An Analysis of the Demand Functions Faced by New England Region Alpine Ski Resorts

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Abstract
The purpose of this study is to examine the impact that different factors have on ski resort ticket sales. The primary focus is to examine the effect of price on total sales. This is done using revenue reports collected from Sugarloaf and Sunday River, two ski resorts in Maine owned by Boyne, USA. These sales quantities are regressed across a number of resort related variables such as trails, lifts, weather and other controls to analyze the effect. An instrumental variables approach is used to alleviate issues related to endogeneity between prices and ticket sales. The results show that ticket sales are very sensitive to prices and that demand varies with weather and time related effects such as weekends and vacation weeks.
1 Introduction

Downhill skiing is not only an important source of recreation during the long Maine winters, but it also makes important contributions to the overall Maine economy. During the 2016-17 season the Ski Maine Association reported that downhill skiing contributed over $300 million to the Maine economy in direct expenditures on lift tickets, equipment, and meals and lodging at ski resorts located in Maine. This figure does not include home purchases and property taxes paid by seasonal residents who ski, and does not include any multiplier effects resulting from expenditures made by people employed directly in downhill skiing. Assuming a multiplier of 1.7, based on other recreational activities in Maine, the total contribution to the state economy may well reach $510 million dollars per year.

Maine’s downhill ski resorts contribute to the state economy in ways that go beyond the revenue contribution. First, there are currently twenty ski resorts operating within the state. The two largest resorts, Sugarloaf and Sunday River, account for the bulk of the revenues, but the remaining eighteen resorts also contribute financially to their local economies. With the exception of one resort, The Camden Snow Bowl, all of the resorts are located well inland from the coast, centered primarily in the Western Mountains, Central Maine, and along the Canadian border, areas that are generally deemed to be economically depressed with above average unemployment rates and below average family incomes. Second, tourism is one of the largest industries in the state, employing one out of every six employees and contributing $9 billion to the state economy. The bulk of tourism occurs during the summer months, but the downhill ski industry helps to provide intertemporal diversification by attracting visitors to the state during the winter months.

If Maine’s downhill ski industry is to remain financially viable in the future it will face a number of issues, three of which will be the subject of this study. First, can the resorts devise a pricing strategy that will help them attract skiers and maximize the revenue these skiers contribute to the firm? Resorts such as Sugarloaf employ a price discrimination strategy along three dimensions: (i) length of ticket, (ii) age of buyer, and (iii) time of year. Sugarloaf
prices a multi-day ticket at a significant discount relative to a one-day ticket; for example, an adult skier buying a ticket during the off-peak period would pay $85 for a single day ticket, but could purchase a 7-day ticket for an average price of $75 per day. Sugarloaf also offers discount to younger and older skiers: a one-day ticket during the off-peak period would cost $85 for an adult aged 19-65, $65 for juniors aged 6-12, and $65 for skiers aged 13-18 and over 65 years of age (skiers 5 and under or 80 and older ski for free). Finally, the price of a one-day adult ticket is $85 during off-peak periods and $95 during peak period, defined to be Saturdays and Sundays from December 30 to April 15, December 25-29, January 1, and February 19-23. This study estimates the elasticity of demand for ski tickets at the Sugarloaf and Sunday River ski resorts in an effort to examine this issue.

Second, all ski resorts, regardless of where they are located, will have to deal at some point with the issue of climate change. The waters in the Gulf of Maine are warming faster than 95% of the worlds oceans, leading to record high catches of lobster and record low catches of cod. If this warming effect works inland it may have a decidedly negative impact of Maine’s ski resorts. In an effort to shed some light on this issue, this study examines the impact of weather, measured by both snowfall and average temperatures, on the sales of ski tickets in Maine.

Finally, ski resorts can impact the number of skiers who choose to purchase tickets by altering the capacity of the resort in a number of ways. In the long run resorts can add new lifts or carve out new trails, both of which are very costly but have the ability to significantly increase the number of customers who can ski on a given day. In the short run resorts can increase the number of trails that are open by increasing the amount of artificial snow they create. Unfortunately the data set employed in this study does not contain data on the amount of artificial snow created by the resorts, but it does include data on the number of lifts and trails available and the amount of natural snow. The remainder of this study is organized as follows. Section 2 will call attention to the previous literature in this line of study and underline the theoretical foundation of the estimation mechanism. Section 3
establishes the model to be used. Section 4 will summarize the relevant tendencies of the data set. Section 5 will discuss results and section 6 concludes.

2 Background

2.1 Existing Market Literature

There is a small collection of existing papers that examine the impact of certain features of a resort on the value of a lift ticket. Fonner & Berrens (2011) finds that there is an ideal level of resort crowding for maximizing the value of a ski ticket to consumers. Mulligan and Linares (2003) uses a similar model to examine the impact of high speed detachable lifts, finding that resorts are less likely to invest in such lifts when local competitors have already invested in them. Walsh et al. (1983) uses survey data on willingness to pay in attempt to discern the effect of resort expansions. Lastly, Englin and Moeltner (2004) utilize data on the number of student trips to ski resorts to examine the impact of snowfall on the demand for skiing and find that these snow conditions have a major effect. Many of these models will serve as baselines for determining which variables to include in my own analysis. However, none use a design that is effective at representing an aggregate of the demand faced by ski resort operators. I will address this issue by approaching the topic from a new direction.

2.2 Theoretical Basis

Much of the existing literature regarding the alpine skiing market uses variation of the hedonic pricing model developed by Rosen (1974) to estimate the value of different attributes to consumers. This mechanism defines differentiated products as bundles of attributes and elaborates on a situation where the market is perfectly competitive across the various bundles. Thus, in this model, the price charged is representative of the value that consumers place on the product. However, there are a number of significant flaws with this method when applied to the alpine skiing industry. First, due to a high cost of entry, which limits the number of
firms, it is unlikely that perfect competition across an array of bundles exists. Second, even if I assumed there was free entry into the market, applying this model to the industry implies that resort management is capable of setting their prices to perfectly match the demand of customers on a daily basis. Due to stickiness of ticket prices and human inability to make perfect predictions, it is unlikely that this occurs.

In place of the hedonic pricing model, I will use a model that examines the elasticities of demand. A similar effort can be seen in the work of Nevo 2001 which examined the market share of breakfast cereal products as a function of price, region and product characteristics. There are a number of features from this study that can be applied to my own. There are two primary reasons that this occurs. First, the cereal market, much like the alpine ski market, is composed of differentiated products with limited actors allowing for a some level of market power. This means that Nevo had to overcome similar problems in defining a demand curve with the potential for simultaneous movements in the supply curve. Additionally, this study used market power to represent demand, which has structural similarities to an aggregate form of my own selection, daily revenue recordings.

A crucial aspect of the model presented by Nevo is expressed below. The vector $x$ represents the observable characteristics, $p$ represents the price, $\xi$ represents unobserved product characteristics and $\delta \xi$ represents regional controls. Markets, consumers and products are represented by $t$, $i$ and $j$ respectively. $\epsilon$ represents a stochastic error term. These factors make up the models prediction of the utility $u$ to a given customer of a given product.

$$u_{ijt} = x_j \beta_i^* - \alpha_i^* p_{jt} + \xi_j + \delta \xi_{jt} + \epsilon_{ijt}$$

Similarly in the skiing industry, skiers will derive varying levels of utility from different resort characteristics. As this utility increases for ski resorts or for cereal products, sales would be expected to increase. Nevo measures this change through shifts in market share while I consider quantity sold as my data set is only a limited portion of the market. This paper and that of Nevo create an equation from this differentiated product logic that will
represent the movements both of and along the demand curve in response to changes in product features and prices.

This type of analysis is consistent with a number of different studies that seek to examine the tendencies of elasticity of demand. Tellis (1988) and Bijmolt et al. (2005) both use collections of similar studies to conduct meta-analyses of the factors that make up elasticity of demand. They are able to do these due to an extensive existing body of literature surrounding this topic, primarily in the marketing realm.

3 Methods

3.1 Demand

In this section I attempt to define a function that will give an indication of the factors that influence the demand function faced by ski resorts. The dependant variable in this equation is the quantity of tickets sold at a given resort on a given day. This value is expressed as a function of Prices, Weather, Time, and Resort in the form below:

\[ Q_{i,t} = \alpha + \beta_1 Price_{i,t} + \beta_2 W_{i,t} + \beta_3 RC_{i,t} + \beta_4 T_t + \beta_5 R_i + \epsilon_{i,t} \] (1)

Where \( Q_{i,t} \) is the quantity of tickets sold at resort \( i \) on date \( t \), \( Price_{i,t} \) is the average price charged by resort \( i \) on date \( t \), \( W_{i,t} \) is a vector representing weather variables corresponding to resort \( i \) on day \( t \), \( RC_{i,t} \) is a vector corresponding to resort characteristics for resort \( i \) on date \( t \). \( T_t \) and \( R_i \) are binary variables controlling for time effects and resort respectively. \( \epsilon_{i,t} \) is a stochastic error term.

In proceeding with this model a major concern arises. The data used to estimate this demand function are based on observed levels of quantity and price at their apparent equilibrium on a daily basis. This represents the daily intersections of the supply and demand curve. If the resorts were able to offer a consistent and non differentiated product I could
simply use the observed equilibrium points to trace out a line that maps the demand curve corresponding to each shift in supply. This process is depicted in figure 1.

However, this is not the reality of the industry. Just as supply curves are changing over time there are also changes in the demand functions. For example, at any given price level, it is likely that the quantity of tickets demanded would be higher on a weekend than a weekday even without any changes in supply. This is one of many factors that can lead to shifts in the demand curve. This makes the mapping of the demand curve more difficult as the apparent equilibrium points are the intersection of two non-fixed curves. This means that the price may not be exogenous in relation to the demand equation. A representation of this occurrence is illustrated in figure 2. To overcome this issue I will utilize instrumental variables to estimate the price level in my estimation of demand.

### 3.2 Supply

In the alpine skiing industry the majority of the marginal costs associated with operation are related to the cost of lift operation. This cost takes on two distinct forms: labor and electricity. The cost per unit of these inputs does not vary significantly with changes in lift
operation, however the quantity required will rise significantly with additional lifts. Thus when resorts increase their lift operation, they will be expected to increase their prices. In addition to these factors it is expected that lift costs will vary based on the relative costs of wages and electricity in their local regions. I assume, since the ski industry is relatively small that the resorts are price takers in the labor market and the electricity market. Thus these variables are exogenous determined. This is one of the two factors necessary to utilize the instrumental variables approach. The other is that these variables cannot be correlated with the error term $\epsilon$. There is a potential for this to occur as these could impact household wealth which would in turn affect quantity of tickets demanded. I do not believe this will be the case for electricity given that its small role in the budget for those who can afford to ski. For wages this concern is more significant, but should still be minimized as lift operators tend to be of lower economic status than most customers. The estimation of the curve, expressed below, follows the standard structure of the first stage of a 2-stage standard least squares estimation with Electric Costs and Labor as independent instruments in the estimation of price. All variables retain the same definitions as in the demand equation. $\mu$ is a stochastic error term.
\[ Price_{i,t} = \gamma + \theta_1 Labor_{i,t} + \theta_2 ElecticCosts_{i,t} + \theta_3 W_{i,t} + \theta_4 RC_{i,t} + \theta_5 T_t + \theta_6 R_i + \mu \] (2)

4 Variables and Data

4.1 Tickets

The goal of this study is to map and analyze the demand function for alpine ski tickets. To do this I needed to know how many tickets are sold on a given day. I sought out and was granted permission to access daily ticket reports from the Boyne, USA resorts of Loon, Sunday River and Sugarloaf. Due to a lack of control data, the results of this study focus primarily on Sugarloaf and Sunday River. On a given day a resort can sell 30+ different types of lift tickets that can offer features such as discounted prices, packaged products and multi-day options. To get a representative picture of the demand faced by firms I sought to simplify this variety into a single variable that represented “tickets sold” and could be associated with a single price. Therefore I have limited my scope to adult lift tickets sold, thus not including other revenues recognized at the resorts such as tubing tickets or zip-line associated products. The major issue with this variable that I had to address was the fact that tickets are not always used the day they are purchased. This means that sales figures recorded by the resort do not accurately reflect the demand for skiing on the day they were sold. There are two ways that tickets can be purchased on a day different from their use. The first way is through multi-day ticket purchases. Should a skier decide to go skiing for the weekend they may opt to buy a ticket that is valid both days when they visit the ticket window on Saturday morning. The other method is simply the sale of one day tickets on a day before the ticket is valid. Skiers might select this option in attempt to avoid lines at peak sale hours. Since these discrepancies occur, I cannot use sales data to represent the demand for a ski ticket that day. Instead, I have opted to account for this by using the mountains’ revenue reports which contain the quantity of tickets and average revenue, by
product, recognized on a given day. Since revenue is recorded when a service is provided, not when the transaction occurs, this should give an accurate representation of the equilibrium quantity of tickets on a given day resulting from the intersection of the supply and demand curves. The value I use will be the sum of the quantities of all adult day ticket products sold on a given day. This variable will be the dependent variable in my primary regression and I have expressed it in log form as a means improving interpretative capacity.

Figure 3 shows the tendencies of ticket sales by month. Each point represents the average ticket sales for a day of operation in the given month. If there were no days of operation in the given month at the resort during the sample period (for example there are no days of operation at either resort in August) that month was omitted. From the figure we can observe that both resorts see a sharp increase in ticket sales in the month of December following low sales levels in November and October. We observe that Sunday River typically performs better in this early portion of the season. For both resorts the sales level increases steadily until February where the resorts see peak sales levels. After this point Sunday River sees a drastic drop in sales. Sugarloaf, however, sees only a slight drop from February to March, but falls drastically entering April and May.
Figure 4 shows the tendencies of ticket sales by day of the week. Like the previous chart, each point represents the average number of tickets sold at the given resort on a given day of the week. The trend that quickly emerges is that, not surprisingly, sales tend to be highest on the weekends and lowest midweek at both resorts. It is also interesting to note that sales at Sugarloaf are higher every day of the week except for Saturdays, which have drastically higher sales at Sunday River.

4.2 Price

Price will also be taken from the daily revenue reports at each of the resorts and thus will be representative of a number of different products offered to consumer. Much like tickets this is an aggregated value of the different products sold on a given day. The reports obtained from Boyne contain average revenue recognized for adult tickets on any given day. Each day this is broken down into seven subsections that include single day tickets up through seven day tickets. Typically there is minimal difference between the average revenue recognized per day for a multi-day ticket and a single day ticket, noting that a multi-day ticket offers benefits through convenience. This multi-day ticket option serves as a mechanism to aide preference
based price discrimination and is an alternative to many other employed discounts that allow
price discrimination based on discount eligibility. When calculating the total tickets I simply
took a total of these seven product groups. To determine the corresponding price I calculated
a weighted average of the price based on the percent of adult tickets sold in each category
that day. The result is that this price variable takes into account all variation in price offered
by the resort. It is important to do this rather than simply taking the peak ticket prices
as there are a significant number of special deals offered to consumers. These range from
locals deals to corporate discounts to packaged products. Since there is an unmanageable
amount of these variations between the three resorts it is necessary to look at these offers in
aggregate. Since resorts have the ability to vary the frequency of these discounts or deals,
variation in their use levels are in part determined by the resort. This is very similar and is
comparable to the theoretic approach to firms setting prices based on anticipated supply and
demand levels. It is hypothesized that $\beta_1$, the coefficient corresponding to price will have a
negative sign as consumers will desire more tickets if the price is reduced.

In figures 5 and 6 we can see how average ticket price varies across day of the week and
month for the two resorts. We can observe that these price levels exhibit variation relatively
in sync with the ticket sales levels in figures 3 and 4, however prices appear to have less
extreme shifts than sales levels across both frameworks. The fact that there is a similar
trend for both prices and sale quantities supports the assumption that there is an endogenous
relationship between price and ticket sales. This necessitates the use of the instruments as
specified in the methods section.

4.3 School Vacation Days

In figure 7 we can see the average ticket sales per day at the three Boyne, USA resorts
over the month of February. It becomes evident very quickly that there is a significant peak
in ticket sales just before the 20th day of the month for both Maine locations (Sunday River
and Sugarloaf). The sales levels around this day are nearly three times that of the sales at
FIGURE 5: Mean Ticket Prices Paid by Month and Resort

FIGURE 6: Mean Ticket Prices Paid by Day of the Week and Resort
FIGURE 7: Variation in average ticket sales over February by day of the month

the beginning or the end of the month at either resort. This indicates that there is something special about this time period that increases sales. The clear explanation is that this is the time of the month where President’s day typically falls. This holiday, which falls on the third Monday in February every year, determines the week of February vacation for public school students in both Maine and Massachusetts. Since these areas make up the majority of the market for the two resorts it is likely that they are a factor in demand. It is especially of note that Loon, which we expect would have a more New Hampshire centric customer base, has a slightly different peak and follows a different path from the other two locations. This is consistent with the fact that New Hampshire does not follow the same vacation weeks as Maine and Massachusetts.

Similar patterns can be observed in the month of December as ticket sales typically increase during the period when students are on holiday break. Since this variation appears to have an impact on the level of tickets sales I have generated a dummy variable that equals 1 whenever the observation is a weekday during the ski season where schools are not in session. On a typical year this includes Thanksgiving break, Holiday break, Martin Luther King Jr. Day and February break.
### TABLE 1: Weather Summary

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<th></th>
<th></th>
<th></th>
<th>Sunday River</th>
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<td>Temp</td>
<td>New Snow</td>
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#### 4.3.1 Weather Variables

In my regression equation I use three local weather-base variables: Temperature, New Snow and Snow Depth. These variables are measured on a daily basis at NOAA weather recording stations. Temperature refers to the high temperature recorded over a 24 hour period at the local measurement facility. At most recording stations daily temperature is recorded as 24 hour high and low temperatures. Since most skiing activity occurs during the day and most high temperatures occur during the day (while most low temperatures occur at night) it makes sense that the high temperatures would be the most relevant for impacting ticket sales. New snow refers to the amount of snowfall recorded during the day of observation, a 24 hour period. I also consider a one day lagged effect of this variable to consider the possibility that skiers look for a "powder day" where new snow has accumulated from the day or night before. Snow depth refers to the depth of existing snow on the ground at the weather observation station.

For Sunday River, all three variables are recorded at the US1MEOX0019 weather station in Bethel, ME. This station is located 3.79 miles from the main base area at Sunday River, South Ridge Lodge. For Sugarloaf the data is recorded at the "USC00172700" station in
Eustis, Maine. This station is located 13.47 miles from the main base area at Sugarloaf.

Table 1 displays how these variables change throughout the year. Each value in the table represents an average day in a given month at the weather recording station. We observe at both locations the coldest months are January, February and December respectively. We also note that every month of the year the average temperature is colder at Sugarloaf than at Sunday River. This makes sense given that Sugarloaf is located further north in an otherwise similar environment. We also observe that while there does not appear to be a trend as to which resort gets more snowfall, for every month December through April the Sugarloaf region appears to have a higher or equivalent accumulated snow depth. This could be a result of less melting in the region due to lower average temperatures.

While it is possible that skiers consider the weather at the ski resort when making a decision to ski, it is also possible that the weather at ”home” plays a larger role in that decision. There are two theoretical reasons why this might occur. The first is that individuals feel the weather is similar enough between their home and the resort that it is not worth the effort of checking the weather at the resort. The other possible reason is a subconscious effect. It is possible that seeing snow or cold temperatures at home makes people think of skiing, which makes them more likely to plan a trip. It is not clear which of these effects would have a larger impact. The closest major urban area to these two resorts is Boston, Massachusetts. Although I do not have skier demographic statistics to support this, it is logical to believe that the Boston population accounts for a large portion of the skiers at the two resorts. Hence, I will also examine the effect of the weather in Boston on the ticket sales.

Figures 8 and 9 show how the temperature in Boston compares to the temperature at the two resorts. These values were collected from the ”USW00014739” weather observation station in Boston, MA. Figure 8 shows how the monthly average temperature has varied over the sample period at the three locations. From this graph we see that across the entire sample, Boston typically exhibits the highest temperatures followed by Sunday River and Sugarloaf respectively. There are only a few outliers where this does not occur. We can also observe
FIGURE 8: Monthly Average Temperatures at each Resort and in Boston over the Sample Period

that the average temperatures follow a similar pattern across the three locations. Figure 9 shows a more focused example, only looking at one month. Instead of taking averages, this more limited sample allows me to show the variation that occurs on a daily basis. As is clear in the chart, there are a number of days in which the typical pattern is not held. Such variation occurs in most one month samples.

Similarly I have included a variable that looks at the daily snowfall observed in the Boston area. Figure 10 shows the daily snowfall totals across the three locations during the 2016-2017 season. While it is clear that are some general weather trends that exist in common between the locations, the area with the most snowfall varies depending on the storm. If consumers are paying more attention to local weather than resort weather, this variation would help capture this difference. Similar results can be obtained by looking at different seasons.

4.3.2 Trails and Lifts

The number of trails and lifts scheduled to operate each day was obtained from the snow reports published daily on the resort website and archived by resort management. I was unable to obtain these reports for Loon, which limited my sample to Sugarloaf and
FIGURE 9: Daily Temperature at each Resort and in Boston over the Month of February 2016

FIGURE 10: Snowfall at each Resort and Boston over the 2016-2017 Season
Sunday River. Figures 11 and 12 show the number of lifts and trails scheduled to open on a each day throughout the 2016-2017 season. Similar images can be obtained for each season, however the scope has been limited to preserve readability of the chart. We can see that there is a steady increase in each at the beginning of the season and a steady decrease at the end of the season. These overall trends for the two features move together throughout the season. While the trail curve is relatively smooth, there are consistent fluctuations in the lift curve. Further investigation reveals that these fluctuations line up with weekends and school vacation days. It makes sense that these fluctuations would only occur with lifts as there are substantial costs associated with running additional lifts, while opening trails is associated with maintenance costs such as grooming, the main daily cost associated with trail maintenance, is not necessary to open a trail.

There are a couple trends that we can observe from this graph that persist year to year. Sugarloaf typically offers more open trails during the mid and late portions of the season and Sunday River typically offers more lifts during the mid and early portions of the season. These trends are consistent with the total amount of trails and lifts at each resort. For the 2016-2017 season, Sunday River had 135 trails and 15 lifts in comparison to Sugarloaf’s 163
trails and 13 lifts.

4.4 Supply Variables

The summary statistics for the two instrumental variables, labor and electric costs, are provided in table 2. The labor cost index is produced by the Bureau of Labor Statistics and considers the relative cost of labor due to wages and salaries for private companies in New England. This value is calculated on a quarterly basis. Electric cost data was obtained from the United States Energy Information Administration. The reported value is the average retail price for commercial electricity in the United States. This value is reported on a monthly basis.

<table>
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5 Results

In this section I will seek to construct the model that will be predictive of the equilibrium quantity of tickets sold on a day given relevant factors. Table 3 shows the breakdown of the construction of the model. Each regression uses electric costs and labor costs as instruments for price as input prices are important determinants in the formation of the supply curve. Since the relative influence of these instruments is expected to vary with the number of lifts open, the variable "lifts" was included as an instrument for price whenever lifts was not included in the ticket sales regression. This is because the expenses of daily operation for resorts should be a factor of the cost of employees and fuel for lifts. Changes in the quantity of lifts in operation will lead to variations in the required number of employees and electric draw. In its final form the variable lifts does not qualify as a instrumental variable as it will be included in the demand regression, however 2-stage least squares regression will still include this variable in the first stage regression (see table 4). Electricity and labor costs continue to maintain their status as instruments for all regressions.

In regression (1) I only consider the instrumented price variable and time based effects in predicting ticket sales. This means I include fixed effects for day of the week, month and year. The result is a positive and significant coefficient on price, indicating that higher prices result in higher sales. It is unlikely that skiing carries giffen good characteristics, so this suggests there may be improper specification.

In regression (2) I add in a dummy variable for resort and in regression (3) I add in weather related variables. Different resorts offer different terrain, accessibility, culture and a number of non measurable differences so it makes sense to consider that there may be fixed effects for distinct resorts. Skiing is an outdoor sport that relies on snowfall, so it is necessary to consider these weather variables when producing the model. The inclusion of these variables alone makes little substantial difference in the regression output. There is a significant and positive relationship that appears between sales at Sugarloaf (relative to Sunday River). The effect of vacation days on sales still remains insignificant. At this point
the weather effects do not show a significant effect on sales. Despite these changes the price coefficient is still significant in the negative direction indicating that there may be further specification issues.

In regression (4) I add variables for trails open and lifts scheduled to operate. These are essential because these determine the product that the skier is consuming. By offering a greater number of lifts and trails the mountain provides an altered product for the consumer, which will vary the consumers desire to purchase access to it. The inclusion of these variables causes a number of changes in the model’s predictions. We observe that price now has a significant negative relationship and this value is significant at the 10% level. Vacation days now have a positive effect on sales, significant at the 1% level. Temperature now has a negative coefficient and is significant, which is consistent with the idea that skiers exhibit a preference for warmer, more comfortable weather. Temperature squared however, is negative and significant at the 5% level of significance. This is consistent with the theory that there is a point where it becomes “too warm” to ski for many consumers. Local snowfall is associated with a positive effect, but this effect is not significant either the day of the snowfall or the day after. Snow depth, however, has a positive effect and is significant at the 1% level indicating that skiers prefer more accumulated snow, which is expected. We also note that trails and lifts both have positive effects, significant at the 1% level for lifts and 10% for trails, indicating that skiers have a preference for increased terrain and access. We also note that the resort variable Sugarloaf is no longer significant, however this is not surprising given that as far as ski resorts go, the two locations have very similar traits.

Following the development of this model, I performed a test for endogeneity. With a chi-squared result of 11.25 and a F test result of 11.53 the respective p values 0.0020 and 0.0019, I can reject the null hypotheses that price was endogenously determined. This means that the use of two stage least squares was necessary for this model. Table 4 shows the first stage results from the final regression model. The coefficients for vacation, resort (Sugarloaf dummy variable), lifts and trails are all statistically significant at the 1% level. This is
consistent with the theory that resorts raise prices during these high demand periods both to collect increased revenue and to minimize overcrowding (Fonner and Berrens 2014). We also note that the instrument variable for electric cost is positive and statistically significant. This supports the theory that this is a relevant instrument variable that impacts prices when controlling for other factors. Labor does not show significant effects and is not in the expected direction which may indicate that this is not a strong instrument for price. It is only necessary to have one functioning instrument so this is not a major issue. The r-squared value of 0.5049 indicates that this model is a decent predictor of price.

### 5.1 Considering Urban Weather Factors

The goal of this paper is to determine the significance of different factors that may influence the demand for ski tickets. Basic logic suggests that weather will have a major influence on the demand for ski tickets and this was supported by my previous regressions. Next, I will look to evaluate whether ticket sales respond to changes in resort weather or
<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
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<tbody>
<tr>
<td>ln(Price)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>vacation</td>
<td>0.156***</td>
<td>(10.96)</td>
</tr>
<tr>
<td>Temperature</td>
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<td>(0.96)</td>
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<td>Temperature$^2$</td>
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<td>Lagged Snow</td>
<td>0.00191</td>
<td>(1.09)</td>
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<tr>
<td>Sugarloaf</td>
<td>-0.111***</td>
<td>(-9.51)</td>
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<tr>
<td>Lifts</td>
<td>0.0157***</td>
<td>(6.61)</td>
</tr>
<tr>
<td>Trails</td>
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<td>ln(Electric Costs)</td>
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<td>ln(Labor)</td>
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<tr>
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<tr>
<td>$R^2$</td>
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</tr>
</tbody>
</table>

Day Effects          | Y            |          |
Month Effects         | Y            |          |
Year Effects          | Y            |          |

$t$ statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 4: First Stage Regression Results: Instrumenting for ln(Price)
"home" weather for skiers. Table 5 allows us to compare a number of different possibilities. Regression (1) is simply a copy of regression (4) from table 3, reproduced here to facilitate comparisons. Regression (2) adds four new variables that consider the effect of weather conditions in Boston. As we see in the table, none of these effects is significant and the sign of lagged snowfall is in the opposite of the expected direction. The addition of these variables also has no substantial effect on the coefficients or the significance of the majority of the non-weather variables in regression (1). The exceptions, temperature and temperature squared, however, are no longer significant. This suggests that some of the relationship between local temperature and ticket sales may have been a result of a relationship between urban temperatures and ticket sales, improperly captured due to the relationship that exists between local temperatures and local urban temperatures. Regression (3) lends even more support to this line of thought as with the omission of local weather variables, the urban temperature coefficient becomes significant at the 10% level. Additionally all four urban weather variables now exhibit the expected signs and are consistent with the signs on the local versions of the variables in regression (1). This would indicate that these weather effects do exist, however the exact location of their observance is not significant. This could be due to the fact that in the net, the average skier does not concern himself or herself with the typically small differences between temperatures in Boston and the ski area. Regressions (4) and (5) repeat the process used in (2) and (3), except the urban location of Boston has been replaced with the more local, but less populated, urban center of Portland, Maine. These weather observations were collected at weather station "USW00014764", the Portland Jetport. Overall the effect is very similar as the local temperature values becomes insignificant again when the urban temperature is added. However, when the temperature variable is omitted the urban temperature variables do not become significant for Portland as was the case for Boston. However, once again we see that the four weather variables exhibit the same signs. The lack of significance could be due to the fact that the population from Portland does not have as much impact on the skier population as the Boston area. Since the coefficients are in
TABLE 5: Comparison of Weather in Urban areas vs. Local Resort Weather

<table>
<thead>
<tr>
<th></th>
<th>(1) ln(Tickets)</th>
<th>(2) ln(Tickets)</th>
<th>(3) ln(Tickets)</th>
<th>(4) ln(Tickets)</th>
<th>(5) ln(Tickets)</th>
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<td>Vacation</td>
<td>1.915***</td>
<td>2.005**</td>
<td>2.071**</td>
<td>1.993**</td>
<td>2.104**</td>
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<td>0.0374</td>
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<tr>
<td>Lagged Snow</td>
<td>0.0268</td>
<td>0.0261</td>
<td>0.0244</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Local Snow Depth</td>
<td>0.0243***</td>
<td>0.0235***</td>
<td>0.0303***</td>
<td>0.0248***</td>
<td></td>
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<tr>
<td>Sugarloaf</td>
<td>-0.738</td>
<td>-0.779</td>
<td>-0.850</td>
<td>-0.778</td>
<td>-0.809</td>
</tr>
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<td>Lifts</td>
<td>0.269***</td>
<td>0.278***</td>
<td>0.305***</td>
<td>0.276***</td>
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</tr>
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<td>Trails</td>
<td>0.00984*</td>
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<td>0.0114*</td>
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<td>0.0307*</td>
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<td>-0.000461**</td>
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<td>0.0163</td>
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<td></td>
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</tr>
<tr>
<td>Temperature Portland</td>
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<td>0.0143</td>
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<td>Temperature Portland^2</td>
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<td></td>
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<td>-1.50</td>
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<td>Lagged Snow Portland</td>
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<td>1502</td>
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<td>1502</td>
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</table>

Day Effects Y Y Y Y Y
Month Effects Y Y Y Y Y
Year Effects Y Y Y Y Y

* t statistics in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

the expected directions and are not excessively far from the 10% significance threshold, the difference does not lead to significant concerns.

5.2 Season Passes Robustness Check

One potential concern with the original specification of the model is that I have not included a variable to consider the number of season passes. Theoretically, the use of season passes could lead to a reduction in sales of tickets as a certain population of the market for day tickets would be eliminated. My primary motivation for omitting this variable was a lack of data across resorts. I have only been able to obtain season pass information from Loon and Sunday River. Since I did not have daily trail and lift data from Loon, including this variable would have effectively limited my sample to Sunday River. In table 6 I present a series of regressions that addresses this concern. Each of these regressions follows the previous form in instrumenting for price. Regression (1) reproduces the original model, but omits Sugarloaf.
values so we can isolate which changes come from the season passes and which come from
the modified sample. Note that the sample size has been drastically reduced, which is likely
one of the reasons that some of the variables exhibit less significance. In particular in this
sample the coefficients for temperature squared and local snow depth both preserve their
signs, but drop slightly below the thresholds for significance. The changes for price and lagged
snow appear to be more substantial. While the sign is preserved for price the magnitude
of the price coefficient has drastically increased and the value is no longer significant. This
higher value, however does suggest that there is a possibility that price is a greater factor in
influencing ticket prices. Lagged snow, has both lost its sign and level of significance. This
may indicate that Sugarloaf, which is typically associated with more expert terrain, draws a
greater crowd on “powder days” which occur the day following a snowstorm. Typically these
power days are a preference of high level skiers.

In regression (2) I add the variable ”SeasonPasses” to the regression. This addition has no
meaningful impact on the coefficients or the significance of any of the other variables and is
not significant itself. This supports the assertion that the effect of season passes is negligible
on ticket sales. One likely explanation for this is that season pass consumers and day ticket
consumers do not make up the same market. That is to say that few people actually view
the two products as substitutes within the recent pricing structures. It is reasonable to
consider that the season pass consumers are typically ”regulars” while day ticket consumers
are typically ”vacationers”. A regular would be either a local or an individual with a house
or condo at or near the mountain. This is someone who skis as a hobby and engages on
a regular basis. A ”vacationer” alternatively is someone who does not regularly ski and is
more likely to be someone who travels a large distance to participate. Peak prices for day
tickets at Sugarloaf in the 17-18 season were $95, while peak prices for a season pass was
$1129. Thus it is easy to see why any regular, who skis more than 12 days a season would be
financial motivated to buy a season pass, while a ”vacationer” would be more likely to simply
purchase day tickets. A similar number of days to payoff a season pass can be obtained for
any year in the sample. The presence of these two markets gives a reasonable explanation as to why season pass sales would not effect day ticket sales.

In regression (3) I consider the possibility that the effect of season pass sales has been masked by the fact that the values closely coincide with the year, hence the effect of season pass sales could be captured by the year fixed effects. This would be a result of the fact that season pass sales remain constant for an entire season, thus their changes could be captured by year variation, making the season pass coefficient improperly insignificant. To address this I omit the year effects. The result of this omission is a completely altered model. Price is now significant in the positive direction, vacation days are no longer significant, local snow depth now has a negative effect that is nearly significant, lifts have a negative insignificant effect and trails have a insignificant positive effect. None of these are consistent with the theory so this suggests specification is a major issue for this model. Even with these changes, the season pass variable, which is in the expected direction, is not significant. The inconsistencies of this model indicate that the year variables contain many factors not accounted for simply by season pass sales. Thus masking of changes due to season passes should not be a concern, especially considering that the removal of the potential masking variable did not result in significant effects for season passes.

5.3 Weather Station Robustness Check

One potential concern with the development of my model is the selection of weather stations for the local weather data. In an effort to produce the most complete model I selected a station for both resorts that was as local as possible while maintaining maximal coverage over my sample period. Although unlikely, it is possible that this selection of weather stations could have introduced a bias into the findings. To ensure this not the case I have selected two alternate weather stations for comparison. Due to the relatively rural nature of both resorts there are few operating stations so I am unable to test on more than one additional location.
In Table 6, I have included a regression that follows the form of the primary model, however the weather variables have all been replaced by the observed levels at alternate stations. For Sunday River, data was collected from the "USC00177336" station in Rumford, ME which is located 10.02 miles from the South Ridge base area at Sunday River. For Sugarloaf, data was collected from the "USC00174324" station in Kingfield, ME which is located 13.47 miles from the Sugarloaf base lodge. The results are nearly identical to the base model. Every coefficient maintains the same sign and all except for temperature and temperature squared maintain or gain levels of significance. It is worth noting that these two weather stations were originally not selected to their insufficient coverage of the sample (Kingfield station) or their relatively higher distance from the resort (Rumford station). It is likely that the resulting variations in temperature and reduction in sample size could account for the loss of significance for these two variables. It is especially of note that the signs of the coefficients did not change and the magnitudes stayed relatively the same. These consistencies support...
\begin{table}
\centering
\begin{tabular}{lll}
\hline
 & (1) & \\
\hline
\text{ln(Price)} & -6.227** & (-2.10) \\
\text{Vacation} & 1.769*** & (4.97) \\
\text{Temperature2} & 0.00353 & (0.30) \\
\text{Temperature2}^2 & -0.000185 & (-1.07) \\
\text{Local Snow 2} & 0.0187 & (1.14) \\
\text{Local Snow Depth2} & 0.0194** & (2.14) \\
\text{Lagged Snow2} & 0.00912 & (0.47) \\
\text{Sugarloaf} & -0.539 & (-1.15) \\
\text{Lifts} & 0.232*** & (3.57) \\
\text{Trails} & 0.0119*** & (2.72) \\
\_cons & 24.22** & (2.46) \\
\hline
\text{N} & 1131 \\
\text{Day Effects} & Y \\
\text{Month Effects} & Y \\
\text{Year Effects} & Y \\
\hline
\end{tabular}
\caption{Base Model with Results for Alternative Weather Station}
\end{table}

Now that I have justified the construction and specification of my model I will break down the full model to explore the relevance and practical applications of the results. In figure 8, I present the full specification of the model, including the coefficients for the time effect dummy variables.

The first variable is one of the most relevant to ski resort management as it is one of the few factors of the quantity of tickets demanded that can be directly modified without substantial investment. There are two different ways that management could achieve this that would show the same results by the construction of the model. They could modify ticket window prices or they could modify the amount of discount tickets available. Either of these

### 5.4 Interpretation of results in context

Now that I have justified the construction and specification of my model I will break down the full model to explore the relevance and practical applications of the results. In figure 8, I present the full specification of the model, including the coefficients for the time effect dummy variables.

The first variable is one of the most relevant to ski resort management as it is one of the few factors of the quantity of tickets demanded that can be directly modified without substantial investment. There are two different ways that management could achieve this that would show the same results by the construction of the model. They could modify ticket window prices or they could modify the amount of discount tickets available. Either of these
would effectively vary the average price paid for tickets. Since both the price variable and
the ticket variable are expressed in log form, the coefficient on price can be expressed as an
elasticity. In that line, according to the model, a 1% increase in prices is associated with a
7.646% decrease in ticket sales, all else fixed. With average ticket sales over the sample period
of 566 per day this corresponds to an average reduction in sales of 43 tickets per 1% increase
in price. At an average price paid of $52 this corresponds to a net $1982.5 loss in revenue for
every 52 cent increase in average ticket prices. At 150 days a year, this increase could result
in a net $297,375 loss in revenue. This highlights the importance for resort management to
make sure prices are not set too high. This high level of elasticity is expected given skiing’s
nature as a luxury good. Consumers are not obligated to ski so if it becomes too expensive
for an individual he or she will simply stop purchasing tickets. Since this variable has been
obtained via instrumentation, I assert that, via the pathway presented in the methods section,
this relationship is causal.

The next group of variables is the dummy variables for day of the week. I omitted the day
Thursday to avoid collinearity so the coefficients represent the relative effects in comparison to
Thursdays. The signs and coefficients indicate that sales are the lowest on Tuesdays followed
by Wednesdays, Thursdays Mondays, Fridays, Sundays and Saturdays. There appear to be
three ”tiers” of sales: Monday to Thursday, and weekends plus Fridays. This is consistent
with the results from the data section for both resorts. Obviously, resort management cannot
alter the day of the week, but they can adapt their pricing and terrain strategies to take
advantage of these tendencies.

After day of the week, there is a group of dummy variables considering the effect of month.
The month of May has been omitted to prevent collinearity. While none of the months have
a significant effect all else fixed, the coefficients indicate that the highest sales are associated
with March and February followed by December and January. While common sense might
suggest that the lack of significance indicates an issue with the model it is important to recall
that these effects are ”all else equal”. This means that the increase in consumers during
certain months may be related to other factors associated with that month such as weather conditions or vacation weeks. Again, resort management cannot control the month, but they can adapt their pricing and operation strategies to take advantage of the month-related trends.

The next group of dummy variables examines the effect of different years. The baseline for these coefficients is 2011, which was omitted. The trend in these variables is that there has been a general increase in ticket sales, all else equal, over time. There are two years where this does not hold and these are the two years that do not have significant coefficients. Since there are so many moving variables from year to year, it is nearly impossible to declare with any level of certainty what might be causing this trend. Although the reason is unclear, it does appear that the market for ski tickets has been growing over time. This is very good news for ski resorts in a region where many mountains are struggling to turn a profit.

The coefficient for vacation is positive and significant at the 1% level. This indicates, as expected, that school vacation days and holidays will see more ticket sales, all else equal. It is also of note that this coefficient is very close to the coefficient for Saturday. The primary reason that vacation days were expected to influence ticket sales was because more potential skiers are free of obligations from work and school. Thus we would expect similar effect to occur for weekend days as well. Seeing this similarity lends further confidence to the specification of the model.

The next group of variables pertains to weather related factors. The first two are the maximum daily air temperature and the square of this value. The coefficient for the temperature variable is positive and the squared variable has a negative coefficient. Both are significant indicating that there is an "ideal" temperature at which both increases and decreases in temperature will lead to decreased sales all else equal. This is expected as increasingly warm weather will lead to deteriorating snow conditions while increasingly cold weather leads to discomfort for skiers. Setting the partial derivative related to temperature for ticket sales equal to zero using these coefficients suggests that this ideal temperature is
20.75°F. This estimate should not be given much weight as its calculation could exacerbate small statistical variation present in the original coefficients. The other three weather related variables pertain to snowfall. All three coefficients are positive which is consistent with the theory that increased snow will lead to increase ticket sales. It is interesting, however, that snow depth has a significant effect, while neither variables considering recent snowfall alone are insignificant. One likely explanation is that consumers have a strong and consistent preferences for snow coverage and are relatively less concerned with how recent the snow arrived. The positive sign on these two snowfall variables does indicate that the theory that new snow increases ticket sales may have merit, just not with the same reliability as increases in trail coverage. This may be due to the fact that preferences for fresh snow are primarily a desire of expert skis, but not necessarily the general consumer.

The final three variables pertain to variations in the terrain and resort environment. The first, a dummy variable for resort (Sugarloaf) was included to control for systematic variation between the two locations. This coefficient has little interpretive value and is not statistically significant. The other two variables have much more interpretive value. The coefficients for lifts and trails open are both significant and positive. This supports the theory that improving the product will lead to increased demand. I classify opening trails or lifts as an improvement because skiers who desire these additional lifts or trails gain excess and those who do not desire them can simply not use them, hence are not negatively affected. It is of note that the coefficients for both of these variables are very small. An additional open lift corresponds with a 0.269% increase in ticket sales. With average ticket sales of 566 this means approximately one extra ticket per day all else fixed. It should be noted that resorts alter their open lifts to match expected demand. The extremely low value for this coefficient indicates that the decisions by resort management of how many lifts and trails to open have been very effective and there would be little systematic gain to further increasing the number of operating lifts. In fact, it is likely that the additional revenue from opening additional lifts would not be sufficient to cover the cost of operation for that lift. Unfortunately since
neither resort made significant changes in total lifts during my sample period I am unable to examine the effect of constructing a new lift on ticket sales. The amount of open trails at a resort is mostly related to conditions so resort management has little influence outside of snow making as to alter this number. Since the coefficient is even smaller for this variable it is evident that increasing the number of trails would be unlikely to lead to sufficient increases in revenue to offset the associated costs.

A likely explanation as to why resorts would choose to operate lifts and make snow with such minimal marginal returns is that their main revenue stream is reliant on meeting at least some threshold level of offerings. This would be consistent with the findings of Fonner & Berrens (2011) which found that high levels of crowding with insufficient lifts led to a less valuable product. Essentially, if resorts fail to meet certain levels, they will lose their customer base and experience drop offs in sales much greater than predicted by the model. Since these two resorts are relatively stable it is unlikely that either has been in this critical position near the required threshold during the sample period, meaning this drop would not be accounted for in my model. It is also worth considering that season pass holders, another major revenue source for resorts, may expect some sort of threshold level. If this is regularly not achieved, it is likely the pass-holder population would drastically reduce.

6 Conclusion

This paper used a instrumental variables approach to estimate the demand function for tickets at New England alpine ski resorts. The use of this approach allowed me to overcome the endogeniety issues related to resort ticket prices. I developed this model based on daily data for resort features, weather conditions and prices at the Sugarloaf and Sunday River ski resorts in Maine. Using electric costs and labors costs as instruments for ticket prices, I established a model that appears to be well specified with all key variables exhibiting signs that correspond with the expected direction. The model revealed that ticket sales are
<p>| | | |</p>
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<tbody>
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<td>ln(Price)</td>
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<tr>
<td></td>
<td>Friday</td>
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<td></td>
<td>November</td>
<td>-0.333 (-0.30)</td>
</tr>
<tr>
<td></td>
<td>December</td>
<td>1.026 (0.80)</td>
</tr>
<tr>
<td></td>
<td>January</td>
<td>0.943 (0.79)</td>
</tr>
<tr>
<td></td>
<td>February</td>
<td>1.236 (0.95)</td>
</tr>
<tr>
<td></td>
<td>March</td>
<td>1.256 (0.96)</td>
</tr>
<tr>
<td></td>
<td>April</td>
<td>0.427 (0.36)</td>
</tr>
<tr>
<td></td>
<td>Y2012</td>
<td>-0.00920 (-0.03)</td>
</tr>
<tr>
<td></td>
<td>Y2013</td>
<td>0.424** (2.37)</td>
</tr>
<tr>
<td></td>
<td>Y2014</td>
<td>0.292 (1.30)</td>
</tr>
<tr>
<td></td>
<td>Y2015</td>
<td>0.664* (1.70)</td>
</tr>
<tr>
<td></td>
<td>Y2016</td>
<td>0.994** (2.01)</td>
</tr>
<tr>
<td></td>
<td>Y2017</td>
<td>1.134* (1.72)</td>
</tr>
<tr>
<td></td>
<td>Vacation</td>
<td>1.915*** (2.64)</td>
</tr>
<tr>
<td></td>
<td>Temperature</td>
<td>0.0178* (1.85)</td>
</tr>
<tr>
<td></td>
<td>Temperature^2</td>
<td>-0.000429** (-2.31)</td>
</tr>
<tr>
<td></td>
<td>Local Snow</td>
<td>0.0315 (1.52)</td>
</tr>
<tr>
<td></td>
<td>Local Depth</td>
<td>0.0243*** (3.41)</td>
</tr>
<tr>
<td></td>
<td>Lagged Snow</td>
<td>0.0268 (1.49)</td>
</tr>
<tr>
<td></td>
<td>Sugarloaf</td>
<td>-0.738 (-1.38)</td>
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<tr>
<td></td>
<td>Lifts</td>
<td>0.269*** (3.61)</td>
</tr>
<tr>
<td></td>
<td>Trails</td>
<td>0.00984* (1.84)</td>
</tr>
<tr>
<td></td>
<td>_cons</td>
<td>30.38* (1.89)</td>
</tr>
</tbody>
</table>

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* t statistics in parentheses
* * p < 0.10, ** p < 0.05, *** p < 0.01

TABLE 8: Full Regression results from base model
highly sensitive to price levels as a 52 cent change in price, all else equal, would be expected to correspond to a $297,375 change in revenue over the course of a year. This highlights the importance for resort management of attention to detail when determining price. As expected, there appears to be a positive shift in the demand curve associated with weekends and vacation weeks. The model also suggests that there is an ideal temperature for ski ticket sales and that, in aggregate, skiers have a more reliable preference for accumulated snow depth than for new snowfall. This indicates that non-expert skiers make up a major portion of the revenue stream for New England alpine ski resorts. The model also finds a positive relationship between open trails and lifts and tickets sold. Further investigation of the model finds that the exact location of the weather has little relevance on its impact on ticket sales. Since weather is fairly consistent across a area such as New England, local resort weather does not have a noticeably different effect on ticket sales than other locations in the general region. Season Passes also do not appear to have a direct effect on ticket sales, likely due to the fact that season ticket holders represent a different market for ski resorts. This means that there is unlikely to be significant erosion effects for season pass or day ticket sales in relation in minor changes in the other product.

This paper uses a new approach to examine an industry with relatively little literature. The findings presented here could be expanded on in future works in a number of different ways. First, there could be an expansion into the effect of snowmaking, which gives resorts greater power over the characteristics of its product. Another way to expand on this work would be to simply expand to a larger resort base. Due to confidentiality and time constraints this paper focused solely on the Boyne, USA owned resorts Sugarloaf and Sunday River. An extension of this work to a larger base of study could lend greater merit to the model. Lastly, in terms of application, there would a large benefit to ski resort management a create and analyze a parallel model that examines the cost structure and supply side of this market more in depth. This could facilitate cross-model comparisons that would allow resorts to determine the levels of various factors that would lead to optimal profits. Any of these three
pathways could provide an interesting base for future research.
7 Works Cited

References


