA) and the migration statistics of the Swiss resident population and was corrected for the population census of 1990 and 2000 (VZ) (Federal Statistical Office, 2023e).

STATPOP
STATPOP takes stock and movement data from the federal government's registers of persons and the harmonized population registers of the communes and cantons and is thus based on a different production method than ESPOP (Federal Statistical Office, 2023c).

VZ
From 1850 to 2000, a census was carried out every ten years by questionnaire among

[3]Taking high-frequency temperature data (per 10 minutes) from three weather stations (in Montana, Andermatt and Davos) for six years and joining this with sunshine data, we find that the maximal temperature throughout a sunny day (above 80% relative sunshine duration) in winter is, on average, at 13.25p.m

the entire population of Switzerland. The results allowed statements about the demographic, spatial, social and economic development of the country (Federal Statistical Office, 2023a).

General Information

The population stocks as of December 31 of a calendar year and January 1 of the following calendar year are not identical in the following cases: (1) adjustment of the stock data to the VZ (1990/91 or 2000/01); (2) changeover from ESPOP to STATPOP (2010/11); (3) territorial status changes at the canton, district or commune level (various years).

The reference population of the demographic balance is the "permanent resident population", which until 2010 included all Swiss nationals with a main residence in Switzerland and all foreign nationals with a residence permit for at least 12 months. The reference population was redefined with the introduction of STATPOP. Since 1.1.2011, it includes persons in the asylum process with a total stay of at least 12 months. (Federal Statistical Office, 2023a, 2023c, 2023e)

Imputation

The population data was gathered in 1888 instead of 1890 and 1941 instead of 1940. As we require the population counts at the exact decade, we impute the two missing years from three population counts each (Büchel & Kyburz, 2020). To impute the population count in 1890 we use

$$pgr_{80,88} = \left(\frac{pop_{88}}{pop_{80}}\right)^{1/8} \tag{C.2}$$

$$pgr_{88,00} = \left(\frac{pop_{00}}{pop_{88}}\right)^{1/12} \tag{C.3}$$

$$pop_{90} = \frac{1}{2} pop_{88} \cdot (pgr_{80,88})^2 + \frac{1}{2} pop_{88} \cdot (pgr_{88,00})^2. \tag{C.4}$$

To impute the population count in 1940 we use

$$pgr_{30,41} = \left(\frac{pop_{41}}{pop_{30}}\right)^{1/11} \tag{C.5}$$

$$pgr_{41,50} = \left(\frac{pop_{50}}{pop_{41}}\right)^{1/9} \tag{C.6}$$

$$pop_{40} = \frac{1}{2} pop_{41} \cdot (pgr_{30,41})^{-1} + \frac{1}{2} pop_{41} \cdot (pgr_{41,50})^{-1}. \tag{C.7}$$

To impute the population count in 1947 we use

$$pgr_{41,50} = \left(\frac{pop_{50}}{pop_{41}}\right)^{1/9} \tag{C.8}$$

$$pop_{47} = pop_{41} \cdot (pgr_{41,50})^{6}. \tag{C.9}$$

C.1.5 Employment Data

The employment rate for the three sectors is publicly available data from the federal population census Federal Statistical Office (2023a) and is based on surveys on the employment status and type of work of permanent residents in a municipality.

The granular employment data for 6-digit ISIC codes is provided by the FSO. All Swiss employees who are subject to social insurance are gathered in the data. This includes self-employed and employed individuals who earn at least 2'300 CHF per year. The labor volume of all full- and part-time workers is then translated to the FTE for each firm in each municipality. Further details on the data can be found in Federal Statistical Office (2023d).

We aggregate this data to the municipality level (2021 jurisdictions) and compute the shares of employed across sectors within municipalities for the relevant ISIC codes.

C.1.6 Tax Data

The FTA data from 1973 and later are aggregated to municipalities and are publicly available bi-annually. Older bi-annual municipality-level tax data from 1947 to 1958 are mostly only as counts of tax subjects in income brackets available and only as scans in PDF format. The exception is the 1947/1948 data, where bracket counts and the overall income of the tax base are available. See Federal Tax Administration (2023) for details and the data.

We digitized the historical tax documents from 1947 to 1958 and merged the data to 2021 municipal jurisdictions. In the end, we only use the 1947/48 data where all data (counts of tax base and the tax subjects' aggregate income) is available for our study area.

Individuals are exempt from taxes if their bi-annual average yearly taxable income is very low. Also, the allowed tax deductions that led to the taxable income changed over the years. An overview of tax changes over the used periods that affect our data can be found in Federal Tax Administration (1950, 2022).

Additionally, we use historical inflation data from Federal Statistical Office (2023b) to deflate the data to 1947 CHF.

C.2 Additional Empirical Results

C.2.1 Empirical Strategy across Time

To study the development of municipalities connected to ski areas across time, we use a panel data model:

$$\ln y_{jt} = \alpha_t + \beta_t I_t D_{jt} + \gamma_j + \varepsilon_{jt} \tag{C.10}$$

where $\ln y_{jt}$ is the logarithm of the outcome (population, income or tax revenue) in municipality j at time t. D_{jt} is a ski area access indicator. It is equal to 0 for all municipalities in the baseline period, which is always before they gain any access. It equals 1 for all periods after the baseline period for those municipalities that ever gain access to a skiing area. Municipalities that have never access to a ski area indicate $D_{jt} = 0$ at any t. D_{jt} is interacted with a time dummy I_t which equals 1 in period t and 0 otherwise. This allows us to recover time-variant estimates of β_t. α_t is a year fixed effect, γ_j a municipality fixed effect and ε_{jt} is the error term.

We estimate β_t in the model of Equation 3.1, the association of ski area access to the outcome in period t, by a sequence of these two-by-two DiD estimations where t is the second period and t_0 is always the first period. In particular, we estimate:

$$\Delta_0 \ln y_{jt} = \Delta_0 \alpha_t + \beta_t I_t D_j + \epsilon_{jt}, \tag{C.11}$$

where $\Delta_0 \ln y_{jt} = \ln y_{jt} - \ln y_{j,t_0}$ is the difference of the outcome at each t to the baseline period, $\Delta_0 \alpha_t = \alpha_t - \alpha_{t_0}$ is a year fixed effect, $D_j = \Delta_0 D_{jt} = D_{jt} - D_{jt_0}$ is the access indicator that equals 1 if municipality j has ever access to at least one ski area in the ski access period (in which almost all ski areas in our sample were built, see Figure 3.2) and 0 otherwise.[4] Note that it is not time-variant for $t > t_0$. The municipality fixed effect γ_j cancels and ϵ_{jt} is the error term.

C.2.2 Spatial Dispersion

We adjust the model in Equation 3.2 by changing the treatment to road distance rings in order to tackle the question of how far in space ski area investments affect outcomes. We follow Butts (2023) and estimate

$$\Delta \ln y_{jt} = \alpha_t + \sum_{r=1}^{R} \beta_r D_{jr} + \varepsilon_j, \tag{C.12}$$

where $\Delta \ln y_{jt} = \ln y_{j,t_1} - \ln y_{j,t_0}$ and β_r are the coefficients of interest that recover the association of each 1km road distance ring r between 1 and 10km. The treatment indicator $D_{jr} = \mathbb{1}\left[\Delta capc_{j,t \in \{t_0,t_1\}} \in (\underline{r}, \overline{r}]\right]$ is a binary treatment indicator that is equal to one if a municipality has access to a capacity increase in at least one ski area in road distance between $\underline{r}$ and $\overline{r}$ (=1km) within the period $t_0 = 1940$ and $t_1 = 1980$ ($t_0 = 1947$ and

[4] We estimate β_t in differences because of the simplicity in implementation and interpretation, especially in regressions with only one additional time period to the baseline period (which is simply a cross-sectional regression).

$t_1 = 1980$ using tax data), or $t_0 = 1980$ and $t_1 = 2020$ ($t_0 = 1980$ and $t_1 = 2015$ using tax data) and zero otherwise. We use capacity increases instead of ski area access as treatment because all areas were built until 1982 and our interest lies in the period after 1980.

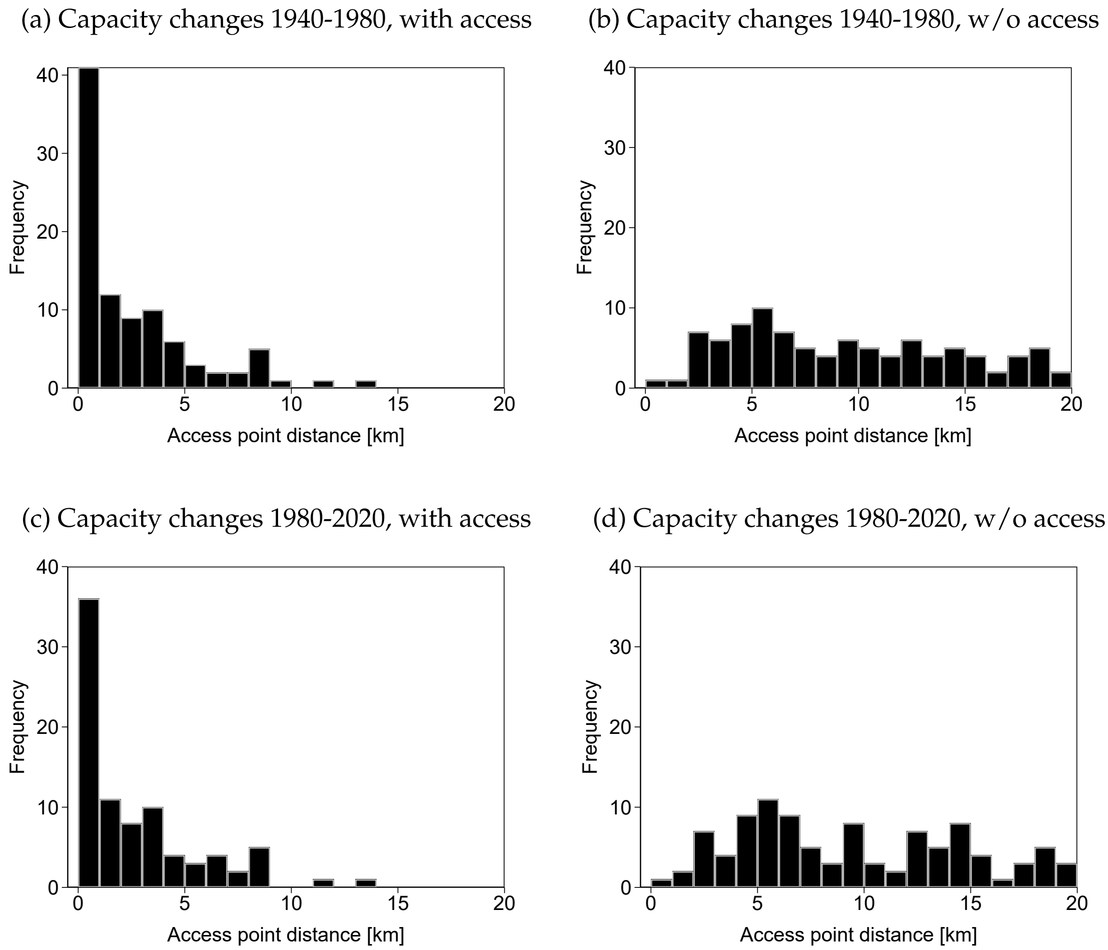
The road distance between ski area access points and municipality centers is computed using the Here API. Municipalities always get the closest ski area access point allocated (i.e., each municipality is only accessed once per time period even if a second ski area is located in less than 10km road distance).

This specification allows for testing the spatial dispersion of capacity changes during the ski area access period and the expansion plus concentration phase. Before we get to the results, we first check how far municipality centers lie from the access points differentiated by the treatment indicator from the Equations 3.2 and 3.3 used in our main specifications.

Considering Figure C.1, we show that variation in capacity changes of below 2km road distance originates almost exclusively from access municipalities in the main specifications. The two first bins at the very left are large in panel (a) (most capacity changes happen within 2km in municipalities with access points in their jurisdiction), whereas almost negligible in panel (b) (almost no capacity changes happen within 2km in municipalities without access). At the bins between 3 and 5 km, capacity changes disperse roughly in equal measure to municipalities with and without access points and the bins above 5km show that most capacity changes are captured by municipalities without access points. The same pattern can be observed in panels (c) and (d) for the period between 1980 and 2020.

Table C.2 shows OLS estimates of the model in Equation C.12 for different numbers of rings and two periods using population as the outcome. It is striking how capacity investments until 1980 correlate strongly with population changes at the inner two rings within 2km. Therefore, between 1940 and 1980, municipalities within a 2km road distance of ski area access points grew substantially more than municipalities farther away.

Figure C.1: Distribution of municipalities' road distance to ski area access points with capacity changes



(a) Capacity changes 1940-1980, with access

(b) Capacity changes 1940-1980, w/o access

(c) Capacity changes 1980-2020, with access

(d) Capacity changes 1980-2020, w/o access

Figure Notes: The bars indicate the distribution of municipalities that are exposed to capacity changes at access points within certain road distances for four groups. Panel (a) shows the distance bins for capacity changes from 1940 to 1980 of municipalities with ski area access in the main specifications in Equations 3.2 and 3.3. Panel (b) shows the same distribution for municipalities without ski area access in the main specification and panels (c) and (d) show the same distribution for capacity changes between 1980 and 2020. Municipalities without access points within 20km are not depicted.

This relationship changes completely when we look at changes between 1980 and 2020. The closest municipalities within 2km grow no longer when exposed to capacity changes. Only municipalities further from the access points than 2km are positively related to capacity changes. As Figure C.1 indicated, capacity changes above 2km might be driven by municipalities with and without access points in their jurisdiction. Consequently, the

SUTVA assumption in the main specification in Equation 3.2 using population data holds before 1980 but is clearly violated thereafter.

Table C.2: Association of ski area capacity with population using road distance rings

Dependent variable	Log permanent residents (1980-1940)					Log permanent residents (2020-1980)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Capacity change at distance $(0,1]$	0.202***	0.202***	0.214***	0.233***	0.238***	0.044	0.066	0.065	0.073	0.068
	(0.061)	(0.062)	(0.063)	(0.064)	(0.065)	(0.053)	(0.054)	(0.055)	(0.054)	(0.055)
Capacity change at distance $(1,2]$	0.344***	0.344***	0.356***	0.375***	0.380***	0.010	0.031	0.031	0.038	0.033
	(0.087)	(0.088)	(0.089)	(0.089)	(0.090)	(0.084)	(0.084)	(0.085)	(0.085)	(0.085)
Capacity change at distance $(2,3]$	0.161	0.161	0.173	0.192	0.197	0.271***	0.292***	0.292***	0.300***	0.295***
	(0.118)	(0.119)	(0.119)	(0.120)	(0.121)	(0.083)	(0.084)	(0.084)	(0.084)	(0.085)
Capacity change at distance $(3,4]$	0.011	0.011	0.023	0.042	0.047	0.208†	0.229†	0.229†	0.237†	0.232†
	(0.077)	(0.078)	(0.078)	(0.079)	(0.080)	(0.117)	(0.117)	(0.118)	(0.118)	(0.119)
Capacity change at distance $(4,5]$	0.023	0.023	0.035	0.054	0.060	0.138†	0.159†	0.159†	0.166*	0.162†
	(0.096)	(0.096)	(0.097)	(0.097)	(0.098)	(0.081)	(0.081)	(0.082)	(0.082)	(0.083)
Capacity change at distance $(5,6]$	−0.003	−0.003	0.009	0.028	0.033	0.100	0.122	0.121	0.129	0.124
	(0.104)	(0.104)	(0.105)	(0.105)	(0.106)	(0.102)	(0.103)	(0.103)	(0.103)	(0.104)
Capacity change at distance $(6,7]$		−0.001	0.012	0.031	0.036		0.198†	0.197†	0.205†	0.200†
		(0.063)	(0.064)	(0.065)	(0.066)		(0.114)	(0.115)	(0.115)	(0.115)
Capacity change at distance $(7,8]$			0.177†	0.196†	0.202†			−0.007	0.000	−0.004
			(0.099)	(0.100)	(0.101)			(0.108)	(0.108)	(0.108)
Capacity change at distance $(8,9]$				0.200†	0.205†				0.096	0.091
				(0.112)	(0.113)				(0.189)	(0.190)
Capacity change at distance $(9,10]$					0.067					−0.056
					(0.075)					(0.130)
Intercept	−0.128***	−0.128***	−0.140***	−0.159***	−0.164***	0.119***	0.098***	0.098***	0.090*	0.095*
	(0.028)	(0.030)	(0.032)	(0.033)	(0.035)	(0.031)	(0.032)	(0.034)	(0.033)	(0.034)
N units with access	114	123	130	139	146	106	119	126	134	142
N units w/o access	111	102	95	86	79	119	106	99	91	83
N overall	225	225	225	225	225	225	225	225	225	225
R^2	0.098	0.098	0.106	0.118	0.119	0.061	0.080	0.080	0.082	0.083

Table Notes: The table depicts OLS estimates of the model in Equation C.12. In particular, the average association of capacity investments within a certain road distance to a municipality with population differences between 1940 and 1980 (columns 1-5) and between 1980 and 2020 (columns 6-10). Standard errors are in parentheses and clustered at the municipality level to account for intra-cluster correlations across time.
† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Tables C.3 and C.4 show OLS estimates of the model in Equation C.12 for different numbers of rings and two periods using aggregate taxable income and tax revenues as outcomes. In line with the population results, capacity investments up to 1980 correlate more strongly with outcome changes at the inner rings. Also, here, the changes disperse more to municipalities further away in the second period between 1980 and 2015. The difference is that there seems to be a relationship of up to 3km before 1980, indicating that SUTVA is somewhat violated. Consequently, the SUTVA assumption in the main specification in Equation 3.2 using income and tax revenue data seems partially violated before 1980 but clearly thereafter.

Table C.3: Association of ski area capacity with aggregate incomes using road distance rings

Dependent variable	Log taxable income (1980-1947)					Log taxable income (1980-2015)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Capacity change at distance $(0,1]$	0.264*	0.289*	0.296*	0.335*	0.352*	0.030	0.054	0.048	0.061	0.058
	(0.124)	(0.124)	(0.126)	(0.126)	(0.127)	(0.065)	(0.066)	(0.067)	(0.068)	(0.069)
Capacity change at distance $(1,2]$	0.422*	0.448*	0.454*	0.493*	0.510*	−0.047	−0.022	−0.029	−0.015	−0.019
	(0.187)	(0.187)	(0.188)	(0.189)	(0.190)	(0.094)	(0.095)	(0.096)	(0.096)	(0.097)
Capacity change at distance $(2,3]$	0.422*	0.447*	0.454*	0.493*	0.510*	0.214*	0.238*	0.232*	0.245*	0.242*
	(0.189)	(0.190)	(0.191)	(0.191)	(0.192)	(0.104)	(0.104)	(0.105)	(0.106)	(0.107)
Capacity change at distance $(3,4]$	0.189	0.215	0.221	0.260	0.277	0.247†	0.271*	0.265*	0.278*	0.275*
	(0.181)	(0.181)	(0.182)	(0.183)	(0.184)	(0.130)	(0.130)	(0.131)	(0.132)	(0.132)
Capacity change at distance $(4,5]$	0.149	0.175	0.182	0.220†	0.237†	0.077	0.102	0.095	0.109	0.105
	(0.123)	(0.124)	(0.125)	(0.126)	(0.127)	(0.106)	(0.107)	(0.108)	(0.108)	(0.109)
Capacity change at distance $(5,6]$	0.116	0.142	0.149	0.187	0.204	0.069	0.093	0.087	0.100	0.097
	(0.234)	(0.235)	(0.236)	(0.237)	(0.238)	(0.120)	(0.120)	(0.121)	(0.122)	(0.123)
Capacity change at distance $(6,7]$		0.394	0.400	0.439†	0.456†		0.245†	0.238†	0.252†	0.248†
		(0.258)	(0.259)	(0.260)	(0.261)		(0.124)	(0.125)	(0.125)	(0.126)
Capacity change at distance $(7,8]$			0.130	0.168	0.185			−0.088	−0.074	−0.078
			(0.147)	(0.148)	(0.149)			(0.071)	(0.072)	(0.073)
Capacity change at distance $(8,9]$				0.463*	0.480*				0.169	0.165
				(0.187)	(0.188)				(0.151)	(0.152)
Capacity change at distance $(9,10]$					0.281					−0.048
					(0.204)					(0.158)
Intercept	1.557***	1.531***	1.524***	1.486***	1.469***	0.598***	0.574***	0.580***	0.567***	0.570***
	(0.052)	(0.052)	(0.054)	(0.055)	(0.057)	(0.034)	(0.035)	(0.038)	(0.039)	(0.040)
N units with access	105	113	119	128	134	107	119	127	135	142
N units w/o access	122	114	108	99	93	120	108	100	92	85
N overall	227	227	227	227	227	227	227	227	227	227
R^2	0.059	0.072	0.073	0.093	0.098	0.042	0.062	0.064	0.070	0.071

Table Notes: The table depicts OLS estimates of the model in Equation C.12. In particular, the average association of capacity investments within a certain road distance to a municipality with taxable income differences between 1947 and 1980 (columns 1-5) and between 1980 and 2015 (columns 6-10). Standard errors are in parentheses and clustered at the municipality level to account for intra-cluster correlations across time.
† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.4: Association of ski area capacity with tax revenue using road distance rings

Dependent variable	Log federal tax revenue (1980-1947)					Log federal tax revenue (2015-1980)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Capacity change at distance $(0,1]$	0.430*	0.466***	0.468***	0.518***	0.539***	−0.005	0.031	0.026	0.046	0.039
	(0.160)	(0.159)	(0.161)	(0.162)	(0.163)	(0.126)	(0.127)	(0.129)	(0.129)	(0.130)
Capacity change at distance $(1,2]$	0.475†	0.510†	0.512†	0.562*	0.584*	−0.140	−0.105	−0.109	−0.089	−0.096
	(0.272)	(0.272)	(0.273)	(0.274)	(0.275)	(0.155)	(0.156)	(0.157)	(0.158)	(0.159)
Capacity change at distance $(2,3]$	0.736*	0.772***	0.774***	0.824***	0.845***	0.151	0.187	0.182	0.202	0.195
	(0.264)	(0.264)	(0.265)	(0.266)	(0.268)	(0.162)	(0.163)	(0.165)	(0.165)	(0.166)
Capacity change at distance $(3,4]$	0.187	0.223	0.225	0.275	0.297	0.539***	0.574***	0.570***	0.590***	0.583***
	(0.245)	(0.246)	(0.247)	(0.248)	(0.249)	(0.188)	(0.189)	(0.190)	(0.191)	(0.192)
Capacity change at distance $(4,5]$	0.150	0.186	0.188	0.238	0.260	0.004	0.039	0.035	0.055	0.048
	(0.220)	(0.220)	(0.221)	(0.222)	(0.223)	(0.196)	(0.197)	(0.199)	(0.199)	(0.200)
Capacity change at distance $(5,6]$	0.287	0.323	0.325	0.375	0.396	0.013	0.048	0.044	0.064	0.057
	(0.314)	(0.314)	(0.316)	(0.317)	(0.318)	(0.181)	(0.182)	(0.184)	(0.184)	(0.185)
Capacity change at distance $(6,7]$		0.548	0.550	0.600	0.621		0.357†	0.353†	0.373†	0.365†
		(0.395)	(0.397)	(0.398)	(0.399)		(0.187)	(0.188)	(0.189)	(0.190)
Capacity change at distance $(7,8]$			0.038	0.088	0.110			−0.056	−0.036	−0.043
			(0.216)	(0.216)	(0.218)			(0.162)	(0.163)	(0.164)
Capacity change at distance $(8,9]$				0.600*	0.621*				0.249	0.241
				(0.284)	(0.285)				(0.243)	(0.244)
Capacity change at distance $(9,10]$					0.352					−0.094
					(0.239)					(0.240)
Intercept	2.204***	2.168***	2.166***	2.116***	2.095***	0.692***	0.657***	0.661***	0.641***	0.648***
	(0.070)	(0.069)	(0.072)	(0.072)	(0.075)	(0.052)	(0.054)	(0.057)	(0.058)	(0.060)
N units with access	105	113	119	128	134	107	119	127	135	142
N units w/o access	122	114	108	99	93	120	108	100	92	85
N overall	227	227	227	227	227	227	227	227	227	227
R^2	0.075	0.088	0.088	0.106	0.110	0.050	0.066	0.066	0.071	0.072

Table Notes: The table depicts OLS estimates of the model in Equation C.12. In particular, the average association of capacity investments within a certain road distance to a municipality with tax revenue differences between 1947 and 1980 (columns 1-5) and between 1980 and 2015 (columns 6-10). Standard errors are in parentheses and clustered at the municipality level to account for intra-cluster correlations across time.
† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C.2.3 Productivity Differences due to the Labor Composition

In this section, we provide a back-of-the-envelope estimate of how much the sectoral employment composition of an access municipality affects the local GDP. We complement employment estimates with GDP and productivity estimates from Rütter and Rütter-Fischbacher (2016). Their estimates are available for three municipality types: Cities, Alpine area and rest. The Alpine area does not perfectly coincide with our study area. It also includes early accessed municipalities and some municipalities with peaks below 750 m.a.s.l. (compare Figure 3.3 to "Abbildung 3" in Rütter and Rütter-Fischbacher (2016)).[5] Nonetheless, these numbers provide estimates of the average sectoral productivity that we combine with our employment associations to give a rough idea of how much access municipalities are affected in terms of local GDP when labor productivity changes across sectors are considered.

Table C.5 shows how the labor composition affects the local GDP. We use an average-sized access municipality wherein 492.3 FTE are employed. Then, we take the difference in worker compositions across sectors of municipalities without (NAC) versus those with access (AC). For this, we calculate the average employment share per sector of municipalities without access and add OLS estimates of the model in Equation 3.3 for each sector to get the employment share of access municipalities. The sectoral employment compositions of those municipalities are depicted in columns (a) and (b) in Table C.5.

Furthermore, we take GDP and employment estimates by Rütter and Rütter-Fischbacher (2016) (columns under (c)), calculate the labor productivity as GDP/FTE ratio (column (d)) and multiply it with the FTE from the employment composition to get a GDP estimate for municipalities with and without access (columns under (e)). The difference between the two yields our effect estimates depicted in the columns under (f) regarding FTE and local GDP.

[5] As the primary purpose of their paper is to evaluate the GDP and employment effects that can be attributed to tourism, their municipality definition is based on Swiss Tourism, the national tourism marketing organization.

Table C.5 shows that municipality employment shifted from agriculture to tourism-related and other services, mainly driven by employment opportunities in the accommodation sector and, to a smaller extent, in the gastronomy and retail sector. As labor productivity is higher in services than agriculture, we estimate that a municipality with access to at least one ski area gains, on average, 1.4 Million 2015 CHF in terms of gross value added compared to a municipality without such access. Accordingly, we estimate an average compositional effect of 2.9% on local GDP.

Table C.5: Association of ski area access with the local GDP in 2015 of an average-sized access municipality

Sectors		(a) Composition NAC		(b) Composition AC		(c) Alpine area GDP & FTE		(d) GDP/FTE	(e) GDP estimate		(f) Effect estimate		
[name]	[ISIC]	[share]	[FTE]	[share]	[FTE]	[Mio. CHF]	[FTE]	[CHF]	NAC [CHF]	AC [CHF]	[FTE]	[CHF]	[%]
Tourism-related services	*	0.18	90.5	0.32	155.5	4,800	72,260	66,427	6,010,402	10,327,463	65.0	4,317,061	71.8
Agriculture and forestry	01-03	0.30	148.3	0.17	85.3	900	26,120	34,456	5,110,929	2,939,477	-63.0	-2,171,452	-42.5
Industry and commerce	10-33	0.10	49.2	0.09	44.8	9,600	62,170	154,415	7,596,725	6,912,492	-4.4	-684,233	-9.0
Energy, water, mining	05-09,35-39	0.02	10.1	0.01	5.1	2,100	7,670	273,794	2,757,125	1,409,110	-4.9	-1,348,015	-48.9
Construction	41-43	0.16	77.7	0.15	75.7	5,400	51,410	105,038	8,158,020	7,951,160	-2.0	-206,860	-2.5
Other services	45-98**	0.24	116.6	0.26	126.0	32,600	201,480	161,803	18,866,238	20,379,836	9.4	1,513,598	8.0
Total		1	492.3	1	492.3	55,400	421,110	131,557	48,499,436	49,919,536	0	1,420,098	2.9

Table Notes: The table depicts an average-sized access municipality in the sample ($n = 94$), its employed and worker composition across six sectors in a counterfactual situation with no access (indicated as NAC, columns under (a)) and with access (indicated as AC, columns under (b)), an aggregate GDP and FTE employment estimate of Rütter and Rütter-Fischbacher (2016) (columns under (c)), the resulting GDP per FTE (column (d)), the resulting compositional GDP effects for both municipality types (columns under (e)) and the effect estimates on sectoral employment as well as local GDP (columns under (f)). The effect estimates on employment are OLS estimates of the model in Equation 3.3. In particular, the average effect of getting access to a ski area between 1940 and 1982 on the sectoral employment share of all employed in FTE in 2015.

* Tourism-related services consist of accommodation (55), gastronomy (56), railways (49.1), cableways (49.39), passenger shipping (50.3), passenger road transport (49.3), passenger air transport, travel agencies (79.11), tourism service (79.12), culture, sports and entertainment (90-93), other tourism-related services (94-96).

** Other services include all ISIC codes between 45-98 that are not listed in the tourism-related services.

There are two reasons why this sectoral composition effect might be underestimated. First, differences in sectoral labor productivity growth rates indicate that local GDP effects might have been substantially greater in 1980 than today: The core tourism-related services such as accommodation and gastronomy experienced negative real productivity growth rates while the agricultural sector became more productive between 1997 and 2014 (Federal Statistical Office, 2016). Extrapolating these sectoral trends backward from 2015 (as in Table C.5) to 1997 leads to an average compositional GDP effect of 7.7%.[6] Thus, the recent trend of low labor productivity in tourism-related services lessens the positive impact on access municipalities.

If the previous argument were true, why did the differences in sectoral labor productivity rates not lead to a similar convergence in incomes and tax revenues? This can be explained by the spatial spillovers after 1980 and the location at which data is measured. Employment and GDP effects are measured at the firm location, whereas the other outcomes are measured at the residence location of the individuals. After adopting the federal Land Use Planning Act in 1980 (Federal Assembly of Switzerland, 1979), commuting to the workplace became more attractive and, thus, spillover effects to neighboring municipalities more likely (consider Appendix C.2.2). Therefore, from 1980 onwards, the converging GDP effects at the firm location dispersed (by increases in commuting) in equal size to municipalities with and without access where incomes, population and tax revenues are measured.

Notice that if we consider only statistically significant employment shifts, namely tourism-related services and agriculture, the estimate for the compositional channel increases to 4.4%.

[6] By assuming the following real annual productivity growth rates in the 18 years between 1997 and 2015: -1% for tourism-related services, 0.8% for other services, 2.3% for agriculture, and 1.2% for the three industry and construction sectors (Federal Statistical Office, 2016).

C.2.4 Federal Tax Base

The results of the regression in Equation C.11 for the tax base across time are depicted in Figure C.2. The changes in aggregate incomes of the access municipalities are represented in panel (a). On average, aggregate taxable incomes are 42% larger in access municipalities as of 1975. The association remains constant after that.

Panel (b) shows that the number of federal taxpayers increased more than the income. Between 1947 and 1985, the number of taxpayers increased by 57% in access municipalities and also remained constant after that.

Figure C.2: Association of ski area access with income

(a) Taxable income (b) Number of federal tax payers

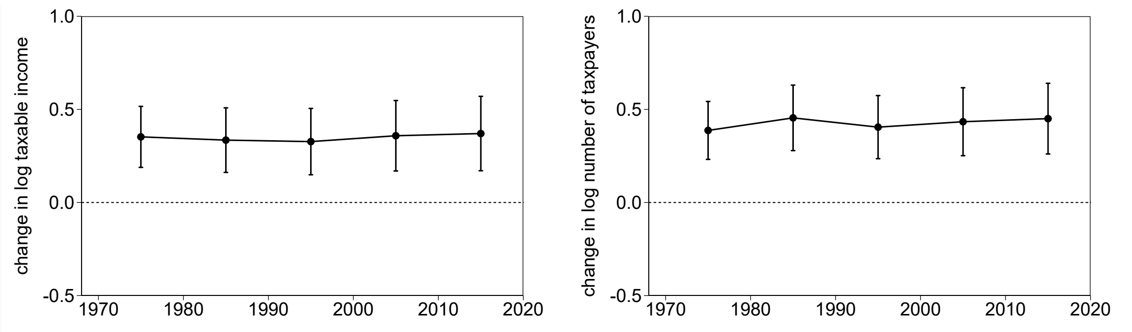


Figure Notes: The points indicate OLS estimates of the model in Equation C.11. In particular, the association of access to a ski area between 1940 and 1982 with the average municipality taxable income (left panel) and the average tax base population (right panel) across time. The base year $t_0 = 1947$. The access municipalities number to $n = 94$ and the control group municipalities to $n = 133$. Standard errors are clustered on the municipality level to account for intra-cluster correlations across time. The point estimates and standard errors follow in Table C.6.

Table C.6: The association of ski area access with income across time

Dependent variable:	Log taxable income (a)	Log number of federal tax payers (b)
Ski area access 1975	0.352***	0.387***
	(0.083)	(0.079)
Ski area access 1985	0.335***	0.454***
	(0.088)	(0.089)
Ski area access 1995	0.327***	0.405***
	(0.090)	(0.086)
Ski area access 2005	0.358***	0.434***
	(0.096)	(0.093)
Ski area access 2015	0.370***	0.450***
	(0.101)	(0.096)
Year fixed effect 1975	1.356***	0.546***
	(0.048)	(0.043)
Year fixed effect 1985	1.680***	0.932***
	(0.050)	(0.047)
Year fixed effect 1995	2.081***	1.198***
	(0.050)	(0.046)
Year fixed effect 2005	2.112***	1.172***
	(0.056)	(0.052)
Year fixed effect 2015	2.165***	1.094***
	(0.062)	(0.056)
N overall	1,135	1,135
R^2	0.906	0.787

Table Notes: The coefficient table corresponds to Figure C.2.
† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C.2.5 Federal Tax Revenue

The results of the regression in Equation C.11 for tax revenues across time are depicted in Figure C.3. The changes in tax revenues of the access municipalities are represented in panel (a). On average, tax revenues are 72% larger in access municipalities in 1975 and remained constant thereafter.

Panel (b) depicts a 53% higher tax revenue per resident in 1975. Looking at changes between 1947 and 2015, the association settles at 40%.

Figure C.3: Association of ski area access with federal tax revenue

(a) Tax revenue (b) Tax revenue per resident

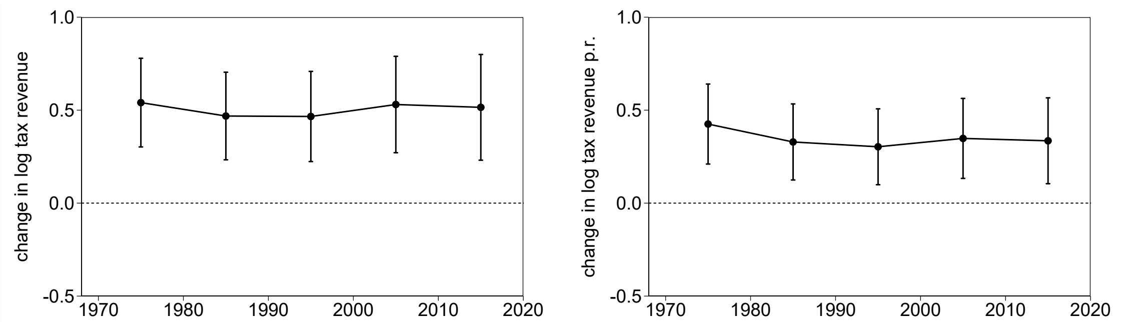


Figure Notes: The points indicate OLS estimates of the model in Equation C.11. In particular, the association of access to a ski area between 1940 and 1982 with the average federal tax revenue (left panel) and the average federal tax revenue per resident (right panel) across time. The baseline period is $t_0 = 1947$. The access municipalities number to $n = 94$ and the control group municipalities to $n = 133$. Standard errors are clustered on the municipality level to account for intra-cluster correlations across time. The point estimates and standard errors follow in Table C.7.

Table C.7: The association of ski area access with federal tax revenues across time

Dependent variable:	Log federal tax revenue (a)	Log federal tax revenue per resident (b)
Ski area access 1975	0.541***	0.425***
	(0.121)	(0.109)
Ski area access 1985	0.469***	0.329**
	(0.120)	(0.104)
Ski area access 1995	0.466***	0.303**
	(0.123)	(0.104)
Ski area access 2005	0.530***	0.348**
	(0.132)	(0.109)
Ski area access 2015	0.515***	0.335**
	(0.144)	(0.117)
Year fixed effect 1975	1.815***	1.909***
	(0.072)	(0.066)
Year fixed effect 1985	2.428***	2.524***
	(0.069)	(0.058)
Year fixed effect 1995	2.852***	2.816***
	(0.070)	(0.057)
Year fixed effect 2005	2.777***	2.756***
	(0.078)	(0.058)
Year fixed effect 2015	2.901***	2.857***
	(0.089)	(0.066)
N overall	1,135	1,135
R^2	0.902	0.926

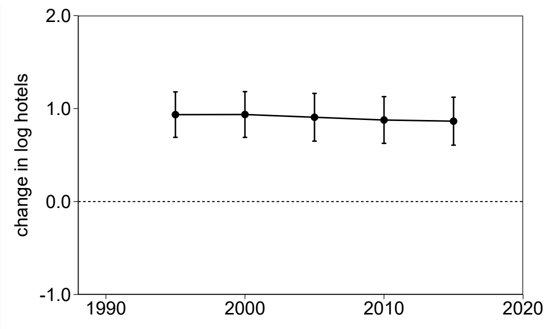
Table Notes: The coefficient table corresponds to Figure C.3.
† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C.2.6 Hotels

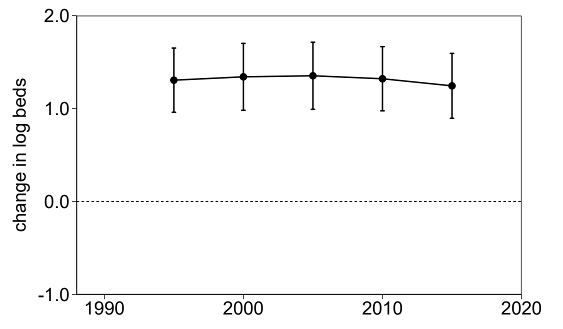
To check whether the association with the accommodation employment share in 2015 is not driven by structural changes after 1995, we use HESTA data on the number of hotels, hotel beds and hotel rooms. The assumption is that a constant supply of hotels of approximately the same size would not induce any strong variation in accommodation employment over time. This is exactly what Figure C.4 confirms. It depicts OLS estimates of the model in Equation 3.3. In 1995, access municipalities had, on average, 155% more hotels, with 269% more hotel beds and 252% more hotel rooms than municipalities without access. These numbers decrease to 137% more hotels, 247% more hotel beds and 224% more hotel rooms in 2015.

Figure C.4: Association of ski area access with hotels

(a) Hotels



(b) Hotel beds



(c) Hotel rooms

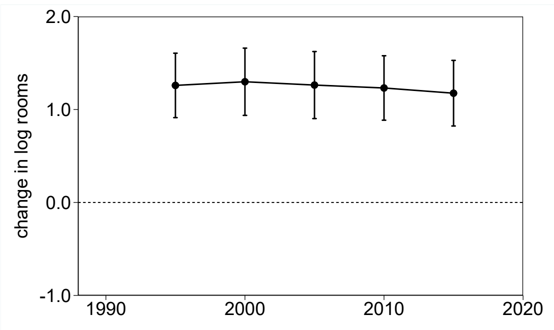


Figure Notes: The points indicate OLS estimates of the model in Equation 3.3. In particular, the association of getting access to a ski area between 1940 and 1982 with the average number of hotels (top left panel), the average number of hotel beds (top right panel) and the average number of hotel rooms (bottom left panel) across time (5 years interval). The access municipalities number to $n = 94$ and the units without access to $n = 133$. Standard errors are clustered on the municipality level. The point estimates and standard errors follow in Table C.8.

Table C.8: The association of ski area access with hotels across time

Dependent variable:	Log hotels (a)	Log beds (b)	Log rooms (c)
Ski area access 1995	0.935***	1.306***	1.259***
	(0.124)	(0.175)	(0.176)
Ski area access 2000	0.936***	1.342***	1.298***
	(0.125)	(0.182)	(0.183)
Ski area access 2005	0.907***	1.353***	1.263***
	(0.130)	(0.183)	(0.183)
Ski area access 2010	0.877***	1.321***	1.231***
	(0.127)	(0.175)	(0.176)
Ski area access 2015	0.865***	1.245***	1.175***
	(0.131)	(0.177)	(0.179)
Year fixed effect 1995	1.012***	4.100***	3.448***
	(0.078)	(0.113)	(0.113)
Year fixed effect 2000	0.972***	4.060***	3.398***
	(0.080)	(0.125)	(0.126)
Year fixed effect 2005	0.942***	4.050***	3.351***
	(0.083)	(0.123)	(0.123)
Year fixed effect 2010	0.974***	4.176***	3.435***
	(0.080)	(0.118)	(0.119)
Year fixed effect 2015	0.916***	4.178***	3.411***
	(0.086)	(0.121)	(0.122)
N overall	1,148	1,148	1,148
R^2	0.635	0.790	0.774

Table Notes: The coefficient table corresponds to Figure C.4.
† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C.2.7 Employment Rate

The points in Figure C.5 depict estimates of the model in Equation 3.3 at decades between 1970 and 2000. Panel (a) depicts the association between ski area access and the employment rate (employed population counts divided by the overall population). The difference in employment rates for municipalities with and without access is statistically indistinguishable from zero after 1980 but hints at a slightly positive trend. In 1970 the employment rate is estimated to be 1.17 percentage points lower in access municipalities compared to those without access, whereas, in 2000, the estimates are slightly positive at 1.3 percentage points. This shows that in the aftermath of ski area access, municipalities tend to gain little at the extensive margin in employment, albeit not statistically significant.

Panels (b) to (d) show the same estimates split by the three economic sectors. The outcomes are defined as counts of employed per sector divided by the overall population. Most notably, access municipalities gained by 1970 3.1 percentage points more employed in the tertiary sector almost exclusively at the expense of the primary sector. Most municipalities had already gained access by that time (86 out of 94) and the association increased slightly to 4.0 percentage points by 1980 and returned approximately to the level of 1970 by 2000. As data is missing before 1970, we do not know whether the employment differences stem from the ski area access period between 1940 and 1982 or were already in place before 1940.

Figure C.5: Association of ski area access with employment rate

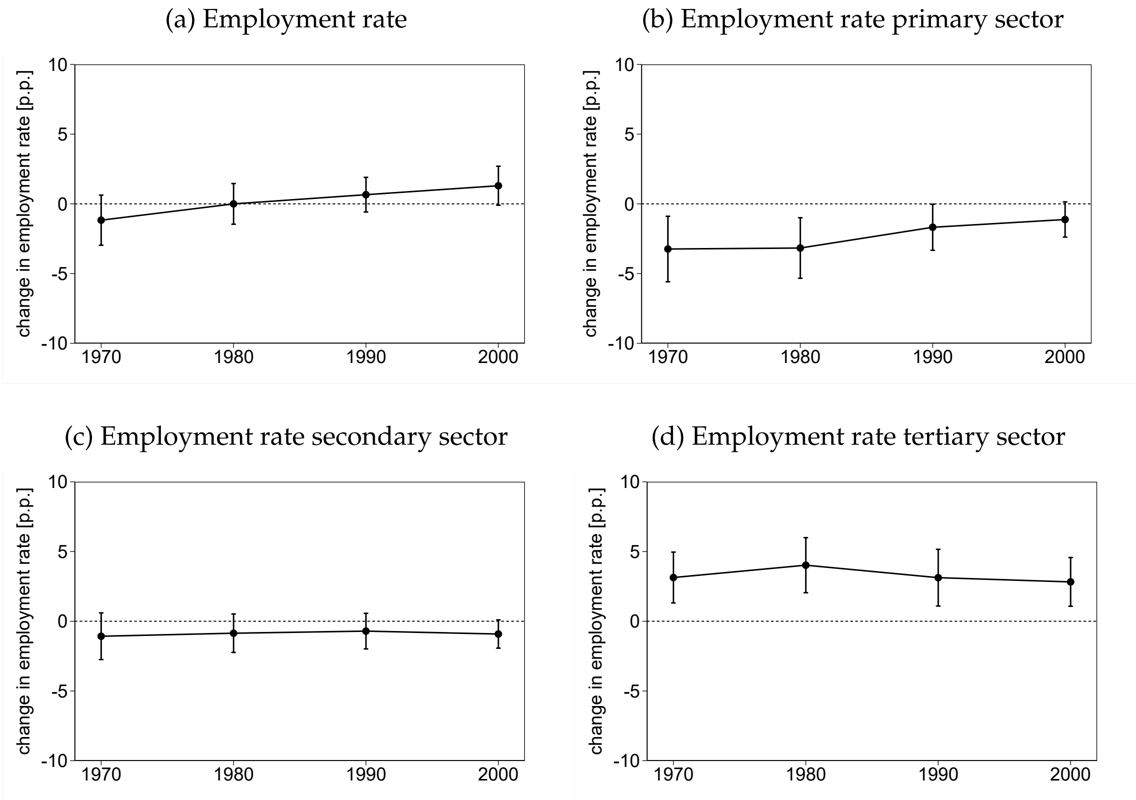


Figure Notes: The points indicate OLS estimates of the model in Equation 3.3. In particular, the association of access to a ski area between 1940 and 1982 with the average employment rate (top left panel), the average employment rate of the primary sector (top right panel), the average employment rate of the secondary sector (bottom left panel) and the average employment rate of the tertiary sector (bottom right panel) across time (10 years interval). The employment rate is defined as counts of the employed (by sector) divided by population counts. The access municipalities number to $n = 94$ and the units without access to $n = 133$. Standard errors are clustered at the municipality level. The point estimates and standard errors follow in Table C.9.

Table C.9: The association of ski area access with the employment rate across time

Dependent variable:	Employment rate			
	Overall (a)	Primary sector (b)	Secondary sector (c)	Tertiary sector (d)
Ski area access 1970	-1.170	-3.240^{**}	-1.075	3.136^{***}
	(0.912)	(1.192)	(0.849)	(0.926)
Ski area access 1980	-0.002	-3.167^{**}	-0.857	4.020^{***}
	(0.740)	(1.101)	(0.699)	(1.001)
Ski area access 1990	0.658	-1.679^{*}	-0.708	3.125^{**}
	(0.630)	(0.838)	(0.648)	(1.032)
Ski area access 2000	$1.299^{\dagger}$	$-1.123^{\dagger}$	$-0.915^{\dagger}$	2.822^{**}
	(0.709)	(0.641)	(0.514)	(0.887)
Year fixed effect 1970	44.777^{***}	15.718^{***}	16.097^{***}	12.954^{***}
	(0.619)	(0.818)	(0.684)	(0.533)
Year fixed effect 1980	45.586^{***}	12.880^{***}	15.360^{***}	16.997^{***}
	(0.487)	(0.756)	(0.513)	(0.530)
Year fixed effect 1990	46.191^{***}	7.547^{***}	13.437^{***}	23.303^{***}
	(0.415)	(0.570)	(0.424)	(0.631)
Year fixed effect 2000	48.226^{***}	5.916^{***}	11.143^{***}	23.494^{***}
	(0.409)	(0.414)	(0.356)	(0.514)
N overall	908	908	908	908
R^2	0.986	0.667	0.871	0.903

Table Notes: The coefficient table corresponds to Figure C.5.
† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C.2.8 Employment: IPW

Table C.10 shows estimates of the model in Equation 3.3 using inverse propensity score weighting. The outcomes are computed using STATENT data across 2-digit ISIC industries in 2015. The treatment is defined in the usual way. Propensity scores are estimated using a binary logit model and the standard errors are computed using the bootstrap with 200 repetitions. Columns (1) to (4) show the resulting estimates of the employment share in accommodation, gastronomy, retail and agriculture, respectively. All estimates are around the same size as in the main specification in Table 3.3.

Table C.10: Association of ski area access with employment shares in 2015 using inverse propensity score weighting

Dependent variable:	Accommodation [%]	Gastronomy [%]	Retail [%]	Agriculture [%]
	(1)	(2)	(3)	(4)
Ski area access	0.048^{**}	0.023^{*}	0.007	-0.093^{***}
	(0.017)	(0.011)	(0.009)	(0.026)
Intercept	0.095^{***}	0.058^{***}	0.046^{***}	0.262^{***}
	(0.013)	(0.008)	(0.008)	(0.022)
N units with access	94	94	94	94
N units w/o access	133	133	133	133
N overall	211	211	211	211

Table Notes: The table depicts estimates of the ATT using inverse propensity score weighting in the model of Equation 3.3. The propensity score is estimated using a logit model with the road distance to the next cantonal center, the Euclidean distance to the next lake, the developable land measure and the sunshine exposure of the developable land as independent variables. The outcomes are the share of accommodation employment (1), the share of gastronomy employment (2), the share of retail employment (3) and the share of agriculture employment (4) of all employed persons in full-time equivalents in 2015. Standard errors are in parentheses and are computed using the bootstrap with 200 repetitions.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C.2.9 Employment: Other Sectors

Table C.11 depicts OLS estimates of the model in Equation 3.3 using STATENT data up across 2-digit ISIC industries in 2015. Column (1) shows estimates of employment shares in forestry. Access municipalities have, on average, the same share of employed full-time equivalents as municipalities without access relative to an employment share of 0.5%. Likewise, columns (2) and (3) show null results for employment shares in manufacturing and retail. Therefore, increases in tourism-related services do not produce spillovers to unrelated industries within the access municipalities. It is still possible that such effects disperse across municipalities of both treatment statuses.

Table C.11: Association of ski area access with employment shares in 2015

Dependent variable	Forestry [%]	Manufacturing [%]	Construction [%]
	(1)	(2)	(3)
Ski area access	-0.000	-0.009	-0.004
	(0.002)	(0.012)	(0.016)
Intercept	0.005^{***}	0.100^{***}	0.158^{***}
	(0.001)	(0.009)	(0.012)
N units with access	94	94	94
N units w/o access	133	133	133
N overall	227	227	227
R^2	0.000	0.002	0.000

Table Notes: The table depicts OLS estimates of the model in Equation 3.3. In particular, the average association of access to a ski area between 1940 and 1982 with the share of forestry and logging employment (column (1)), the share of manufacturing employment (column (2)) and the share of construction employment (column (3)) of all employed in full-time equivalents in 2015. The intercepts are equivalent to the employment shares of the respective sector without ski area access. Standard errors are clustered at the municipality level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C.2.10 Agricultural Land Use

In this section, we check in detail how the negative association with the agriculture employment share in 2015 affects land use in access municipalities compared to those without access over time. We use land use data from the area statistics of the FSO. The data allocate each 100-by-100 meter pixel to a certain land use out of 72 categories.

Figure C.6 shows OLS estimates of the model in Equation 3.3. It indicates that in access municipalities, on average, 6.5 p.p. more land is allocated to alpine agriculture relative to a share of 11.7% in municipalities without access. On the contrary, access municipalities allocate 6.4 p.p. less land to valley bottom agriculture relative to a share of 18.0% in municipalities without access. The agricultural land use remains constant over the observed period. Assuming little technological advances in agricultural production would suggest that employment effects have not substantially changed since 1985.

These results suggest that alpine agriculture complements ski areas on the supply side because the alpine meadows and pastures used in summer for agricultural purposes can easily be used for skiing terrain in winter. Moreover, alpine agriculture also complements ski areas in labor demand. Alpine farmers are known to work in ski areas in winter. In a survey, 64% of alpine farmers in Grisons and 51% in the Bernese Highlands state that they earn off-farm income from winter tourism (Behringer et al., 2000).

Figure C.6: Association of ski area access with agricultural land use

(a) Alpine agriculture (b) Valley bottom agriculture

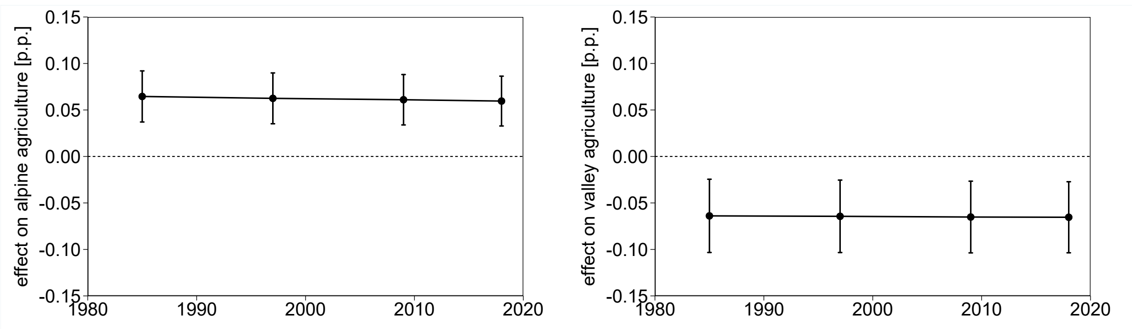


Figure Notes: The points indicate OLS estimates of the model in Equation 3.3. In particular, the average association of access to a ski area between 1940 and 1982 with the average share of alpine agriculture, including alpine meadows and favorable alpine pasture (left panel) and the average share of valley bottom agriculture (right panel). The access municipalities number to $n = 94$ and the control group municipalities to $n = 133$. Standard errors are clustered on the municipality level. The point estimates and standard errors follow in Table C.12.

Table C.12: The association of ski area access with agricultural land use

Dependent variable:	Alpine agriculture [%] (a)	Valley bottom agriculture [%] (b)
Ski area access 1985	0.065***	−0.064**
	(0.014)	(0.020)
Ski area access 1997	0.062***	−0.064**
	(0.014)	(0.020)
Ski area access 2009	0.061***	−0.065**
	(0.014)	(0.020)
Ski area access 2018	0.060***	−0.065***
	(0.014)	(0.019)
Year fixed effect 1985	0.117***	0.180***
	(0.009)	(0.018)
Year fixed effect 1997	0.113***	0.176***
	(0.009)	(0.017)
Year fixed effect 2009	0.110***	0.173***
	(0.009)	(0.017)
Year fixed effect 2018	0.107***	0.171***
	(0.009)	(0.017)
N overall	908	908
R^2	0.657	0.463

Table Notes: The coefficient table corresponds to Figure C.6.
† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C.2.11 Other Land Use

Figure C.7 shows OLS estimates of the model in Equation 3.3. It indicates statistically significant associations for service, mixed and unspecified buildings, camping sites, Alpine sports infrastructure and landscape interventions. As expected, all are closely related to tourism-related service industries. More strikingly, the land use estimates show barely any changes during the expansion and concentration phase. Thus, ski area access did not induce any significant land use changes across municipality types after 1985.

Table C.13: The association of ski area access with land use

Dependent variable:	Industry & comm. (a)	Housing (b)	Public buildings (c)	Service & unspec. (d)
Ski area access 1985	−0.00017	0.00058	−0.00011	0.00045†
	(0.00013)	(0.00151)	(0.00014)	(0.00027)
Ski area access 1997	−0.00025	0.00023	−0.00014	0.00049†
	(0.00017)	(0.00196)	(0.00016)	(0.00027)
Ski area access 2009	−0.00028	0.00036	−0.00025	0.00050†
	(0.00018)	(0.00235)	(0.00017)	(0.00027)
Ski area access 2018	−0.00027	0.00100	−0.00028	0.00054*
	(0.00021)	(0.00301)	(0.00017)	(0.00027)
Year fixed effect 1985	0.00063***	0.00662***	0.00060***	0.00098***
	(0.00011)	(0.00113)	(0.00010)	(0.00014)
Year fixed effect 1997	0.00087***	0.00898***	0.00070***	0.00109***
	(0.00015)	(0.00155)	(0.00012)	(0.00013)
Year fixed effect 2009	0.00093***	0.01055***	0.00082***	0.00106***
	(0.00015)	(0.00185)	(0.00013)	(0.00014)
Year fixed effect 2018	0.00102***	0.01195***	0.00087***	0.00104***
	(0.00018)	(0.00212)	(0.00014)	(0.00013)
N overall	908	908	908	908
R^2	0.232	0.242	0.226	0.318

Table Notes: The coefficient table corresponds to panels (a) to (d) in Figure C.7.
† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure C.7: Association of ski area access with land use

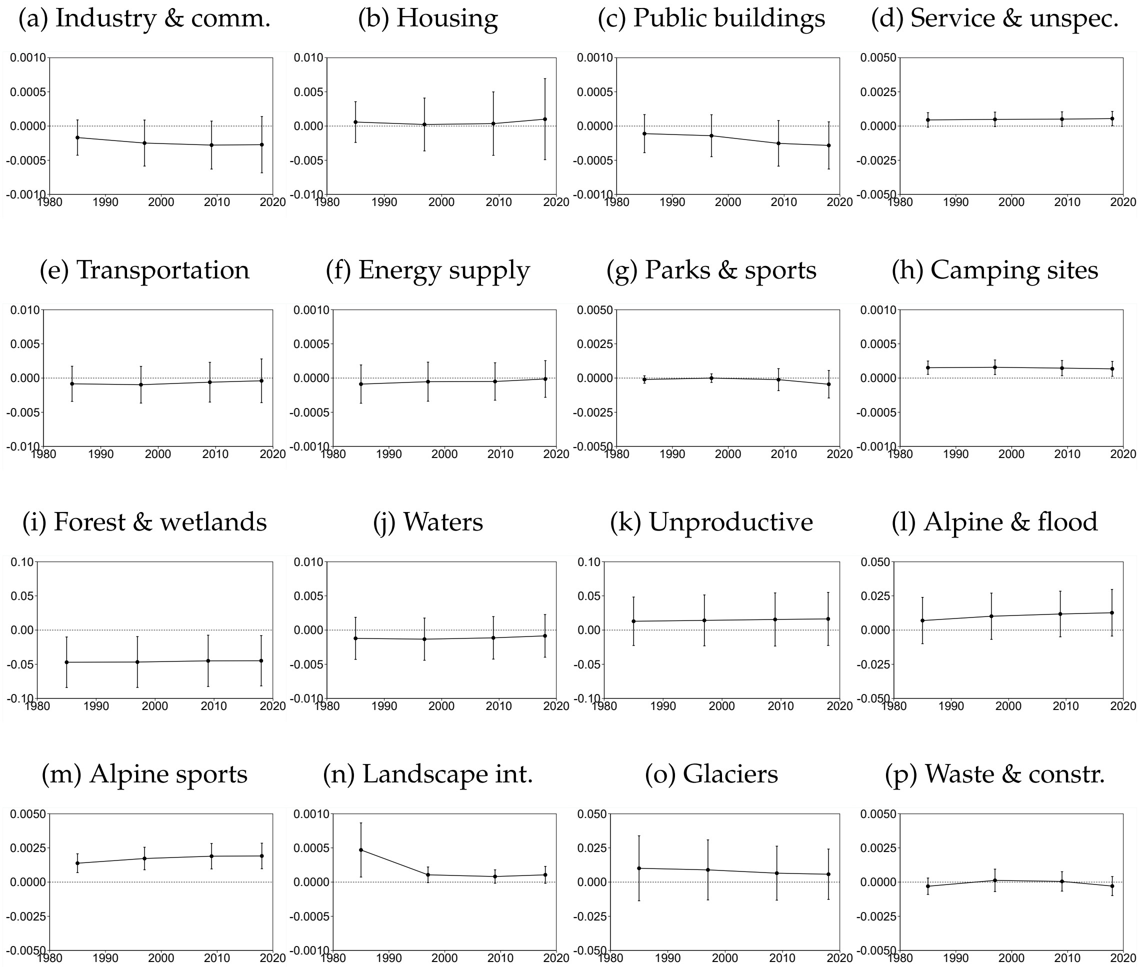


Figure Notes: The points indicate OLS estimates of the model in Equation 3.3. In particular, the average association of access to a ski area between 1940 and 1982 with the average share of the respective land use. The access municipalities number to $n = 94$ and the control group municipalities to $n = 133$. Standard errors are clustered on the municipality level. The point estimates and standard errors follow in Table C.13, C.14, C.15 and C.16.

Table C.14: The association of ski area access with land use

Dependent variable:	Transportation (e)	Energy supply (f)	Parks & sports (g)	Camping sites (h)
Ski area access 1985	-0.00084	-0.00009	-0.00011	0.00015^{**}
	(0.00130)	(0.00014)	(0.00014)	(0.00005)
Ski area access 1997	-0.00097	-0.00005	-0.00000	0.00016^{**}
	(0.00136)	(0.00014)	(0.00016)	(0.00005)
Ski area access 2009	-0.00061	-0.00005	-0.00012	0.00015^{*}
	(0.00147)	(0.00014)	(0.00041)	(0.00006)
Ski area access 2018	-0.00040	-0.00001	-0.00045	0.00013^{*}
	(0.00162)	(0.00014)	(0.00051)	(0.00006)
Year fixed effect 1985	0.01045^{***}	0.00035^{**}	0.00043^{**}	0.00007^{**}
	(0.00076)	(0.00011)	(0.00013)	(0.00002)
Year fixed effect 1997	0.01175^{***}	0.00035^{**}	0.00059^{***}	0.00008^{**}
	(0.00083)	(0.00011)	(0.00014)	(0.00002)
Year fixed effect 2009	0.01218^{***}	0.00034^{**}	0.00114^{**}	0.00012^{***}
	(0.00082)	(0.00011)	(0.00037)	(0.00003)
Year fixed effect 2018	0.01255^{***}	0.00034^{***}	0.00152^{**}	0.00012^{***}
	(0.00084)	(0.00010)	(0.00048)	(0.00003)
N overall	908	908	908	908
R^2	0.554	0.082	0.096	0.176

Table Notes: The coefficient table corresponds to panels (e) to (h) in Figure C.7.
† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.15: The association of ski area access with land use

Dependent variable:	Forest & wetlands (i)	Waters (j)	Unproductive (k)	Alpine & flood (l)
Ski area access 1985	-0.04705^{*}	-0.00121	0.01286	0.00696
	(0.01875)	(0.00156)	(0.01797)	(0.00860)
Ski area access 1997	-0.04673^{*}	-0.00133	0.01415	0.01011
	(0.01888)	(0.00157)	(0.01889)	(0.00857)
Ski area access 2009	-0.04500^{*}	-0.00114	0.01549	0.01174
	(0.01903)	(0.00158)	(0.01970)	(0.00846)
Ski area access 2018	-0.04485^{*}	-0.00085	0.01630	0.01266
	(0.01865)	(0.00158)	(0.01967)	(0.00864)
Year fixed effect 1985	0.30144^{***}	0.01219^{***}	0.18196^{***}	0.09969^{***}
	(0.01361)	(0.00116)	(0.01273)	(0.00639)
Year fixed effect 1997	0.31341^{***}	0.01226^{***}	0.18531^{***}	0.09803^{***}
	(0.01381)	(0.00116)	(0.01331)	(0.00626)
Year fixed effect 2009	0.32162^{***}	0.01250^{***}	0.18724^{***}	0.09575^{***}
	(0.01399)	(0.00118)	(0.01377)	(0.00613)
Year fixed effect 2018	0.32217^{***}	0.01250^{***}	0.19364^{***}	0.09504^{***}
	(0.01377)	(0.00119)	(0.01370)	(0.00621)
N overall	908	908	908	908
R^2	0.808	0.490	0.642	0.704

Table Notes: The coefficient table corresponds to panels (i) to (l) in Figure C.7.
† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.16: The association of ski area access with land use

Dependent variable:	Alpine sports (m)	Landscape int. (n)	Glaciers (o)	Waste & constr. (p)
Ski area access 1985	0.00138***	0.00047*	0.01008	−0.00030
	(0.00035)	(0.00020)	(0.01205)	(0.00030)
Ski area access 1997	0.00172***	0.00011†	0.00892	0.00012
	(0.00042)	(0.00006)	(0.01114)	(0.00042)
Ski area access 2009	0.00189***	0.00008	0.00652	0.00005
	(0.00047)	(0.00005)	(0.01001)	(0.00036)
Ski area access 2018	0.00191***	0.00011†	0.00574	−0.00029
	(0.00047)	(0.00006)	(0.00933)	(0.00035)
Year fixed effect 1985	0.00007*	0.00033***	0.03792***	0.00208***
	(0.00003)	(0.00007)	(0.00818)	(0.00026)
Year fixed effect 1997	0.00010*	0.00019***	0.03211***	0.00178***
	(0.00004)	(0.00004)	(0.00748)	(0.00019)
Year fixed effect 2009	0.00008**	0.00012***	0.02692***	0.00173***
	(0.00003)	(0.00003)	(0.00688)	(0.00021)
Year fixed effect 2018	0.00008**	0.00014***	0.02410***	0.00192***
	(0.00003)	(0.00003)	(0.00646)	(0.00027)
N overall	908	908	908	908
R^2	0.161	0.169	0.154	0.323

Table Notes: The coefficient table corresponds to panels (m) to (p) in Figure C.7.
† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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Declaration of Authorship

I declare herewith that I wrote this thesis on my own, without the help of others. Wherever I have used permitted sources of information, I have made this explicitly clear within my text and I have listed the referenced sources. I understand that if I do not follow these rules that the Senate of the University of Bern is authorized to revoke the title awarded on the basis of this thesis according to Article 36, paragraph 1, litera o of the University Act of September 5th, 1996.

Selbständigkeitserklärung

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Pascal Troxler