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The Investment Competition among Swiss Ski Areas

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Abstract

In recent years, ski area operators in Switzerland have faced a decreasing demand due to climate change, exchange rate pressure and demographical changes among other factors. At the same time, ski lift and snowmaking capabilities have increased – partly with financial aid from public funds. It is therefore crucial to find out how much ski area investments retain demand and affect the competition for the remaining guests. We link firm-level data from ski areas to natural snowpack data and use Two-Way Fixed Effect (TWFE) estimators to study (i) how ski areas lower their dependency on natural snow by investing in snowmaking facilities, (ii) the effect of ski lift investments on skiing demand and revenue and (iii) the impact of lift investments on the spatial competition between neighboring ski areas. We find that ski areas with above-median snowmaking capabilities lower their dependency on natural snow by two-thirds. Ski lift investments induce a one-time positive average effect of 4.1% on demand and 1.9% on revenue in the winter following the construction. Finally, we document negative effects of ski lift expansions of neighboring areas within a road distance of up to 50 kilometers on demand.

Key words: Ski area operators, investment competition, ski area expansion, ski lift replacement, snowmaking, spatial competition, tourism

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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; Troxler et al., 2023). 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 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.

Figure 1: Development of ski area supply and demand

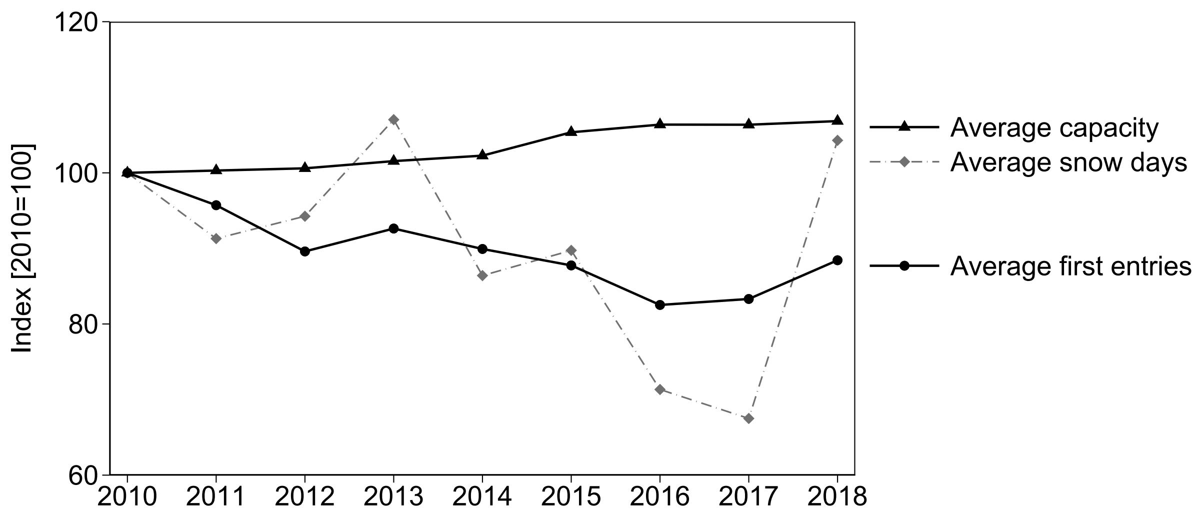

Figure Notes: Average ski area capacities (data from *bergbahnen.org*, measured as persons per hour transported times vertical kilometers) and first entries (data from Seilbahnen Schweiz (SBS) and annual reports of ski area operator firms) of a balanced panel with 46 Swiss ski areas and their mean consecutive 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.

[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).

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 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.

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

[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).

[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).

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, 2022; 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

[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 causing an increase in demand.

[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.

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 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; Troxler et al., 2023; Wallimann, 2022) 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

[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).

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 the use of road distances, using various novel data sources and applying this to the case of Switzerland.

We continue by providing background information in Section 2 and present the data in Section 3. Then, we show our empirical and identification strategy in Section 4 that we use to compute the results in Section 5. Finally, we discuss our findings in Section 6 and conclude in Section 7.

2 Background

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 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 4.2.2 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 C.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 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

[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).

takes around 10 months. If the project surpasses that phase, it enters the plan approval phase of another 9 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.

3 Data

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 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. 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 where 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.

Table 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, mostly replacement lifts) and 10 at the extensive margin (expanding the ski area to new terrain,

[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 A.1 for details.

Figure 2: Ski areas in Switzerland and coverage of samples

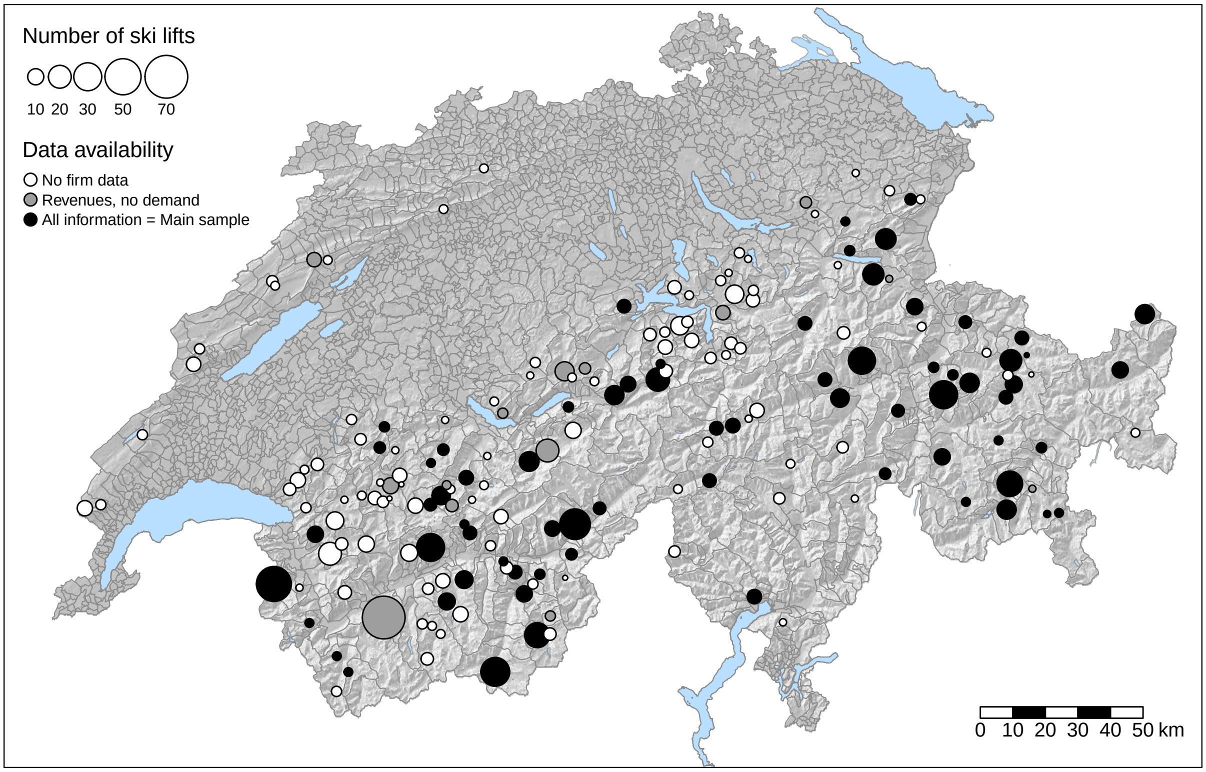

Figure Notes: Points indicate the centroid (in 2009) of Swiss ski areas. The point size depicts the number of ski lifts per ski area in 2018. Black points show ski areas from which all data is available (including revenue and demand data from SBS) and correspond to the main sample. Grey points show areas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

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 C.5.

[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).

Table 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.

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 and capacity. Because we are interested in local competition, we identify ski lift investments at 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 Troxler et al., 2023, 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.

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 4 in Appendix A.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

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

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 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 A.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 A.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 C.10, where we change the baseline level to see whether this assumption drives the results.

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

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

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 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 a recent project from Troxler, 2023). 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 A.6 for a detailed description of how the weather index is constructed.

3.5 Summary Statistics

We provide summary statistics of the main sample in Table 2. It shows statistics for different variables with a mean comparison in the last column to check the sample's representativeness.

[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 A.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 C.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.

Table 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**
Neighboring ext. investments, 0-25km [#]	1,849	0.02	581	0.02	0.17	0.00	2.00	0.01
Neighboring ext. investments, 25-50km [#]	1,849	0.06	581	0.08	0.31	0.00	3.00	0.02
Neighboring int. investments, 0-25km [#]	1,849	0.32	581	0.32	0.69	0.00	4.00	0.00
Neighboring int. investments, 25-50km [#]	1,849	0.83	581	0.98	1.36	0.00	11.00	0.15**
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 Switzerland. In other words, the results are more valid for ski areas that actually invest frequently.

[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.

4 Method

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:

$$\ln Y_{it} = \alpha_i + \delta S_{it} + \eta W_{it} + \theta_t + \varepsilon_{it}, \tag{1}$$

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 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 specification (1) to estimate whether ski areas with a high snowmaking capability can reduce their dependency on natural snow. In particular, we estimate

$$\ln Y_{it} = \alpha_i + \delta_0 S_{it} + \sum_{g=1}^{G} \delta_g D_g S_{it} + \eta W_{it} + \theta_t + \varepsilon_{it}, \tag{2}$$

where all parameters and variables are defined as in (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

[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 C.6 and report no change in the results.

[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

low tendency to produce snow and whether this reduces natural snow dependency.

4.2 Lift Investments

4.2.1 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

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

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 (1). The binning at the endpoints is crucial because we assume that treatment effects remain constant beyond the event window. The maximum 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,

$$C_{i,t-k} = \begin{cases} \sum_{s=-\infty}^{-3} c_{i,t-s}, & \text{if } k = -3 \\ c_{i,t-s}, & \text{if } -3 < k < 5 \\ \sum_{s=5}^{\infty} c_{i,t-s}, & \text{if } k = 5, \end{cases} \tag{4}$$

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 A.9. For our last objective, the effect of neighboring investments on ski area outcomes, we add the investments at neighboring ski areas to (3) using four road distance rings r. This yields

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

facilities when they have a high chance of reducing natural snow dependency.

where all coefficients and variables are defined as in (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 (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 ($\tilde{C}^{ext}_{irt}$) and new ski lifts without such an expansion ($\tilde{C}^{int}_{irt}$).

All estimates in (3) and (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 (3) and (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

[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.

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.

By estimating (3), we are confident in identifying a causal effect of lift investments (and accompanying infrastructure) on the outcome. Thus, in the following section, we discuss all the assumptions we impose for identifying such an effect.

4.2.2 Identification

In this section, we address the assumptions for the identification of β_k in specification (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 (Schmidheiny & Siegloch, 2023).

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 2.1). 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 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 C.2 for the empirical evidence on this).

To illustrate this, consider Figure 3. It shows the number of replaced lifts and their concession status across the development periods of ski areas (see Troxler et al., 2023, for a detailed description of those periods). In the aggregate, 71% of concessions of all ever-replaced lifts in

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

ski areas were initially prolonged. That figure changed from 43% to 74% to 87% 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 3: Concession status of replaced lifts at replacement

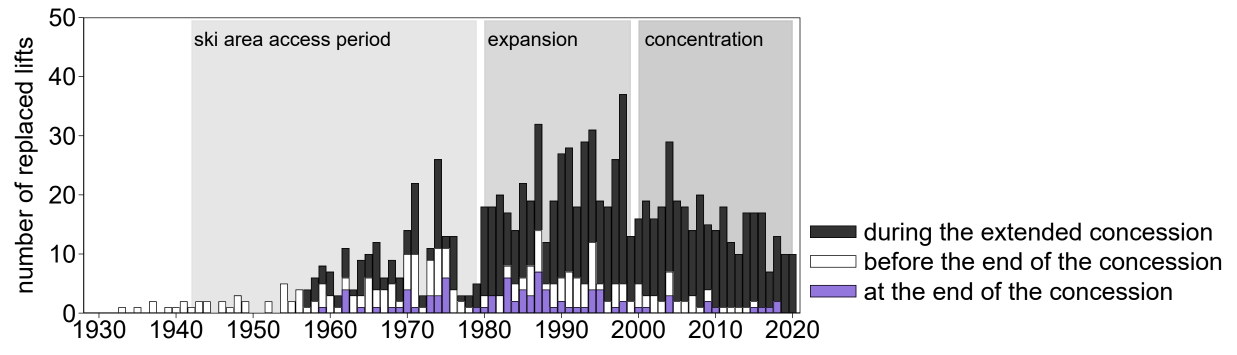

Figure Notes: A concession of a large lift is granted for 25 years (covers most lifts) and for 10 years for a small lift (covers ground-based lifts such as t-bars and very small cablecars with a capacity of maximum 8 persons per direction of travel, see Swiss Federal Council, 2020). At the end of the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

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 5.2). Including all our sensitivity checks, we estimate more than twenty event studies and find not a single pre-treatment effect 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.

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 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 run specification (3) without ski areas that implemented substantial season-pass discounts or dynamic pricing in Appendix C.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.

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 is a direct violation of SUTVA. We show in Section 5.3 that neighboring ski lift investments do not affect ski area outcomes on average.

[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.

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.

Treatment Homogeneity

In our main specification (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 & 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 C.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 C.8 for results on this.

[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).

5 Results

5.1 Natural Snow Dependency

In Table 3, we show Ordinary Least Squares (OLS) estimates of specification (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 (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 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 specification (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 3, we show OLS estimates from (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 (2) and recover partial effects for each group g.[27] The group estimates are depicted in Figure 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 is statistically insignificant for the ski areas above the third quartile. Thus, variations in natural snow days still positively affect 75% of the sampled ski areas.

Figure 4: Effect of natural snow days on winter outcomes across snowmaking capability

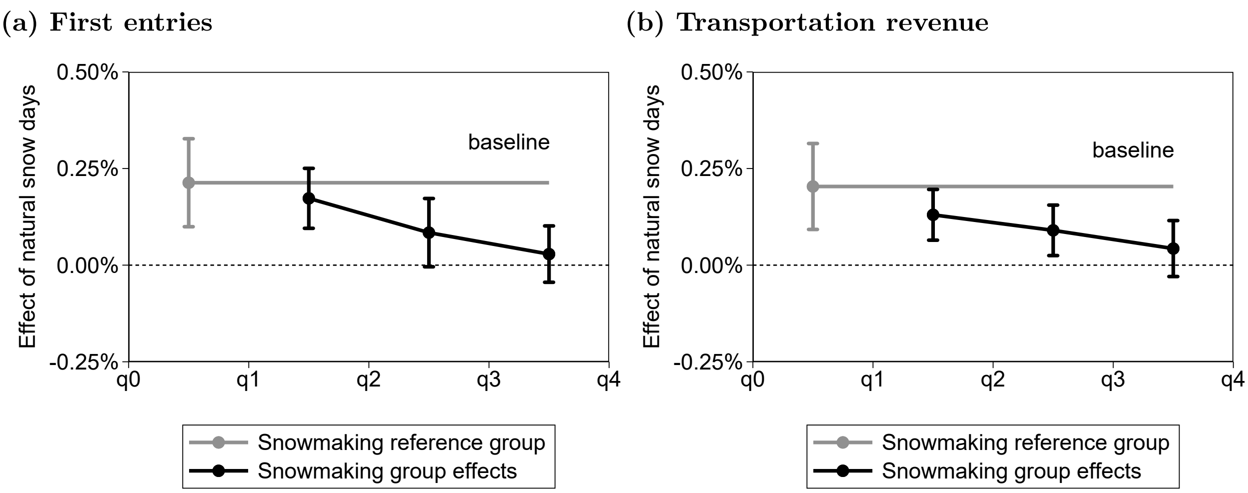

Figure Notes: Each point depicts group estimates of specification (2) across snowmaking capability groups split at quartiles. In particular, the first point from left (grey) depicts the point estimate of consecutive snow days for the reference group (below the first quartile) and the other points (purple) 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 $D_2 = \mathbb{1}[snowmaking \in (q2, q3]]$). 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.1.

Panel (b) in Figure 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

[27] The partial effect is the partial derivative of the expected value of (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 $g = 1$.

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 3 as well as in the two regressions in Figure 4 (and the corresponding coefficient table in Appendix B.1). Thus, the weather conditions do not affect seasonal ski area outcomes, all else being equal.

5.2 Lift Investments

Figure 5 depicts the results from specification (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.

Figure 5: Effect of new ski lifts on first entries and transportation revenue

(a) First entries **(b) Transportation revenue**

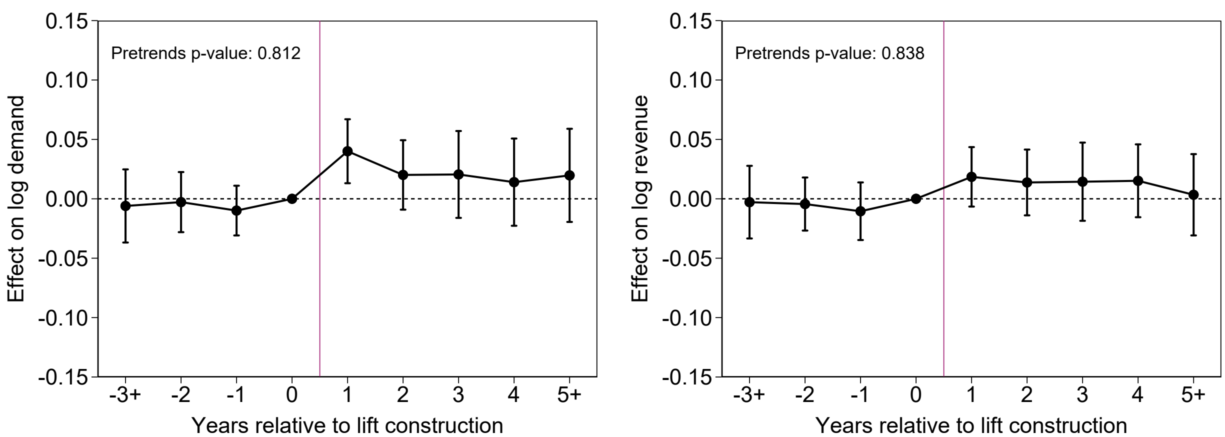

Figure Notes: Both panels show estimates of specification (3) across time. Period 0 indicates the winter before the lift construction (which is in the same year) and period 1 the winter of the lift opening. Panel (a) shows the estimates with the log of winter first entries as the outcome using the unbalanced 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.

In panel (b) of Figure 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 areas increase their transportation revenues after a lift investment.[28]

When we estimate (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 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.

Figure 6: Effect of new ski lifts on first entries by guest type

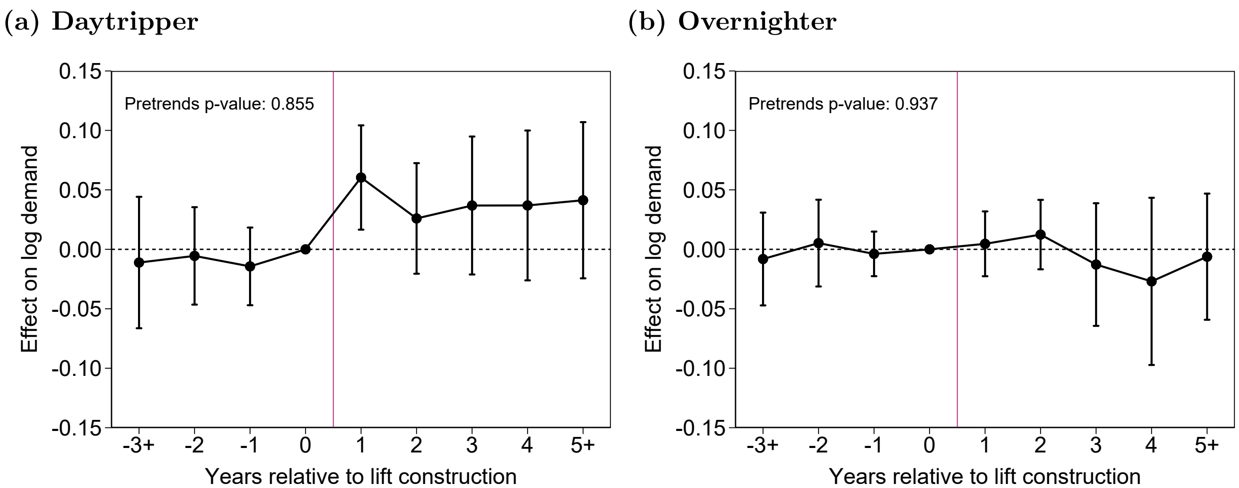

Figure Notes: Both panels show estimates of specification (3) across time. Period 0 indicates the winter before the lift construction (which is in the same year) and period 1 the winter of the lift opening. Panel (a) shows the estimates with the log of winter first entries from daytrippers as the outcome 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.

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.

5.3 Neighboring Lift Investments

We estimate specification (5) including neighboring ski lift investments distinguished by road distance rings of 25 kilometers. Figure 7 depicts the results. Panel (a) shows the

[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 C.5 for these results and coefficient tables.

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.

Figure 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**

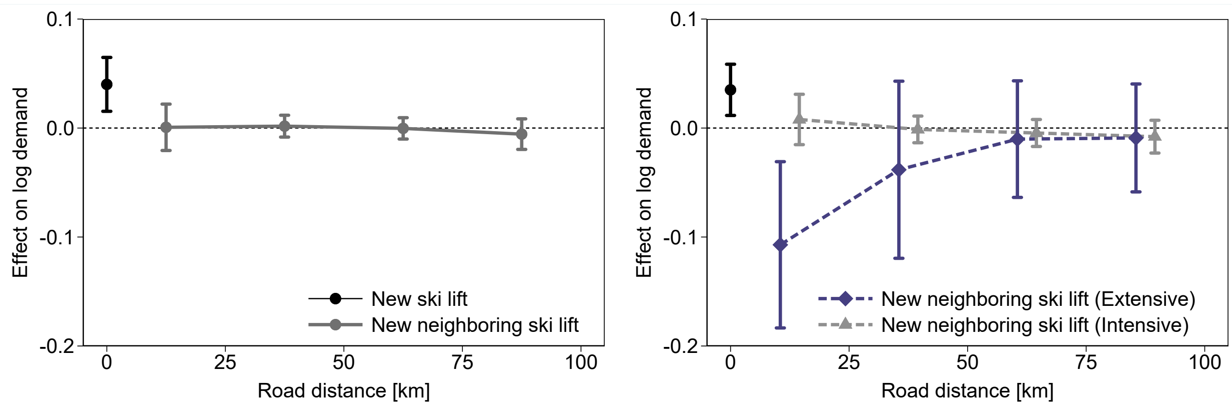

Figure Notes: The plots show point estimates and 95% confidence intervals of the first lags in specification (5). The horizontal axis indicates the four road distance rings of 25 kilometers each. The road distances are calculated using the closest two access points between each ski area pair. Panel (a) 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.3.

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 7 depicts. It also shows that expansions affect neighbors negatively up to 50km before the point estimate decays to almost zero in the 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 C.11). Second, extensive expansions occur in relatively large ski areas typically surrounded by smaller ski areas. The smaller relative effects in large areas

[29]Notice that we estimate the effects of neighboring ski area expansions relatively imprecise compared to those without expansions because we document only 9 extensive ski lift investments between 2009 and 2018 in our main sample. In Appendix C.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.

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]

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.

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.

[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.

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 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.

8 Literature

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Appendix

A Data Processing

A.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 A of a parallel project in which we look at the historical development of ski areas and their relation to the local economic growth (Troxler et al., 2023).

Similar to Troxler et al. (2023), 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.[31] 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.

[31] 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.

A.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.[32]

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. Because we are primarily interested in having a measurement that allows us to differentiate between actual travel distances rather than Euclidean distances, the assumption is not far-fetched. Euclidean distances suffer the problem, that they do not incorporate 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.

A.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.[33] We keep those areas as separate entities but remove them as neighbors because investments happen in their own area rather than in a neighboring area.

A.4 Firm Data

The firm data consists of yearly survey data of ski area operator firms conducted by SBS. It represents to a large extent 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

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

[33] 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 2017/2018. However, these investments show still up as leads in our empirical model.

manually adjust data with annual reports found on the web. All reports used are listed in Table 4. 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[34] of which we try to get the most comprehensive coverage. These are consistently reported across firms and show quite good 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 $1,000$.

[34] 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 (making the assumption 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.

Table 4: 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 the website 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.

A.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 that are not published yet. 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 A.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 that contains the centroid of Zermatt 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

$$x^m_{at} = x_{at} - (x_{at} \mod 1000) + 500 \tag{6}$$

$$y^m_{at} = y_{at} - (y_{at} \mod 1000) + 500. \tag{7}$$

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 turn out to be at the bottom of the valley. To address this, we first match the grid midpoints to a 3-dimensional shapefile from the Federal Office of Topography (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 out 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 that lies 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 for our purpose sufficiently accurate 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 which corresponds to a median density of snow 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 such that they 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).

A.6 Weather Index

To construct the weather index, we start at the daily weather index by Troxler (2023). It is close to the definition in Section 3.4 of his paper 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. We refrain from using precipitation data in this paper as it correlates strongly with the snowpack of a ski area. As we want to control for weather conditions bar the snow conditions, we do not use precipitation data.

The following steps lead to the weather index:

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 the partial index for sunshine duration is left as obtained from the raw data.

4. We take data from Troxler (2023) and regress daily ski 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. We construct the daily weather index by Troxler (2023) 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 187 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 Troxler (2023), Appendix A.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 use daily data (including the night) to construct our index. 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 (Malasevska et al., 2017; Troxler, 2023). That is, an optimal skiing temperature. We use estimates from the Appendix of Troxler (2023) (Tables 7 to 9) of each of the three areas to calculate optimal skiing temperatures (using Equation (23) in his paper). We find an optimal minimum temperature for area 1 at -3.3°C at 2,002 m.a.s.l., for area 2 at -6°C at 1,766 m.a.s.l. and for area 3 -2.55°C at 1,283 m.a.s.l. Using the thumb rule of temperature gradients across altitudes,[35] we find optimal temperatures at the area centroids in the year 2010 is -3.16, -8.52 and -5.83°C for the three areas. From this we simply conclude that the optimal minimum temperature for skiing, regardless of the altitude, lies somewhere between -3.2 and -8.5°C. Thus, we slightly adapt the partial temperature index from Troxler (2023) to

$$\widetilde{\underline{temp}}_t = \begin{cases} 100, & \text{if } \underline{temp}_t = [-3.2, -8.5] \\ 100 - (|-8.5 - \underline{temp}_t|) * 10, & \text{if } \underline{temp}_t < -8.5 \text{ and } |-8.5 - \underline{temp}_t| \leq 10 \\ 100 - (|-3.2 - \underline{temp}_t|) * 10, & \text{if } \underline{temp}_t > -3.2 \text{ and } |-3.2 - \underline{temp}_t| \leq 10 \\ 0, & \text{otherwise.} \end{cases} \tag{8}$$

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 Troxler (2023) 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 5.

[35] 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)

Table 5: 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 Troxler (2023).
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The daily weather index is then computed using

$$\tilde{W}_{idt} = \omega Sun_{idt} + (1 - \omega) Temp_{idt} \tag{9}$$

where $\omega = 0.0081/(0.0057 + 0.0081) = 0.59$ is computed using the coefficients on the two respective partial indices in Table 5.

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 5. 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.

A.7 Remoteness Measure

To perform a decomposition of the ski area demand into overnighers and daytrippers (see Appendix A.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 that are labeled by two towns, we simply 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.[36] 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

$$daytrip_i = \sum_{j=1}^{J} \frac{pop_j}{\min t_{ij}} \tag{10}$$

where i is a ski area, j is an agglomeration center, pop indicates the population of the agglomeration in 2009[37] 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 for each access point averaged across the two figures. When an area can be accessed by more than one access point then we take always the shorter travel time as travel time to that area.

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

$$rmte_i^h = \frac{1}{daytrip_i} \Big/ \max_{i \in n}(daytrip_i). \tag{11}$$

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

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

[37] 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.

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,

$$rmte_i^m = rmte_i^h - \left(\frac{\min_{i \in n}(rmte_i^h)}{2}\right) \tag{12}$$

$$rmte_i^l = rmte_i^h - \min_{i \in n}(rmte_i^h). \tag{13}$$

The summary statistics of the three remoteness measures are shown in Table 6. 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.[38] The other two measures are used in Appendix C.10.

Table 6: 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.

A.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 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 for each area the demand composition at each area split by overnighters and daytrippers.

[38] Two reasons speak for a rather high daytripper share compared to the overnighter share. First, notice that in the demand decomposition (see Appendix A.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 fails most certainly.

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 other hand, 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. (so far you used first entries from winters for this, maybe use overall first entries).

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

$$D_{it} = A_{it} + B_{it} \tag{14}$$

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. Making the assumption 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

$$\underbrace{\frac{D_t - D_{t-1}}{D_{t-1}}}_{=\Delta D} = (1-\omega)\underbrace{\frac{A_t - A_{t-1}}{A_{t-1}}}_{=\Delta A_t} + \omega \underbrace{\frac{B_t - B_{t-1}}{B_{t-1}}}_{\Delta B_t} \tag{15}$$

where $\omega = \frac{B_{t-1}}{D_{t-1}}$ is the initial share of overnighters.[39] We set ω to be equal to the lower remoteness measure, i.e. $\hat{\omega} = rmte^l$ (see in Appendix A.7 how it is derived). We conduct sensitivity checks in all results depending on other evaluations of ω (see Appendix C.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.

A.9 Data Example of the Event Window

[39] 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 (15) and rearrange until your left with $\frac{D_t - D_{t-1}}{D_{t-1}}$.

Table 7: **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 Coefficient Tables

B.1 Natural Snow Dependency

Table 8: 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 4. Standard errors are in parentheses and clustered at the ski area level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

B.2 Lift Investments

Table 9: 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 5 and Figure 6. Standard errors are in parentheses and clustered at the ski area level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

B.3 Neighboring Lift Investments

Table 10: 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 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 11: 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 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.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

C Additional Empirical Results

C.1 Samples

In the following results, we use a large variety of different 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 taking part in price competition), or because we look at other time spans (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 12, we show the coverage of all samples used in the remainder and is analog to

Table 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). In rows (4) and (6) these two samples are balanced. This is achieved by first 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 12: 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	C.3, C.4, C.10, C.11, C.12
(3)	[2009 – 2018] Revenue unbalanced	739	83	8.9	112	9	103	74.4	C.5
(4)	[2010 – 2018] Revenue balanced	558	62	9.0	78	5	73	59.0	C.5, C.8
(5)	[2009 – 2018] Demand unbalanced	592	72	8.2	84	9	75	63.1	C.5
(6)	[2010 – 2018] Demand balanced	405	45	9.0	59	5	54	46.2	C.5, C.8
(7)	[2009 – 2018] No price	543	72	7.5	73	6	67	63.1	C.6
(8)	[2009 – 2018] Demand no m. treatments	299	38	7.9	17	0	17	18.6	C.7
(9)	[2009 – 2018] Demand no gaps	534	62	8.6	74	9	65	54.7	C.7
(10)	[2009 – 2018] No mergers	540	67	8.1	68	3	65	56.5	C.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 that are known to take part in dynamic pricing, and substantial season discounts for single passes or for multiple area 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 C.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.

C.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

$$y_{kit} = S'_{it-3}\beta + \delta z_{kit} + \alpha_i + \theta_t + \varepsilon_{kit}, \tag{16}$$

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 (16) as logit. In particular, we estimate

$$Pr(y_{kit} = 1 | S'_{it-3}, z_{kit}, \alpha_i, \theta_t) = \frac{exp(S'_{it-3}\beta + \delta z_{kit} + \alpha_i + \theta_t)}{1 + exp(S'_{it-3}\beta + \delta z_{kit} + \alpha_i + \theta_t)} \tag{17}$$

where all variables and coefficients are defined as in (16).

In Table 13, 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 14 shows the Pseudo Maximum Likelihood Estimates (PMLE) of the logit specification (17). It shows quantitatively and qualitatively the same results as with 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 13: 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 (0.003)	0.002 (0.003)	0.001 (0.003)	0.001 (0.003)			
Snow days (t-1)		−0.000 (0.003)	0.000 (0.003)	0.000 (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*** (0.003)	0.033*** (0.003)	0.033*** (0.003)	0.033*** (0.003)	0.033*** (0.003)	0.033*** (0.003)	0.033*** (0.003)
Intercept	0.044*** (0.006)	0.056*** (0.008)	0.073*** (0.010)	0.084*** (0.011)	0.056*** (0.008)	0.072*** (0.011)	0.082*** (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 (16). 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 is operating with an extended concession and zero when the lift is operating 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 14: 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 (17). 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 is operating with an extended concession and zero when the lift is operating with the original concession. Standard errors are in parentheses and clustered at the ski area level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C.3 Natural Snow Dependency With Lower Snow Density

As discussed in Section 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 8 and Table 15. 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 5.1.

Figure 8: Effect of natural snow days on winter outcomes across snowmaking capability with a natural snow density of 190kg/m^3

(a) First entries **(b) Transportation revenue**

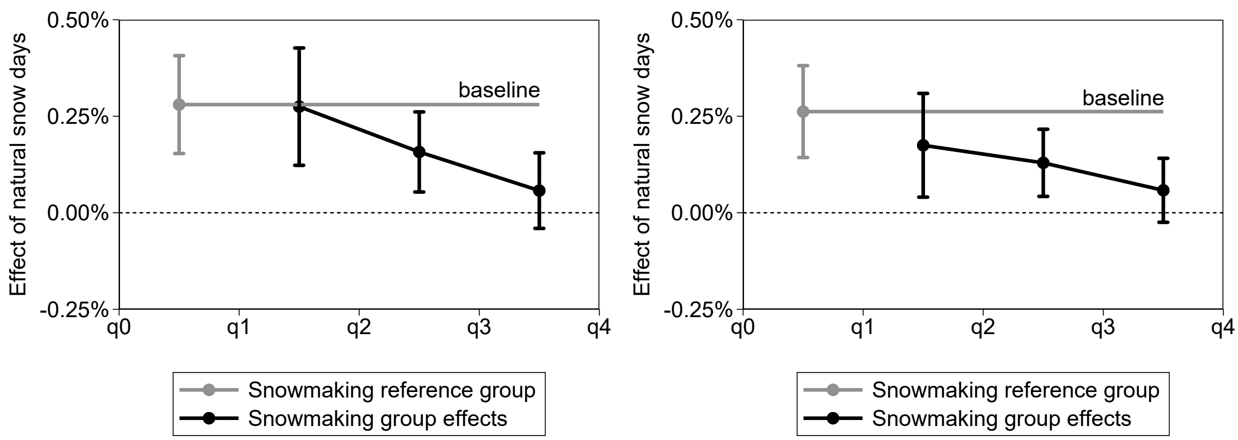


Figure Notes: Each point depicts group estimates of specification (2) across snowmaking capability groups split at quartiles. In particular, the first point from left (grey) depicts the point estimate of consecutive snow days for the reference group (below the first quartile) and the other points (purple) 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 $D_2 = \mathbb{1}\big[snowmaking \in (q2, q3]\big]$). 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 15.

Table 15: 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 8. Standard errors are in parentheses and clustered at the ski area level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

C.4 Natural Snow Dependency Across Altitude

Similarly to the snowmaking capabilities, we estimate (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 9 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 9: Effect of natural snow days on winter outcomes across altitudes

(a) first entries **(b) Transportation revenue**

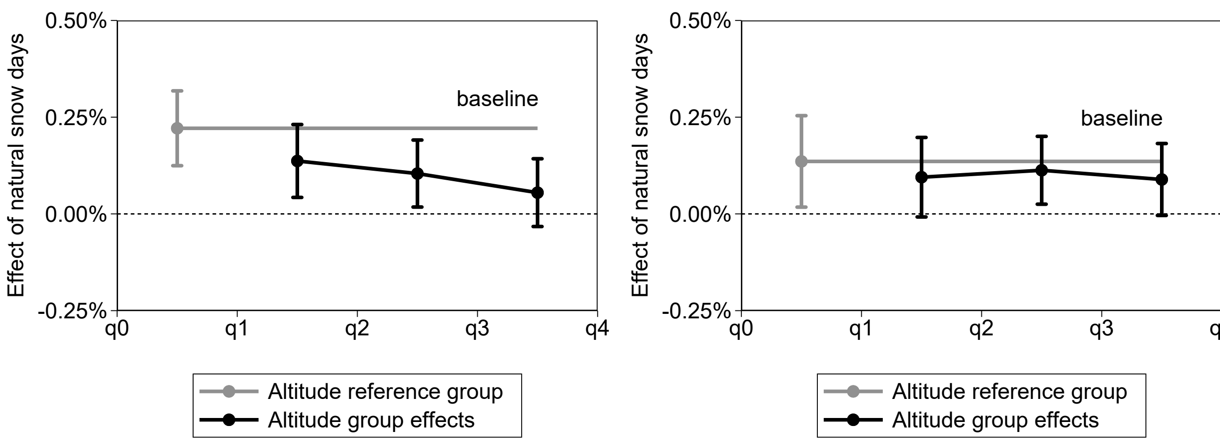


Figure Notes: Each point depicts group estimates of specification (2) across altitude groups split at quartiles. In particular, the grey point depicts the point estimate of consecutive snow days for the reference group (below the first quartile) and the purple points depict the partial effects of consecutive 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 16.

Table 16: 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

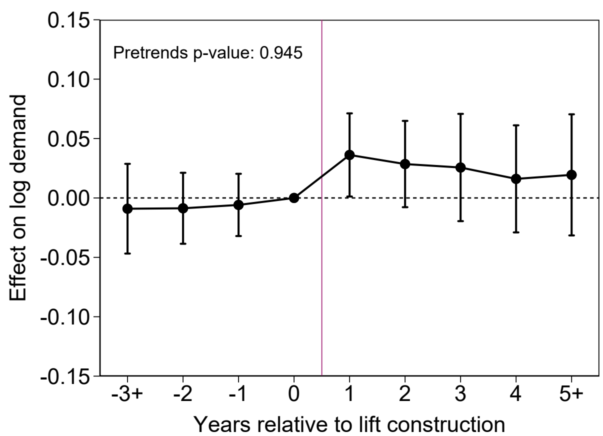
Table Notes: The coefficient table corresponds to Figure 9. Standard errors are in parentheses and clustered at the ski area level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

C.5 Balanced and Unbalanced Samples

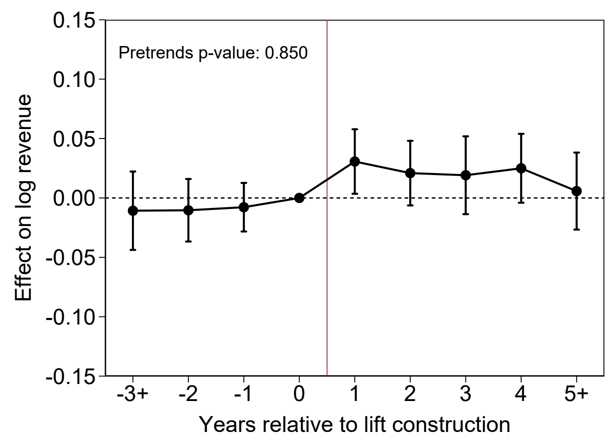
To ensure that our results are not driven by the sample selection procedure described in Section 3.1, we draw four additional samples and run our main results from Section 5.2 with these samples. We show in Figure 10 that our results remain qualitatively and quantitatively the same as in Section 5.2 when the balanced instead of the unbalanced panels are used. Our results are thus not driven by sample selection.

Figure 10: Construction of new lifts on winter first entries and transportation revenue using other samples

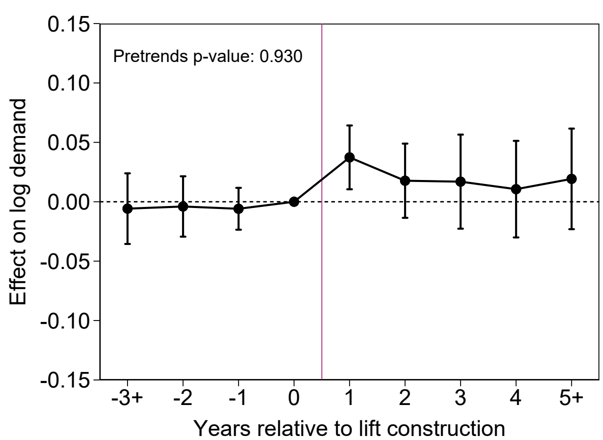
(a) First entries, balanced



(b) Transportation revenue, balanced



(c) First entries, unbalanced



(d) Transportation revenue, unbalanced

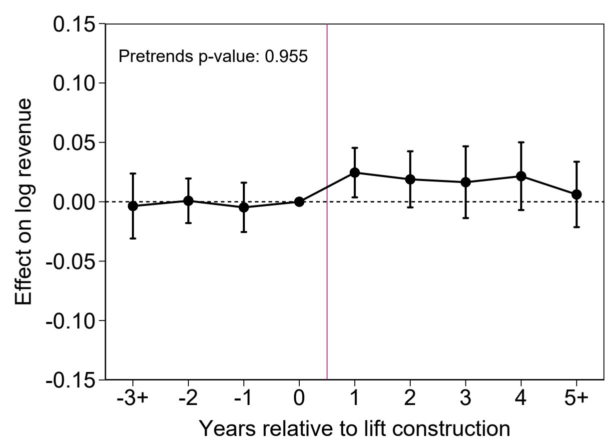


Figure Notes: All panels show estimates of specification (3) across time. Period 0 indicates the winter before the lift construction (which is in the same year) and period 1 the winter of the lift opening. Panel (a) and (c) show the estimates with the log of winter first entries as the outcome using the balanced and unbalanced demand sample and panel (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 17.

Table 17: 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 10. Standard errors are in parentheses and clustered at the ski area level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

C.6 Without Price Competition

We show in Table 18 that our results remain qualitatively and quantitatively the same as in Section 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.[40] Our results are thus not driven by price competition between ski areas.

Table 18: Event study estimates 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

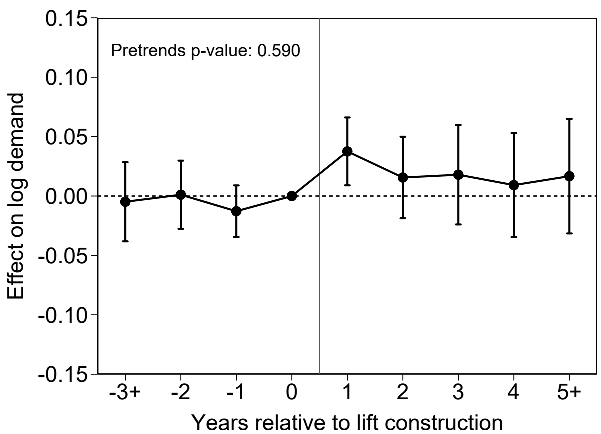
Table Notes: The table provides estimates of (1) and (2) using the sample without price competition. Standard errors are in parentheses and clustered at the ski area level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

We show in Figure 11 that our results remain qualitatively and quantitatively the same as in Section 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.

[40] 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)

Figure 11: Construction of new lifts on winter first entries and transportation revenue without price competition

(a) first entries



(b) Transportation revenue

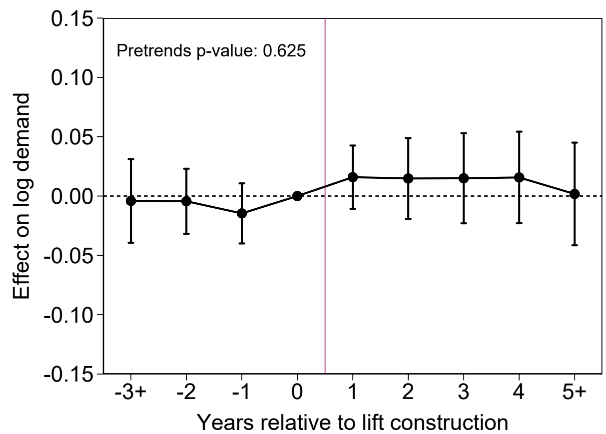


Figure Notes: Both panels show estimates of specification (3) across time. Period 0 indicates the winter before the lift construction (which is in the same year) and period 1 the winter of the lift opening. Panel (a) shows the estimates with the log of winter first entries as the outcome using the unbalanced 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 19.

Table 19: **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

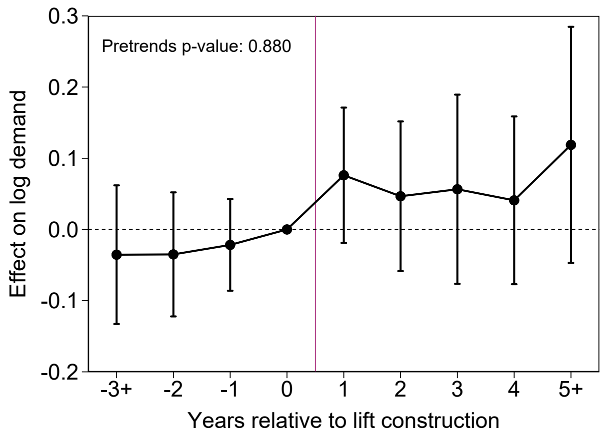
Table Notes: The coefficient table corresponds to Figure 11. Standard errors are in parentheses and clustered at the ski area level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

C.7 Treatment Effect Heterogeneity Across Time

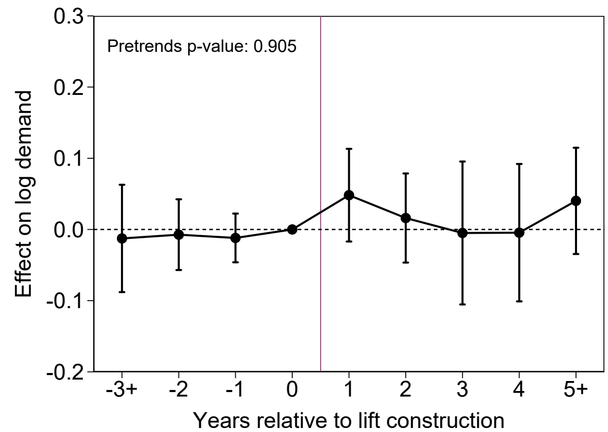
In Figure 12, we show that the effects across different estimators that account for treatment heterogeneity across time are similar in sign and size. Notice that each of the estimators uses different control groups. The estimator by Sun and Abraham (2021) uses never-treated units as the control group whereas the estimator by de Chaisemartin and D'Haultfœuille (2023) uses never-treated and not-yet treated units as the control group.

Figure 12: Construction of new lifts on winter first entries with treatment heterogeneity across time

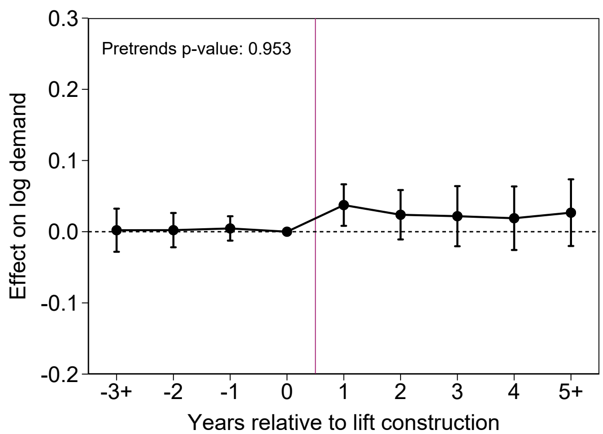
(a) Baseline, w/o multiple treatments



(b) Sun and Abraham (2021)



(c) Baseline, w/o gaps



(d) de Chaisemartin and D'Haultfœuille (2023)

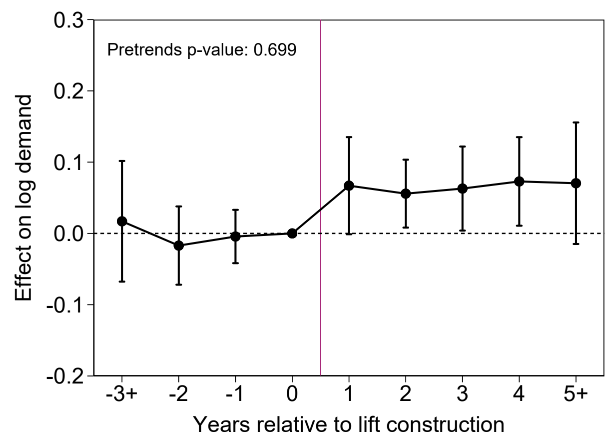


Figure Notes: The figure plots the coefficients and 95% confidence intervals of three estimators. The baseline estimates use specification (3) with the samples as stated in the title and described in Appendix C.1. The estimator in panel (b) from Sun and Abraham (2021) is implemented with the Stata command *eventstudyinteract* and uses also 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 (which is 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 20.

Table 20: Event study estimates with treatment heterogeneity across time

Dependent variable:	Log demand			
	(a)	(b)	(c)	(d)
Year 3 before lift construction	−0.035 (0.048)	−0.013 (0.038)	0.002 (0.015)	0.017 (0.043)
Year 2 before lift construction	−0.035 (0.043)	−0.007 (0.025)	0.002 (0.012)	−0.017 (0.028)
Year 1 before lift construction	−0.022 (0.032)	−0.012 (0.017)	0.005 (0.009)	−0.004 (0.019)
Year 1 after lift construction	0.076 (0.047)	0.048 (0.033)	0.037* (0.015)	0.067 (0.035)
Year 2 after lift construction	0.047 (0.052)	0.016 (0.032)	0.024 (0.017)	0.056* (0.024)
Year 3 after lift construction	0.056 (0.066)	−0.005 (0.051)	0.022 (0.021)	0.063 (0.030)
Year 4 after lift construction	0.041 (0.058)	−0.005 (0.049)	0.019 (0.022)	0.073 (0.032)
Year 5 after lift construction	0.119 (0.082)	0.040 (0.038)	0.027 (0.023)	0.070 (0.043)
Snow days	0.002*** (0.001)	0.002** (0.001)	0.001*** (0.000)	–
Weather index	0.006 (0.004)	0.008 (0.005)	−0.000 (0.003)	–
Intercept	3.814*** (0.204)	3.856*** (0.245)	6.116*** (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 12. Standard errors are in parentheses and clustered at the ski area level. The Stata command *did_multiplegt_dyn* that is 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 −.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

C.8 Treatment Effect Heterogeneity Across Ski Area Size

In Figure 13 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 specification 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 in reality not have a diminishing effect on demand. For example, some lifts are closed due to the fact that a new lift is much larger and replaces the access to more slopes than just the lift at the same spot. Redundant lifts are then removed and overall capacity decreases even though all slopes have now more comfortable access.

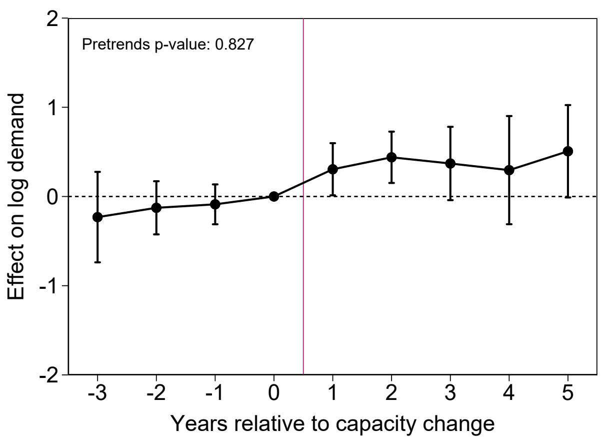
Second, capacity data is not as complete as lift data. The imputation of the missing data is an estimation by itself and does therefore not always represent reality (see Appendix A.1 for the imputation of missing capacities).

Third, when looking at Figure 13, a parallel trend violation seems apparent even though the pre-trends p-values are not statistically significant. Considering the first two reasons, it is hard to tell from why this violation occurs. Therefore, 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 the previous section.

Figure 13: Ski area capacity changes on winter first entries and transportation revenue

(a) first entries



(b) Transportation revenue

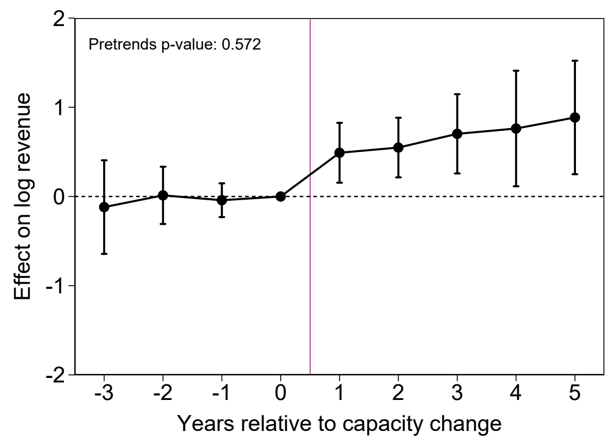


Figure Notes: Both panels show estimates of specification (3) across time. Period 0 indicates the winter before a capacity change (which is in the same year) and period 1 the winter where the change unfolds. Panel (a) shows the estimates with the log of winter first entries as the outcome using the balanced 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 21.

Table 21: Event study estimates with treatment heterogeneity across ski area size

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 13. Standard errors are in parentheses and clustered at the ski area level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

C.9 Without Mergers

We show in Figure 14 that our results remain qualitatively and quantitatively the same as in Section 5.2 when all observations from ski areas known to have been linked over the observed period are removed.[41] Our results are thus not driven by mergers between ski areas.

Figure 14: Construction of new lifts on winter first entries and transportation revenue without ski area mergers

(a) First entries **(b) Transportation revenue**

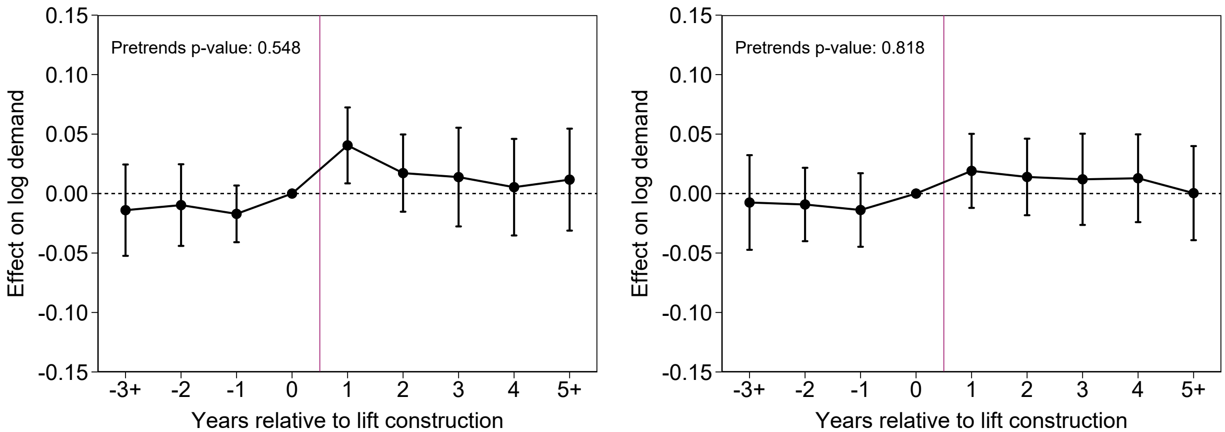


Figure Notes: Both panels show estimates of specification (3) across time. Period 0 indicates the winter before the lift construction (which is in the same year) and period 1 the winter of the lift opening. Panel (a) shows the estimates with the log of winter first entries as the outcome using the unbalanced 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 are known to have been 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 22.

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

Table 22: 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

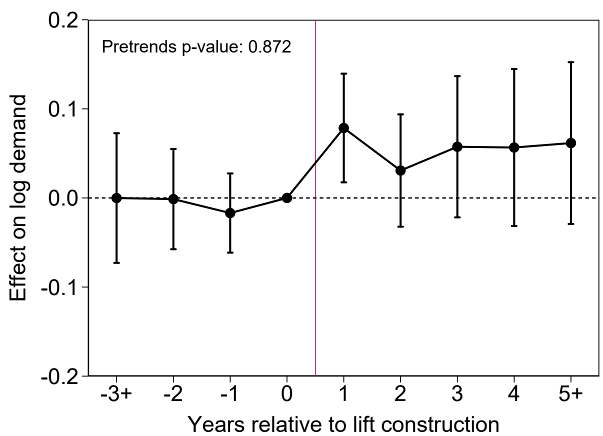
Table Notes: The coefficient table corresponds to Figure 14. Standard errors are in parentheses and clustered at the ski area level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

C.10 Varying Remoteness Measure

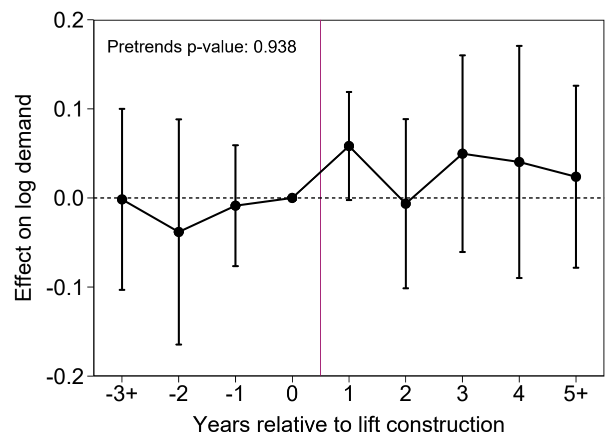
In the following section, we apply two other remoteness measures (see Appendix A.7) on specification (3). In Figure 15, we show that changing the baseline of the remoteness measure does neither alter our main results quantitatively nor qualitatively. Only in terms of precision, the low baseline in the remoteness measure from the main text performs better than the mid or high baseline.

Figure 15: Construction of new lifts on winter first entries and transportation revenue using other samples

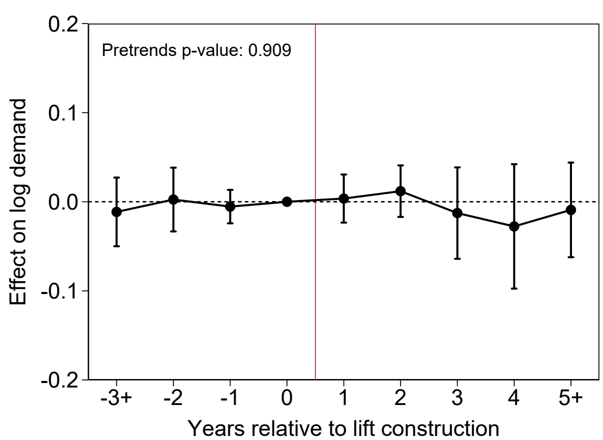
(a) Daytrippers, mid baseline



(b) Daytrippers, high baseline



(c) Overnighters, mid baseline



(d) Overnighters, high baseline

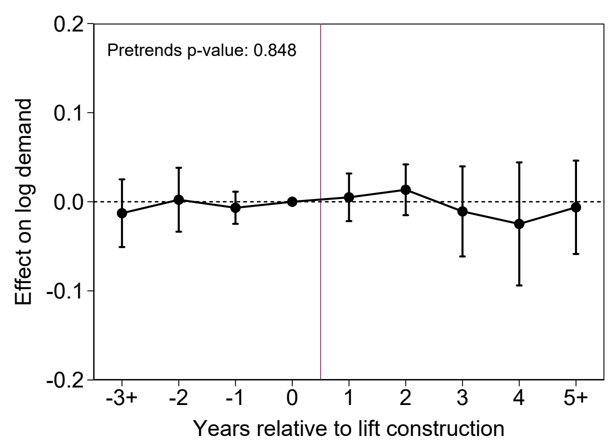


Figure Notes: All panels show estimates of specification (3) across time. Period 0 indicates the winter before the lift construction (which is in the same year) and period 1 the winter of the lift opening. Panels (a) and (b) show the estimates with the log of winter first entries from daytrippers as 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 23.

Table 23: 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 15. Standard errors are in parentheses and clustered at the ski area level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

C.11 Extensive vs. Intensive Ski Lift Investments

We adjust specification (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:

$$\ln Y_{it} = \alpha_i + \sum_{k=-3}^{5} \left(\beta_k^{ext} C^{ext}_{i,t-k} + \beta_k^{int} C^{int}_{i,t-k} \right) + \delta S_{it} + \eta W_{it} + \theta_t + \varepsilon_{it}, \qquad (18)$$

where all coefficients and variables are defined as in specification 3. The results are depicted in Figure 16 and in Table 24. Notice that the extensive investments are quite imprecisely estimated because there were only 9 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, after a lift investment the change in demand is very similar across the few ski areas affected.

Figure 16: Effect of new ski lifts on first entries across lift types

(a) Extensive investments **(b) Intensive investments**

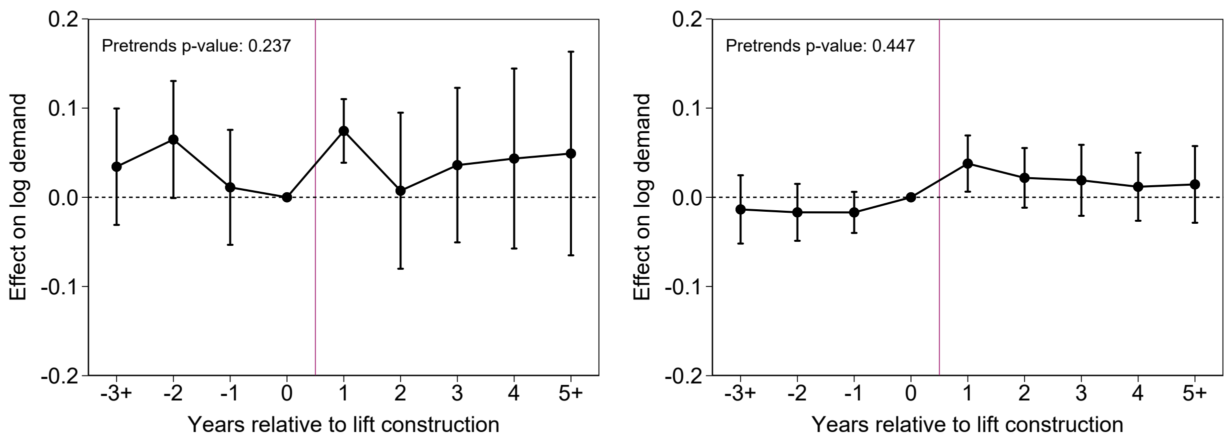


Figure Notes: Both panels show estimates of specification (18) across time. Period 0 indicates the winter before the lift construction (which is in the same year) and period 1 the winter of the lift opening. Panel (a) shows the point estimates of the extensive investments and panel (b) the point estimates 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 24.

Table 24: Coefficient table of the event study estimates across space

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 16. Standard errors are in parentheses and clustered at the ski area level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

C.12 Evidence of Spatial Competition

We show that a neighboring extensive ski lift investment within 25km affects demand negatively in Section 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. Because, 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.[42] After this procedure, we estimate (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).

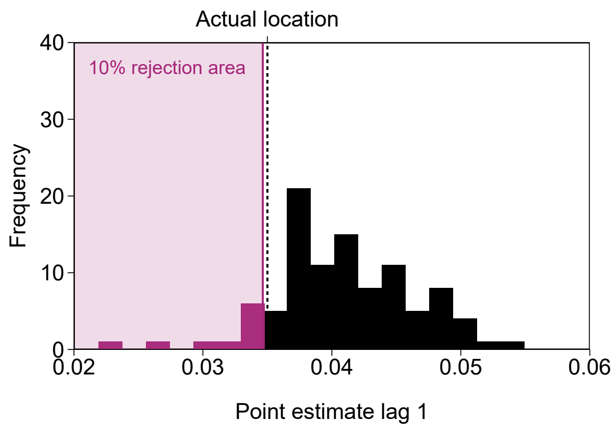
We perform 100 repetitions of the random shuffling and find that without the spatial competition, the demand effect of the first lag (i.e., in the winter of the lift opening) revolves around zero. This is depicted by the histogram of the coefficients (of the first lag) from the random shuffling in panels (b) to (d) in Figure 17. 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 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 17: 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

[42] 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 (5).

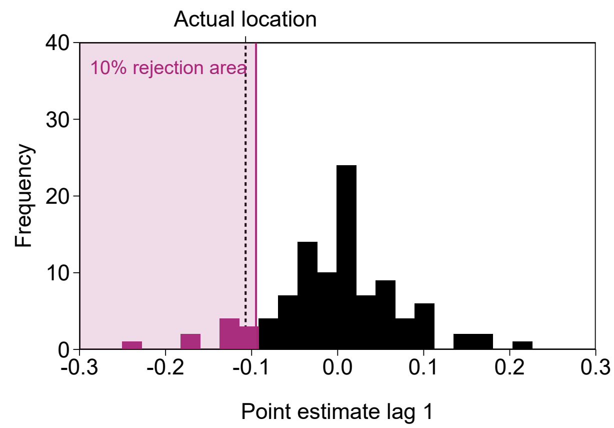
stealing for road distances between 25 and 75 kilometers on a 10% level.

Figure 17: Histogram of coefficients when location is random versus actual location

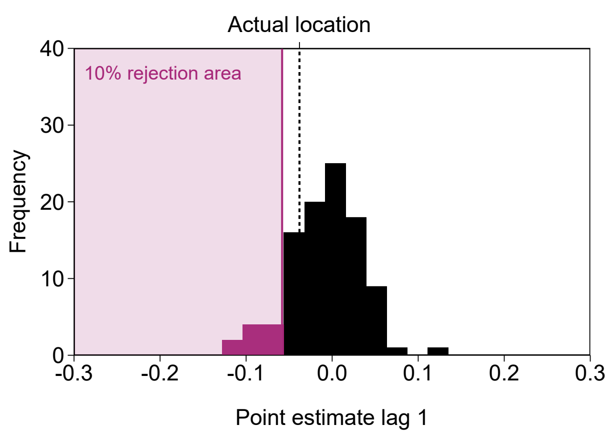
(a) New ski lift, 0km



(b) Neighboring expansion, 0-25km



(c) Neighboring expansion, 25-50km



(d) Neighboring expansion, 50-75km

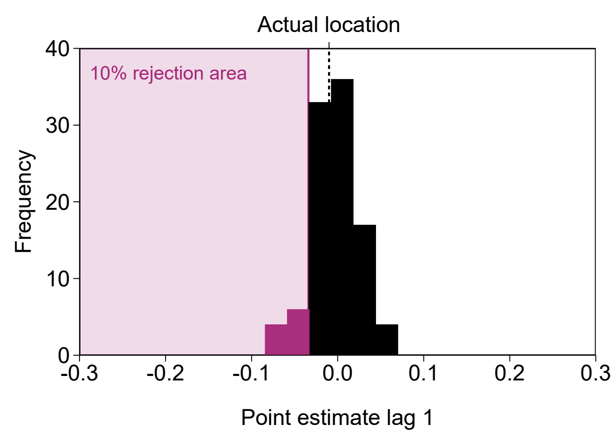


Figure Notes: The bars show the distribution of point estimates of the first lag from (5) using random locations (as described in the text) versus the point estimate of the same estimation using the real locations (vertical dashed line) corresponding to the fourth row in Table 11. In panels (b) to (d), 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.

Panel (a) in Figure 17 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).

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