Do Snow Parks Affect Ski Resort Ticket Prices?

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August 8, 2025

Abstract

A snow park is a specially designed slope featuring jumps, rails, ramps, and other freestyle elements for skiers and snowboarders. Resorts can choose whether to build and maintain a snow park, making this feature particularly suitable for a causal study, as it represents a deliberate business decision rather than a fixed characteristic. This project investigates the impact of snow park presence on ski resort ticket prices.

1. Introduction

Skiing and snowboarding represent a global industry generating billions of dollars annually, with over 3,000 resorts operating across Europe, North America, and Asia. Despite its popularity, ski resorts face unique economic challenges due to the short and unpredictable nature of the ski season. Most resorts can operate only when snow depth reaches at least 50–100 centimetres, typically limiting the active season from mid-December through late March. Resorts located at higher altitudes may enjoy slightly longer operational periods.

Because of this narrow window, resorts must maximize their income in a very short time. Lift tickets become the primary revenue source, and resort management carefully sets prices to achieve maximum profit without discouraging potential customers. Ticket prices vary significantly, from roughly twenty dollars to over two hundred and fifty dollars per day. Many observable factors influence these prices, including the number and speed of lifts, the extent of snow-making facilities, the overall skiable terrain, altitude, and the proportion of expert-level trails. Among these factors, the decision to operate a snow park is an intentional strategic choice. However, not all resorts offer a snow park, and its direct impact on ticket pricing remains unclear.

2. Existing Knowledge

Prior research shows that lift ticket prices are influenced by features such as summit altitude, number of lifts, snow-making capability, total skiable acreage, and trail difficulty. These features alone explained around 90% of pricing variation across U.S. resorts in a 2021 study [1]. Similarly, a 2008 Austrian study showed that price is associated with lift infrastructure, altitude, snow reliability, and shared ticket options [2]. However, neither study accounted for snow parks, leaving a gap this project aims to address.

3. Datasets

To fill this gap, we plan to combine two comprehensive datasets: The first dataset, available on Kaggle, includes detailed information from approximately five hundred ski resorts worldwide.

Important variables include the binary indicator for snow park availability, posted day-ticket prices, the number of lifts, trail details, and snow-making capacities: Hyperlink to the dataset

The second dataset, from Rank-Tank, aggregates skier reviews to provide popularity ratings for roughly three thousand ski resorts. Although it offers valuable popularity insights and basic resort information, it does not include snow park availability. By cross-referencing the Kaggle dataset with Rank-Tank, we will integrate snow park data with the broader review-based rating information: Hyperlink to the dataset

Our initial exploration of the data reveals a surprisingly negative correlation between snow park presence and ticket price, warranting deeper analysis.

4. Outcome Variable: Price

We have selected the posted day-ticket price as our main outcome measure because, in a competitive market, prices typically reflect the perceived value of a product or service. Economic theory suggests that firms maximize profits by setting prices at the highest point customers are willing to pay. Thus, if visitors perceive a ski resort to offer superior amenities—such as longer seasons, better lifts, or engaging features like snow parks—they will generally be willing to pay higher prices. Conversely, if features like snow parks attract a younger or more price-sensitive audience, ticket prices might adjust downward.

This economic logic is supported by broader research into "experience goods," where customers rely on indirect quality signals to inform their willingness to pay. For instance, Ashenfelter demonstrated in a notable study on Bordeaux wines that wines produced in warmer, drier years achieve significantly higher auction prices, clearly indicating that buyers pay attention to perceived quality indicators—even those beyond producers' direct control [3]. Similarly, the previously mentioned U.S. ski resort study reinforced this point, demonstrating that objective resort characteristics reliably predict pricing, aligning closely with consumer preferences[1].

To further validate our results, we plan to cross-check our pricing analysis with resort popularity rankings obtained from Rank-Tank. This additional step ensures robustness and provides context for interpreting our causal findings, allowing us to determine whether resorts with snow parks achieve higher overall popularity despite potentially lower prices.

5. Causal Diagram (DAG)

Based on conducted research, we've constructed the following causal diagram (DAG) representing the key relationships between variables influencing our outcome - ticket price.

Important Note: Some variables we've included in the same "group" as they are similar or have similar effect.

Altitude and Region. Higher-altitude regions may have longer seasons, influence infrastructure investment (e.g., snowmaking), and may correlate with demand and pricing. In this group we include everything that comes from different regions as: weather conditions, rate of climate change, number of snow days, demographics about the population in the region etc.

Trail Details. Includes the number, length and difficulty of ski runs; often tied to both snow park presence and ticket price. This influences number of lifts, their quality mainly determined by foundation year and trails (for example stiff trails can restrict building of more comfortable lifts).

Note that region doesn't influences lifts directly, it dictates the trail details, which afterwards influences the properties of the lifts.

Snow making is directly related to the region. In regions with lesser days with snow, it's preferably to invest into equipment into this adaptation method. Resorts with advanced snow making systems can ensure reliable conditions even during poor snowfall years, making it more feasible and less risky to operate a snow park. Snow making might also reflect financial investment level, which correlates with the resort's ability to afford a snow park. Note: We didn't find direct correlation between snow making and prices, although several resources implied so. We will study this variable carefully and more in depth in our work.

In addition we have a Mediator and Alternative Pathway - popularity. It is influenced by SnowPark presence and independently affects Price. It serves as a potential mediator, capturing customer preferences and resort reputation.

Unobserved variables are: Foundation date and Resort Orientation - wethether the resort targets families, teens, or expert skiers may influence both snow park investment strategy and their pricing.

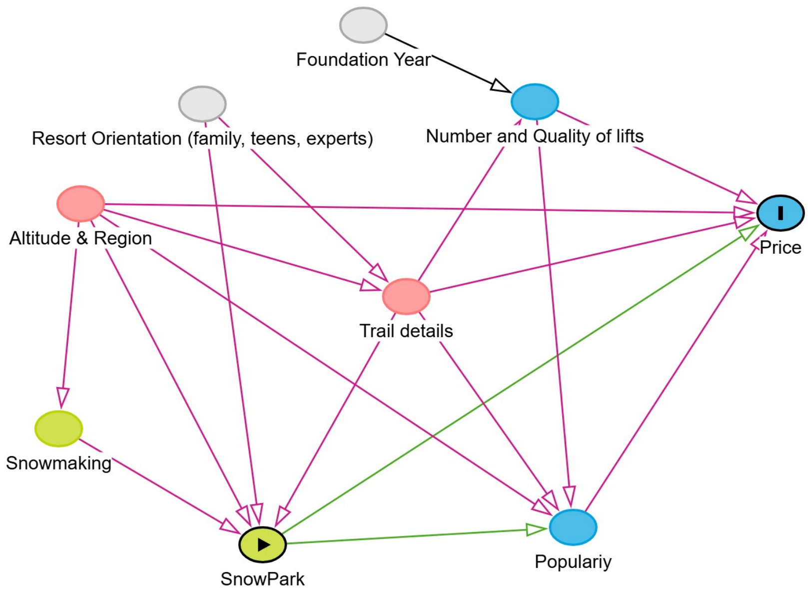

Figure 1: Directed Acyclic Graph (DAG) illustrating hypothesized causal relationships.

6. Challenges

Challenges with data integration:

Ski resorts do not have a unique ID, so it is hard to join different data sets; we can manually join the tables using the resort name combined with its location as a unique key, which can vary slightly in different sources.

In addition we have an usual overall challenges with observational studies, such as:

- Treatment assignment could be non random since the resort self assigns itself to the treatment group (the resort chooses whether it opens a snow-park).
- Limited information (Confounding): We don't have information like when the resort was created, and other unmeasured variables that can be confounders.
- We can never adjust for all the potential confounders.
- False or Missing Data due to errors in measurement.

This could lead to a violation of 4 key assumptions in causal inference:

1. SUTVA (Stable unit treatment value assumption) - Resorts could influence each other in a competition. If one lowers the prices, this may affect the others to do so as well.

2. Overlap - Some types of resorts can never have snow parks, for example, resorts in France don't build snow parks. This could be an obstacle in estimating the causal effect for these types of resorts.

3. Consistency - overall the consistency assumption can be difficult to verify, especially in observational studies where the exact mechanisms of treatment are not always clear. In our case there could be a variation in sizes of snow park that could lead to different outcomes

4. Ignorability - as we said earlier there could be unmeasured factors that influence both the decision to have a snow park and ticket prices. For example, resorts that are more oriented towards youth/families could place lower prices whilst both having a snow park.

7. Estimation Methods

To estimate the causal effect of having a snow park on ski resort ticket prices, we plan to use multiple estimation strategies:

1. Propensity Score Matching

   We will estimate the probability that a resort has a snow park using logistic regression with observed covariates (altitude, lifts, region etc.). Resorts with snow parks will be matched to similar resorts without snow parks based on this score, as seen in the Lectures.

2. Meta Learners

   We will use machine-learning-based estimators to model potential outcomes under treatment and control. We will use T and S Learner as we saw in the tutorials.

3. Doubly Robust Estimation

   We will also use Doubly Robust Estimation as it's more robust, if either the propensity score model (IPW) or the outcome model is correctly specified

We wanted to use Instrumental Variable but couldn't find any viable variably that would affect only the presence of snowpark.

8. Robustness Checks

To test the stability and credibility of our causal conclusions, we will perform a variety of robustness checks inspired by the methodology presented in class.

1. Placebo Treatment Test We will randomly assign the "snow park" treatment to resorts (unrelated to the actual presence of a snow park). The purpose of this is to ensure that no significant effect on ticket prices is observed.

2. Alternative Outcome While ticket price will be our main outcome variable, we will repeat the analysis using resort popularity rankings from Rank-Tank as a secondary outcome. (fake-outcome) This will help validate whether snow parks increase popularity even if they affect prices differently.

3. Random Confounder We will add randomly generated variables as additional covariates/confounders. This should give similar results to our original estimated effect.

4. Simulation In this step, the goal is to simulate some hidden confounder that affects both treatment and the outcome. The goal here is to estimate how strong this confounder should be to overturn our findings.

9. References

[1] Murphy, Jared. "Quality Analysis of Lift Ticket Prices in the United States Using Logistic Regression." *Empirical Economic Bulletin*, 14(1), 2021.

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