Research Article

Price differentiation in the alpine skiing industry—The challenges of demand shifting and capacity constraints under pandemics

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ABSTRACT

The implementation of variable pricing at ski resorts can shift demand from peak periods to off-peak periods if at least some skiers have the flexibility and willingness to do so. This is often referred to as diversion, or demand shifting, and can directly affect the profit-maximizing prices ski resorts should set for their tickets. In this paper, we first model how diversion is related to various levels of the intra-weekly price differences at a ski resort. Then we use this model to recalculate the optimal variable prices a ski resort should set when accounting for the demand shifting and capacity constraints. The results show that the optimal prices the ski resort should set are influenced by both diversion and capacity constraints. The latter aspect is particularly relevant in the ongoing global pandemic. Ski resort managers can make direct use of our modelling framework and results when implementing new pricing strategies.

Management implications:

- Variable pricing at ski resorts can shift demand from peak periods to off-peak periods.
- The demand shifting will directly affect the optimal prices managers of ski resorts should set for the tickets.
- Managers can use the proposed framework to model diversion as a function of intra-weekly price differences and use these results in a subsequent optimization model.
- Our framework and results are also useful when implementing new pricing strategies during periods of strong capacity constraints (such as the ongoing pandemic).

1. Introduction

In the last few years, more and more ski resorts around the world have introduced various types of price differentiation with success (Vanat, 2020). A few examples are pricing depending on the weather forecast (e.g., ski resorts Pizol and Belalp in Switzerland), online discounts and early-bird discounts (e.g., Arosa-Lenzerheide in Switzerland), and dynamic pricing based on historical booking and sales data (e.g., Zermatt Bergbannen in Switzerland, and Val Cenis in France).

Although price differentiation has a number of advantages, such as overall sales increase, demand extension, and utilization of available capacity by shifting some of the demand to off-peak days (see, e.g., Haugom & Malasevska, 2018; Malasevska & Haugom, 2018), it can also

result in an undesirable situation if high willingness-to-pay (WTP) customers choose to move their consumption and purchase ski passes at lower prices. This phenomenon is referred to as *diversion*, *demand shifting*, or *cannibalization* in the literature, and can directly affect the revenue-maximizing prices ski resorts should set for their ski passes (see Phillips, 2005). This calls for a deeper understanding of the concept and the relation between demand shifting, customer perception of value, price elasticity, and customers' WTP.

The main purpose of this study is to examine how demand shifting is affected by intra-weekly price differentiation. To this end, we propose to model the number of skiers who will move their demand using logistic regression. This model enables meaningful interpretation of several interesting characteristics such as the maximum rate of diversion, price

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difference at maximum diversion rate, and the maximum fraction of skiers who will shift their demand given very large price differences (the asymptotic value in the model). This modelling approach also indirectly provides an attention check of the respondents by estimating the diversion rate at a price difference of zero.

We then use the results of the diversion model directly in an optimization model to examine how revenue-maximizing prices are affected considering various capacity constraints.

The article is organized as follows. Section 2 presents a brief literature review, Section 3 presents the methodology, Section 4 presents questionnaire design, sample, and data preparation, and Section 5 presents the empirical results. Finally, Section 6 provides conclusions and discussions.

2. Literature review

2.1. Demand–capacity management

A well-known issue for service providers is that demand must be met as it arises because it cannot be stored. The optimal capacity for most services is lower than the maximum capacity. In the case of alpine skiing, capacity is usually exceeded during peak times (e.g., weekends and holidays). However, Heskett, Sasser, and Hart (1990) point out the importance of maintaining demand as close to the optimal capacity as possible. Demand above optimal capacity as well as demand below optimal capacity not only reduces the company's profit but also affects the quality of the service experience (Kandampully, 2000; Lovelock, 1992). When the demand for alpine skiing is higher than the ski resort's optimal capacity, skiing quality suffers as the congestion in both the ski slopes and ski lifts reduces the utility alpine skiers' experience when visiting a ski resort. This will in turn change skiers' WTP for such skiing days (Haugom & Malasevska, 2019; Walsh, Miller, & Gilliam, 1983). Similarly, when demand is less than capacity, the overall social atmosphere suffers due to the lack of fellow skiers—an important service element of alpine skiing (Kandampully, 2000). Consequently, price differentiation can be used to balance capacity with demand while simultaneously increasing profitability (Klassen & Rohleder, 2001).

There are many studies focusing on demand–capacity management. Sasser (1976) is one of the first who suggests that capacity and demand can be managed using peak period and off-peak period pricing. Lovelock (1984) examines five methods of managing demand and relates each method to three possible capacity constraints: insufficient, sufficient, and excess capacity. The author concludes that the availability of good data is essential for planning and evaluating effective and appropriate demand management strategies. Kimes (1989) points out the need to develop simple and accurate revenue management techniques to assist small and medium-sized capacity-constrained service companies. Klassen and Rohleder (2001) study demand–capacity management options and stress that many service companies have limited the possibilities for precise control of demand and therefore struggle to obtain benefits from demand and capacity management. Moreover, the authors emphasize that price differentiation could be categorized as one of the demand–capacity management options that does not require very advanced planning before implementation. Klassen and Rohleder (2002) examine the appropriateness of various capacity–demand management options in service industries and conclude that price differentiation is a useful option for service industries with fixed capacity and fluctuating demand pattern. However, they suggest that an aggressive approach when price differentiation is applied simultaneously with customer education about when demand is busy and when it is slow could diminish returns on demand-smoothing efforts. Pullman and Thompson (2003) present an integrative revenue-maximizing model for determining the optimal capacity management strategy for a ski resort. The authors suggest that queue information at ski resorts is much more effective for utilizing existing capacity than other marketing tools such as price. Thompson (2015) assesses the effectiveness of offering

discounts to restaurant visitors for dining early or dining late as a tool for service capacity–demand management using back-of-the-envelope calculations. Although estimations show the most effective results when the cannibalization fractions of full-fare customers are included, their accuracy is still rather poor. The author concludes that the effect of the implementation of the early-bird offers on the company's revenues is more complex than just a simple demand-shifting effect. Recently, Kim, Kim, and Jun (2020) find that increasing prices during peak periods to reduce waiting lines and increase profitability at a small restaurant is an inefficient revenue management strategy from a long-term perspective because customers loyalty could decrease. Yet, Wirtz and Kimes (2007) stress that although customers are not willing to accept premium pricing in peak periods, they are willing to accept discounted prices at non-peak times. It is because customer behaviour is usually based on customers' price expectations or a reference price that they form based on previous purchase experience or knowledge of market prices (Huefner & Largay, 2008; Kahneman, Knetsch, & Thaler, 1986; Schroeder & Louviere, 1999). Accordingly, if the current sales price is higher than the reference price, customers tend to perceive it as a loss and vice versa, because as claimed by Prospect theory, customers are more sensitive to losses than gains in the market place (Kahneman & Tversky, 1979). Additionally, the price difference between various service offerings has to be reasonable and perceived as notable from the consumer perspective in order to be effective (Abrate, Nicolau, & Viglia, 2019; Kimes & Wirtz, 2002; Susskind, Reynolds, & Tsuchiya, 2004). Therefore, understanding demand and consumers' reactions to price changes are crucial factors in any price optimization model with revenue-maximizing expectations (Vives, Jacob, & Payeras, 2018).

2.2. Price differentiation in the alpine skiing industry

Price differentiation is grounded in the principle that a company's revenue can be maximized by charging different prices to different customers for the same products or services, based on the customer's estimated economic value of an offering (Phillips, 2005; Swann, 2009). Price differentiation has been extensively studied in various service industries (for review see, e.g., Denizci Guillet & Mohammed, 2015; Wang, Yoonjoung Heo, Schwartz, Legohérel, & Specklin, 2015). One of the first studies to examine price differentiation from the alpine ski resort perspective is the study by Perdue (2002) that finds a positive effect of heavily discounted ski season passes (75% discount) on skiers' loyalty and overall ski resort revenue. Holmgren and McCracken (2014) investigate how different groups of skiers (half-day, local, multiday, college, season pass, and student) accept price differentiation at one ski resort. The findings indicate that half-day skiers and students are in the more price-sensitive and less loyal customer segments as they are likely to switch ski resorts to obtain a discount. Haugom and Malasevska (2019) find that almost 50% of current active skiers will increase their skiing activity on midweek days if the price is reduced in this sub-period compared with the regular (weekend) price. Only 15% (mostly couples without children and skiers with low skiing interest) will reduce their skiing activity on weekends due to such price differentiation. In general, ski resorts have the potential to increase their revenues by adopting price differentiation because price sensitivity differs across time, across characteristics of alpine skiers, across congestion in the main lifts and the capacity constraints on the slopes, as well as across different weather conditions (Haugom, Malasevska, & Lien, 2020; Malasevska & Haugom, 2018; Malasevska, Haugom, & Lien, 2017). Haugom, Malasevska, & Lien (2020) reveal that price differentiation that simultaneously incorporates multiple attributes that are important to consumers provides even better outcomes. To the best of our knowledge, there are no studies on optimal price differentiation taking into account both demand shifting at various price levels and capacity constraints at a ski resort. The current paper fills this gap.

3. Methodology

3.1. Modelling price–response functions

The price–response function (PRF) is a fundamental input in any price and optimization problem, and it can be directly linked to an assumption regarding the consumers' WTP for a product or service. If we define $w(x)$ as the WTP distribution across the population, we can derive the price–response function $d(p)$ from the WTP distribution as:

$$d(p) = D \int_p^\infty w(x) dx \tag{1}$$

where p = price, and $D = d(0)$ the maximum demand achievable.

Two common price–response functions are the linear and the logit price–response functions. The linear price–response function is an easily tractable model of market response. A weakness of this function is that it assumes that demand changes from a given price increase will be the same, no matter the base price. Hence, the WTP is uniformly distributed between 0 and a maximum value. The logit price response function has a more realistic WTP distribution (see Phillips, 2005), similar to a normal distribution, but with fatter tails. For this reason, and because it has performed well in previous empirical research (see Malasevska & Haugom, 2018, Huang, Leng, & Parlar, 2013), we choose to focus on the logit specification in this study. The logit price–response function can be defined by:

$$d(p) = \frac{K e^{(a+bp)}}{1 + e^{a+bp}} \tag{2}$$

Here, K, a, and b are parameters with $K > 0$ and $b < 0$. a can be either greater or less than 0. Parameter b specifies price sensitivity, and K indicates the market size. The highest point of the distribution curve is the same point at which the price–response curve is steepest. This point occurs at $p = (a/b)$. The logit price function will be estimated by non-linear regression.

3.2. The price optimization problem

We assume that the alpine ski resort's strategic goal is to determine optimal prices, which maximize the total contribution, given the resort's capacity constraints. This optimization problem can be expressed as:

$$\max_p Z(p) = (p - c)d(p) \quad s.t. \quad d(p) \leq X \tag{3}$$

where $Z(p)$ is the total contribution, c is the incremental cost, and X is the ski resort's capacity during a season. According to Malasevska and Haugom (2018), we can assume that the incremental costs per additional skier are close to zero. Hence, the ski resort maximizes total contribution by maximizing revenue:

$$\max_p R(p) = pd(p) \quad subject \ to \quad d(p) \leq X \tag{4}$$

The optimal unconstrained price, $\widetilde{p}$, is given by:

$$R'(p) = d(p) + pd'(p) = 0 \tag{5}$$

Solving for $p : \widetilde{p} = -d(p)/d'(p)$, where $d'(p) < 0$

If $d(\widetilde{p}) \leq X$, then $\widetilde{p}$ is also the optimal constrained price. If, by contrast, $d(\widetilde{p}) > X$, the ski resort needs to charge a higher price to maximize contribution. The resort must then calculate a price at which demand is exactly equal to the capacity constraint. Fig. 1 illustrates the optimization problem. The optimal price level without considering the capacity constraint is given where the price elasticity equals -1.[1] This unconstrained optimal price generates demand that exceeds the
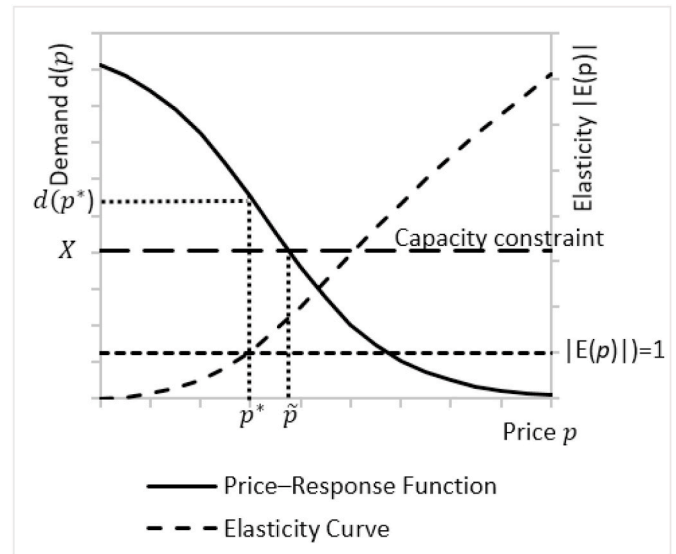

Fig. 1. Pricing with a capacity constraint.

capacity, $d(\widetilde{p}) > X$. In such a situation, the resort needs to calculate the runout price $(\widehat{p})$, that is, the price at which demand exactly equals capacity.

Today, nearly all ski resorts in Norway charge a constant price for various ski passes over the entire winter season. However, as demand follows predictable patterns (see Malasevska and Haugom, 2018), they all can adjust prices to fully take advantage of the (relatively) fixed capacity over time. This is called variable pricing and can increase revenues substantially (see Hinterhuber & Liozu, 2014). A side effect arising from variable pricing is a shift in demand from peak periods to off-peak periods, as at least some skiers have the flexibility to shift their skiing activity between periods. This is called diversion, or demand shifting, and can significantly impact the optimal variable prices the ski resort should set.

In our analysis, we divide the market into two sub-periods: skiing on midweek days (Monday–Thursday) and skiing on the weekend (Friday–Sunday), where the WTP is highest in the latter sub-period. If we consider no diversion, the optimization problem is:

$$\max_{PMW,PWE} R(p_{MV}, p_{WE}) = p_{MW} d_{MW}(p_{MW}) + p_{WE} d_{WE}(p_{WE})$$
$$subject \ to$$
$$d_{MW}(p_{MW}) \leq X_{MW} \ and \ d_{WE}(p_{WE}) \leq X_{WE} \tag{7}$$

p_{MW} is the price of a day pass for midweek days, p_{WE} is the price of a day pass for weekends, $d_{MW}(p_{MW})$ and $d_{WE}(p_{WE})$ are the respective demand functions, and X_{MW} and X_{WE} are the respective capacity constraints.

3.3. Modelling demand shifting

The simplest way of modelling demand shifting is to assume that a constant number of customers shift from an expensive to a cheaper day for every NOK (1 NOK ≈ 0.12$US and 0.10€) in price difference between these days. This linear approach has an obvious weakness. Customers have their preferences, and it is likely that relatively few customers will change their demand from an expensive to a cheaper day for small price differences. For the same reason, there is a limit to the number of customers who will move their demand no matter what the price difference is. In between small and large price differences, it is reasonable to assume that the fraction shifting from the high-to the low-priced period increases with increasing price differences. This description of demand shifting can be modelled with the following logit demand shifting function:

$$s(q) = \frac{Ve^{(\lambda + \mu q)}}{1 + e^{(\lambda + \mu q)}} \qquad (8)$$

where q is the price difference between day pass on the weekend and midweek ($q = p_{WE} - p_{WD}$), and $s(q)$ is the diversion fraction—i.e., the fraction of weekend skiers shifting the demand from the weekend to the midweek period—with $0 \le s(q) \le 1$. V, λ, and μ are parameters to be estimated with $V > 0$ and $\mu < 0$. λ can be either greater or less than 0. Parameter μ specifies the sensitivity of price differences, and V indicates the maximum fraction of skiers shifting their demand from the weekend to the midweek period.

3.4. Estimating the capacity constraint

We discussed the distinction between maximal and optimal capacity, the importance of maintaining the demand as close as possible to the optimal capacity in section 2.1, and how to model it in section 3.2. This section introduces a method for calculating capacity constraints for a sample, given the ski resort constraints. The purpose is to calculate a relevant capacity, which can be included in the calculations of optimal prices. The first step is to calculate the ski resort's capacity utilization for day passes on midweeks and weekends, given by the actual demands for day passes divided by the capacities exclusive season passes. Letting $U_{MW}(p)$ and $U_{WE}(p)$ be the resort's capacity utilization for day passes in per cent during midweek and weekends, the capacity utilization is given by:

$$U_{MW}(p) = \frac{D_{MW}(p)}{Y_{MW}} \ and \ U_{MW}(p) = \frac{D_{WE}(p)}{Y_{WE}} \qquad (9)$$

where $D_{MW}(p)$ and $D_{WE}(p)$ are the population demand on midweek and weekends, respectively, at the actual price level (p), and Y_{MW} and Y_{WE} are the resort's capacity constraint on midweek and weekends.

The next step is to calculate the sample's capacity constraints by dividing their estimated demand functions with the resort's actual capacity utilization, given by equation (9):

$$X_{MW} = \frac{d_{MW}(p)}{U_{MW}(p)} \ and \ X_{WE} = \frac{d_{WE}(p)}{U_{WE}(p)} \qquad (10)$$

where $d_{MW}(p)$ and $d_{WE}(p)$ are the sample's demand on midweek and weekends, based on the estimated demand functions given by equation (2).[2]

The following example illustrates the calculations. The ski resort's optimal capacity where the data collection took place is 5600 skiers per day, which, corrected for season pass users, gives a season capacity of 581,400 day pass visitors, distributed into 355,300 on midweek days and 226,100 on the weekends. The resort's visitor data indicates that the capacity utilization for day passes was on average 23% during midweek days and 74% on the weekend. There were, of course, periods, such as the winter holidays and Easter, when the capacity utilization was much higher and even above the capacity limit, but we use average numbers for the various sub-periods in our analyses. Given the actual price level, the sample's demand was estimated to be 697 on midweek days and 1337 on weekends. Based on this information, we calculate the sample's capacity constraint for day passes over the season to be 3168 on the midweek (697/0.23) and 2031 on the weekend (1337/0.74).

3.5. An optimization model with demand shifting and capacity constraints

We formulate the following model that included diversion between weekends and midweek days and capacity constraints:

$$\max_{p_{WD}, p_{WE}} R(p_{MW}, p_{WE}) = p_{MW} d_{MW}^{*}(p_{MW}) + p_{WE} d_{ME}^{*}(p_{WE})$$

$$subject \ to \qquad\qquad (11)$$

$$d_{MW}^{*}(p_{MW}) \le X_{MW} \ and \ d_{ME}^{*}(p_{WE}) \le X_{WE}$$

where

$$d_{MW}^{*}(p_{MW}) = d_{MW}(p_{MW}) + s(q) K_{WE}$$

$$d_{ME}^{*}(p_{WE}) = d_{WE}(p_{WE}) - s(q) K_{WE}$$

$$d_{MW}(p_{MW}) = \frac{K_{MW} e^{(a + b p_{MW})}}{1 + e^{(a + b p_{MW})}}$$

$$d_{WE}(p_{WE}) = \frac{K_{WE} e^{(a + b p_{WE})}}{1 + e^{(a + b p_{WE})}}$$

K_{MW} and K_{WE} represent the total market for midweek and weekends, respectively, and $s(q) K_{WE}$ represents the demand shift, the number of skiers shifting from weekends to midweek.

4. Questionnaire design, sample, and data preparation

This study uses a sample of skiers at a resort in Norway's Inland region. Data collection was performed in February and March 2019 by graduate Bachelor students in business administration at Inland Norway University of Applied Sciences, Lillehammer. The data collection was carried out at the ski resort on various weekdays and at different times during the day to avoid sampling bias. As this research's main objective is to analyse price–response functions for day passes, a criterion for participating in the survey was that they did not have a season ticket. A total of 779 questionnaires were either partly or fully completed.

The questionnaire was designed so that it would be possible to estimate price–response functions and diversion between midweek and weekends for different price levels. The respondents who had not answered the questions needed to perform these estimations were excluded from the sample. In addition, we excluded all respondents under the age of 18 years, as they were less likely to spend their own money when purchasing a ski pass.

Some of the questionaries were only partly completed or had logical shortcomings. A thorough examination of all the recorded data and the students' additional comments during the interviews was necessary before using the data for empirical analyses. A few adjustments were performed in the preliminary process of preparing the final data set. These adjustments involved

(1) ensuring that there was a non-positive relation between price and demand and
(2) ensuring that there is a positive relation between price differences between midweek days and weekends and the desire to switch from weekend to midweek days at a given price level for the weekend.

In a few cases, (1) and (2) were not fulfilled, and one can then assume, using economic theory, that the respondents had misinterpreted the questions and, thus, had incorrectly placed the given frequencies in their survey response. We used interpolation in cases with intermediate missing values.

The total number of observations used in the analysis was 421 after these modifications. Approximately 33% were locals, whereas 23% stayed at rental apartments or cabins when visiting the ski resort, 11% stayed at hotels, 26% were private cabin owners, and the remaining 7% were non-locals who came only for a day. The average age was approximately 36 years, and the average number of skiing days during a typical season was just over 10. Eighteen per cent of the respondents were students, whereas 73% were full-time employees. Almost half of

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[2] The calculation is based on the assumption that the sample and population's capacity utilization is equal.

the respondents were couples with children. Table 1 presents the background variables used in this study.

Fig. 2 presents the distribution of skiing between midweek days and weekends among the participants in the survey. The figure shows that 32% of the respondents only ski on the weekends and that the proportion who ski mostly on midweek days is low. For approximately 20% of the respondents, the skiing activity is the same on midweek days and weekends. The clear predominance of skiing activity on the weekends among the participants corresponds well with the ski resort's actual visitor numbers. Their visitation data for the winter season 2019/20 show that approximately 70% of the visits are on the weekends.

5. Results

5.1. Estimation of price response functions

The participants in the survey were asked how many midweek- and weekend days during a season they would ski at the resort at various price levels. The generated data of the sample's demand at different price levels is shown in Fig. 3, and it shows that the difference in demand between midweek days and weekends decreases with the price level.

We have formally examined the relation between prices and quantity demanded for midweek days and weekends by estimating price–response functions, given by the logit specification expressed in

Table 1
Sample characteristics.

Variable		Characteristics
N		421
Gender (%)	Male	67.06
	Female	32.94
	Total	100.00
Age (years)	Average	36.32
	Median	36
	Standard division	12.12
Distance (km)	Average	198.42
	Median	150
	Standard division	200.90
Approximate number of skiing days during a typical season (at this ski resort in parenthesis)	Average	10.36 (5.55)
	Median	8 (4)
	Standard division	8.86 (5.85)
Net income household (%)	Below NOK 100,000	4.57
	NOK 100,000–300,000	12.26
	NOK 300,001–600,000	13.94
	NOK 600,001–900,000	19.47
	NOK 900,001–1,200,000	18.27
	More than NOK 1,200,000	20.91
	Prefer not to answer	10.58
	Total	100.00
Family status (%)	Single	23.87
	Single with children	4.53
	Couple	22.43
	Couple with children	48.21
	Total	100.00
Current occupation (%)	Working full time	73.27
	Working part-time	7.88
	Unemployed	1.19
	Student	17.66
	Other	0.00
	Total	100.00
Accommodation when visiting the ski resort (%)	Home	33.17
	Own cabin	26.49
	Rental apartment/ cabin	23.15
	Hotel	10.98
	Other	6.21
	Total	100.00

formula (2). The results are shown in Table 2. The price sensitivities, indicated by parameter *b*, are (in absolute value) highest on midweek days, but the difference between the two periods is small. Our findings align with previous studies within the alpine skiing industry (see, e.g., Malasevska and Haugom (2018)) and indicate higher price sensitivity on midweek days.

The highest point of the distribution curves for WTP for midweek days is NOK 243 and for weekend NOK 333, demonstrating that the price–response curves are steepest at these price levels.

The estimation results and calculated price elasticities are illustrated in Fig. 4. The left vertical axes show the actual and estimated values for different price levels, and the right vertical axes show the calculated values for the elasticities (dashed lines) for different price levels. The figure shows that the market size is clearly largest on weekends, but, otherwise, there are small differences in demand characteristics between midweek and weekend. The elasticities are slightly higher on the midweek than those on the weekend for low price values, and the opposite is true for high price values. This indicates that price changes at low prices have a larger impact on demand on midweek days than on weekends, and changes at high prices have a larger impact on demand on weekends than on midweek days.

5.2. Estimation of a demand shift function

To estimate the demand shift function, we asked the participants, given different price differences between weekends and midweeks, if they would switch from a weekend day to a midweek day, if they had initially intended to ski on a weekend day. The estimated results, using the logit function expressed in formula (8), are shown in Table 3 and illustrated in Fig. 5. The x-axis in the figure shows the price differences, and the y-axis the fraction of skiers shifting from weekends to weekdays. Parameter V in the regression has the value of 0.556, indicating that the maximum fraction of skiers shifting demand from weekend to midweek is 56%, no matter how high the price difference is. This is the upper asymptote for the predicted fraction in Fig. 5. The curve has an S-shape, demonstrating that a change in price differences at low and at high price difference levels has a modest impact on the fraction of skiers shifting demand from weekend to midweek. The inflection point is where the diversion rate increases the most and is obtained by $-(\lambda/\mu)$. Our results show that this point is obtained for a price difference of NOK 153, demonstrating that the predicted demand shifting curve is steepest around that price difference.

5.3. Price optimization and revenue

We have calculated optimal prices for the ski resort, given different conditions concerning diversion and capacity constraints. Various capacity limitations are particularly relevant today due to various statutory restrictions as a result of the Covid 19 pandemic. The results are summarized in Tables 4 and 5 and show daily capacity constraints, calculated seasonal capacity constraints,[3] and corresponding optimal prices, demands, and revenues.

A fruitful starting point for discussing the significance of capacity constraints is to consider a case where there is no capacity limit or where the demand is far below the capacity level. In that case, the optimal price for midweek and weekend without demand shifting is, respectively, NOK 263 and NOK 295, and is given where the price elasticities equal 1 in absolute value (see Section 3.2). The corresponding prices with demand shifting are NOK 270 and NOK 292, and the total revenue is highest without demand shifting. The small difference in optimal prices for midweek days and weekend days, both absolute and relative, is due to the fact that price sensitivity differs relatively little between the two

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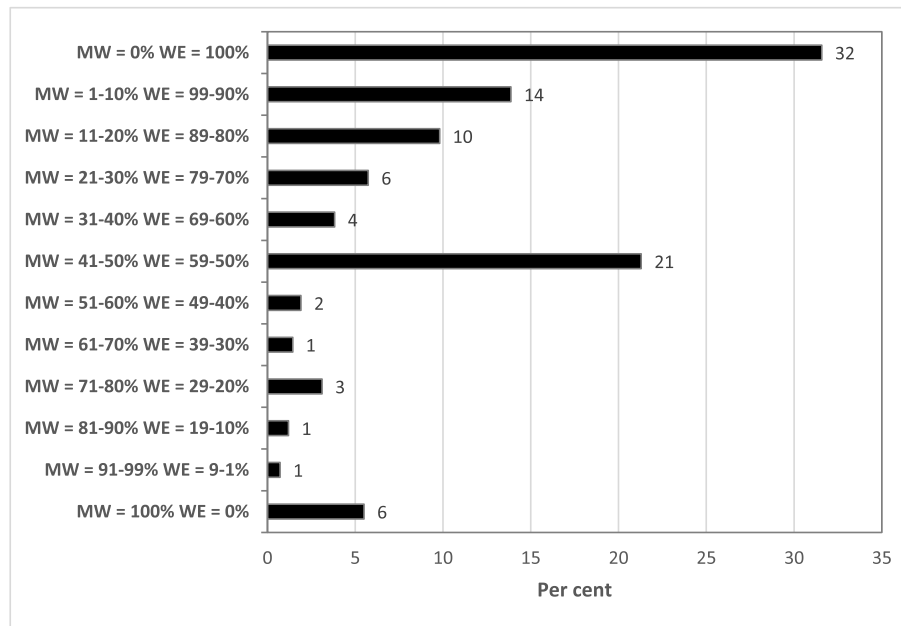[3] For an explanation of the calculation of the capacity constraints in the figure, see Section 3.4.

Fig. 2. Percentage of participants skiing on midweek days and weekends. MW = Midweek (Monday–Thursday), and WE = Weekend (Friday–Sunday).
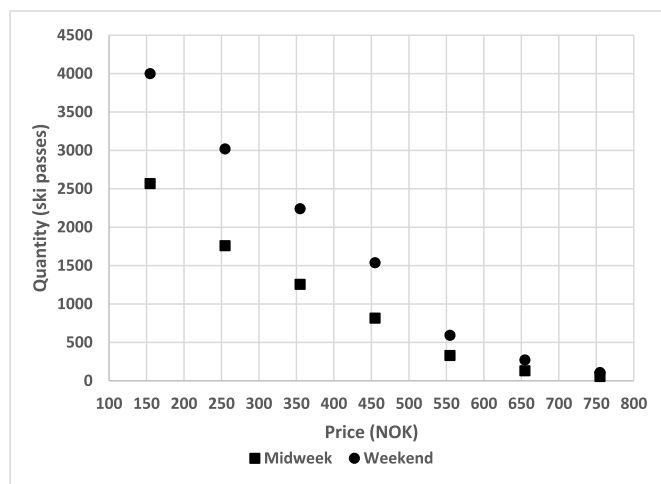

Fig. 3. Scatterplots of price and skiing frequency for midweek days and the weekend. The age of all respondents is > 18 years.

Table 2
Logit PRFs: Summary of the parameter estimates and model fit.

	Variable	Coefficient	p-value
Midweek	K	3883.784	0.010
	a	1.723624	0.081
	b	−0.0070946	0.003
	AIC = 85.55, BIC = 85.38		
Weekend	K	4874.05	0.001
	a	2.651188	0.016
	b	−0.0079654	0.002
	AIC = 92.09, BIC = 91.93		

periods.

When we take capacity constraints into account in price optimization, the price differences become significantly larger. This is because capacity utilization is higher on the weekends, and therefore the resort must set a runout price on an earlier total capacity stage than is necessary on the midweek days. For instance, if the capacity constraint is

5600 daily visitors, the price difference with diversion is 36% (NOK 95). The demand shift from weekend to midweek ("Diversion" in Table 5) increases with the capacity restrictions as long as only weekend demand is equal to the capacity limit. If midweek demand also equals capacity, it will be optimal for the resort to use a runout price on both midweek and weekend days, thus decreasing the demand shift.

Figs. 6 and 7 illustrates the optimization solutions for the resort on midweeks and weekends respectively, given no constraints, and daily capacities of 5600 and 2000 visitors. In the first case the optimal solution without and with diversion is point A and B, respectively. With a daily capacity of 5600 visitors, the capacity utilization on midweek days is so low that it will not affect the pricing solution, while on weekends, it is necessary to set a runout price. In this case, point C gives the optimal combination of price and day visitors on midweek days and weekends, without demand shifting. With demand shifting, the optimal solution moves from point C to point D in both figures. The capacity limit still determines how many visitors there can be on the weekends, and therefore, the only change here is the price. On midweek days, both price and number of visitors increase, but the price increase is marginal.

The negative correlation between capacity constraints and optimal prices, shown in Tables 4 and 5, can easily be seen by moving down the capacity constraints in Figs. 6 and 7. If, for example, the ski resort must reduce the daily capacity from 5600 to 2000 visitors, the optimal price for midweek days and the weekend would increase by 80% and 57%, respectively, taking demand shifting into account. The optimal solutions with and without demand shifting at a capacity of 2000 visitors are illustrated with point E and F in the figures. The need for price changes is a current issue for the ski resort due to the ongoing pandemic. If instead, the resort decides to keep prices unchanged at the optimal level corresponding to the capacity constraint of 5600 visitors per day, revenue will be approximately 40% lower at a constraint of 2000 per day, as illustrated in Fig. 8. The solid black line shows the revenue at different capacity levels, given that prices are optimal in a situation with demand shifting. The solid grey line shows revenues if the resort keeps prices unchanged at the optimal level, given a capacity of 5,600, and the dotted line shows the difference in per cent between the two solid lines.

5.4. Subset analysis

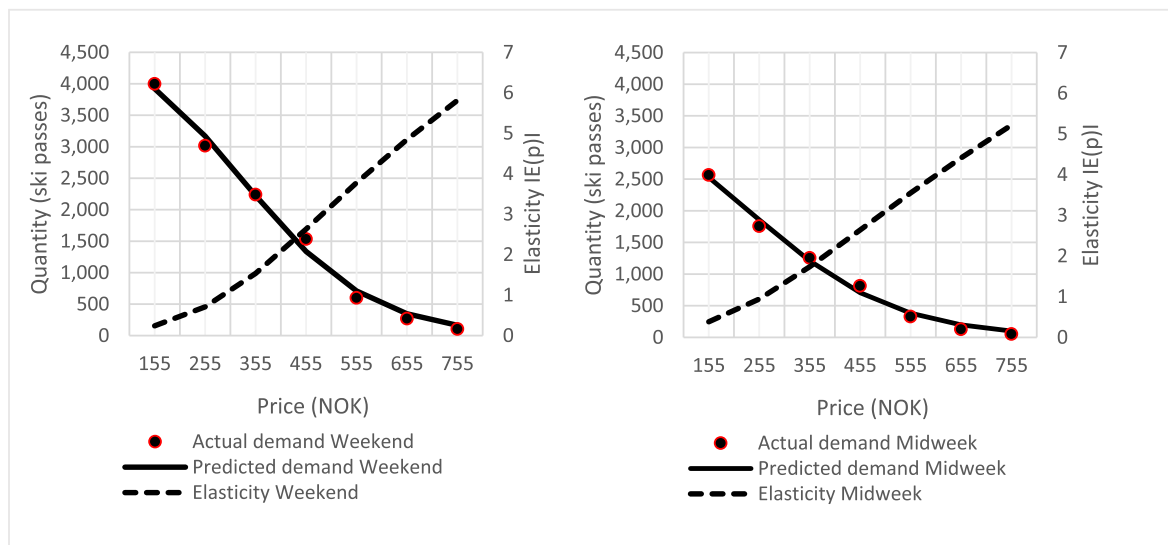We have run the model for different subsets of the sample based on

Fig. 4. Actual and predicted values and elasticities using logit PRF for midweek (left panel) and weekend (right panel).

Table 3
Logit demand-shift function: Summary of the parameter estimates and model fit.

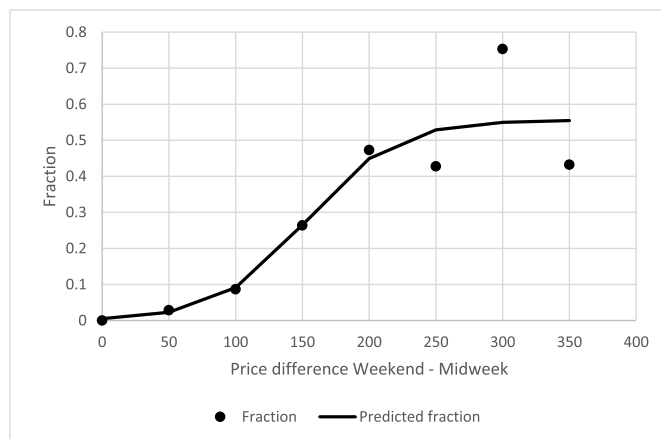|	Variable	Coefficient	p-value
Logit	V	0.5560082	0.001
	λ	−4.687215	0.170
	μ	0.0306263	0.186
	R2 = 0.9458 (Adjusted R-squared = 0.9133)		
	AIC = −9.54, BIC = −9.31		

Fig. 5. Actual and predicted demand-shift values using the logit function.

specific criteria of the respondents to test if they have their own significant results. In the first case, we compare the respondents working full time with those who do not. The purpose is to test the results when leisure time availability is not a major barrier. In the second case, we compare results taking into account different accommodations when visiting the ski resort, and in the third case, we test the importance of distance to the ski resort, more precisely, if the results for skiers within 70 km driving distance to the ski resort differs from those beyond a 70 km driving distance. In all cases, the optimal price for every subset is higher on weekends than on midweek days, both with and without diversion. This means that the price sensitivity on weekends is generally higher than on midweek days for all groups. The results are summarized in Table 6, and Figs. 9–11 illustrate the predicted demand shift values using the logit demand shifting function (8).

Skiers working full time are less price sensitive than those not working full time. At the previously calculated optimal midweek price for the whole sample without diversion (NOK 263), the price elasticity for those working full-time is −0.90 and for the others it is −1.22. The optimum price for the former group is thus higher than NOK 263 and lower for the latter group. We get nearly the same results looking at the corresponding price setting for the weekend. At the optimal weekend price (NOK 295), the elasticity for full-time workers is −0.92, and for the others, it is −1.23. These are not surprising results since one should assume that those who work full time generally have a higher income than other groups and thus have a higher willingness to pay and are less price sensitive. A more surprising result is the small differences in diversion between the two subsets. For price differences up to NOK 150 between weekdays and weekends, the demand shift is almost the same for those who work full time and those who do not. For higher price differences, there is a somewhat higher demand shift among those who do not work full time. Since the diversion is almost the same, there are

Table 4
Optimal prices, seasonal demand for the sample, and revenue, without demand shifting. Calculation of the sample's capacity constraint for day passes over the season is based on the daily capacity in the resort (see Section 3.3). NC. = No constraint.

Daily capacity in the ski resort	The sample's seasonal capacity contstraint		Optimal price (NOK)		Demand		Revenue (NOK)
	Midweek	Weekend	Midweek	Weekend	Midweek	Weekend	
NC.	NC.	NC.	263	295	1780	2801	1,294,794
5600	3061	1801	263	400	1780	1801	1,188,650
4000	2124	1151	263	480	1780	1151	1,021,128
3500	1831	948	263	511	1780	948	953,009
3000	1538	745	299	548	1538	745	868,568
2500	1245	542	346	594	1245	542	752,639
2000	952	339	399	659	952	339	602,912

Table 5
Optimal prices, seasonal demand for the sample, and revenue, with demand shifting. Calculation of the sample's capacity constraint for day passes over the season is based on the daily capacity in the resort (see Section 3.3). NC. = No constraint.

| Daily capacity in the ski resort	The sample's seasonal capacity contstraint		Optimal price (NOK)		Demand (Diversion)		Revenue (NOK)
	Midweek	Weekend	Midweek	Weekend	Midweek	Weekend	
NC.	NC.	NC.	270	292	1785 (48)	2786 (−48)	1,293,335
5600	3061	1801	264	358	2162 (388)	1801 (−388)	1,216,374
4000	2124	1151	298	408	2124 (576)	1151 (−576)	1,102,541
3500	1831	948	334	439	1831 (512)	948 (−512)	1,028,051
3000	1538	745	374	474	1538 (451)	745 (−451)	927,520
2500	1245	542	419	514	1245 (390)	542 (−390)	799,993
2000	952	339	475	563	952 (331)	339 (−331)	642,699
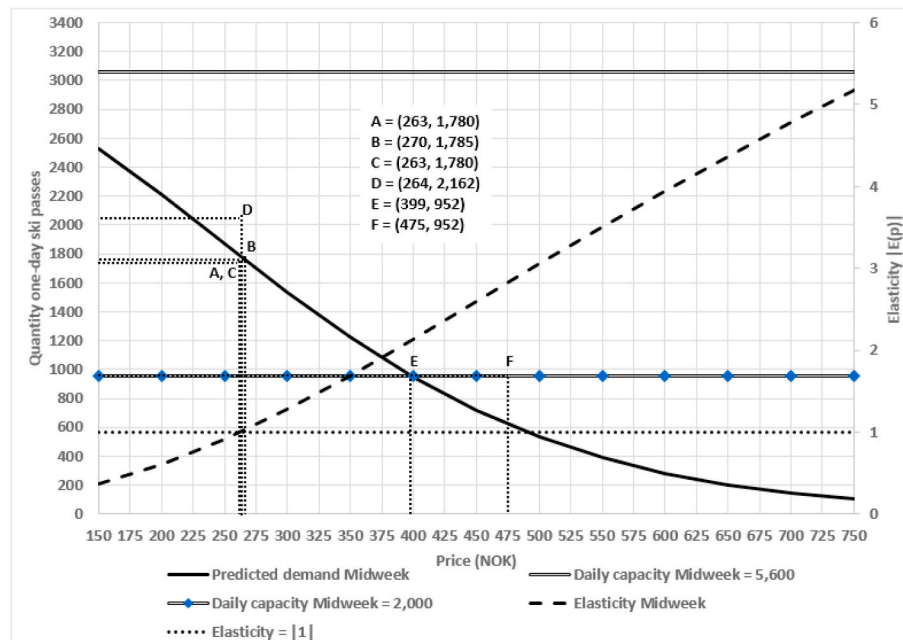
Fig. 6. Predicted demand, capacities, and optimal prices. Midweek. A: No constraint and without diversion. B:No constraint and with diversion. C: Daily capacity = 5600 and without diversion, D: Daily capacity = 5600 and with diversion, E: Daily capacity = 2000 and without diversion, F: Daily capacity = 2000 and with diversion.

also small differences in optimal price adjustments when this is considered.

In the analyzes of subgroups based on accommodation, we find that those who live in their own cabin or apartment when they visit the ski resort on midweek days are more price sensitive than those who stay at home or rent a cabin/apartment. The picture is opposite on weekends, which is intuitively easy to understand. Cabin/apartment owners usually are less at the ski resort on weekdays than on weekends and thus have a higher willingness to pay on weekends. Their investment in the destination can also have influenced their willingness to pay for ski experiences. Again, looking at the calculated optimal midweek price for the whole sample without diversion, the price elasticities for those staying at home, those staying at their own cabin/apartment, and those renting a cabin/apartment is 0.92, 1.16 and 0.95, respectively. Corresponding values at the optimal weekend price are 1.02, 0.93, and 1.04. The shift demand functions for the three subgroups are quite similar, so given the optimal midweek and weekend prices for the whole sample, the diversion effect will be nearly the same. On the other hand, if the resort chose price differentiations based on the optimal prices for the subsets, the diversion effect for the cabin/apartment owners will be much larger than in the other subgroups due to a larger price difference between midweek and weekend, as we can see in Table 4.

Skiers who live within a 70 km radius of the ski resort have a lower willingness to pay and a higher price sensitivity than those who live

further away, but the difference is minor on midweek. The result confirms the findings of Schroeder and Louviere (1999) and Malasevska and Haugom (2018) that there is a positive correlation between the travelling distance and the willingness to pay for an entrance fee. The difference between optimal prices for the two distance groups increases on midweek days and stays nearly unchanged on weekends when we consider diversion.

The analysis highlights some general rules about optimal price setting. Firs, when a firm implements price differentiation, it will always be optimal to set the highest price in the period, or for the customer group, with the greatest price sensitivity. In such cases the prices must be set so that the price elasticities in both markets (period 1 and 2 or customer group 1 or 2) are equal to 1 in absolute value. If the elasticity between the markets differs, it is optimal to increase the price in the market with the lowest elasticity and decrease the price in the other market until equality between the elasticities appears. Second, the firm should always consider the possibility of diversion. The higher the diversion rate is, the lower is the optimal price differentiation in relative terms when considering the possibility of demand shifting. In an extreme case with 100% diversion, the prices should be the same in both markets. Our study shows that the maximum diversion rate (the upper asymptote in the demand shifting Figs. 5 and 9–11) is 55–60% for the whole sample and the subsets. Third, if the optimal prices induce a demanded quantity that exceeds capacity, the firm needs to calculate a
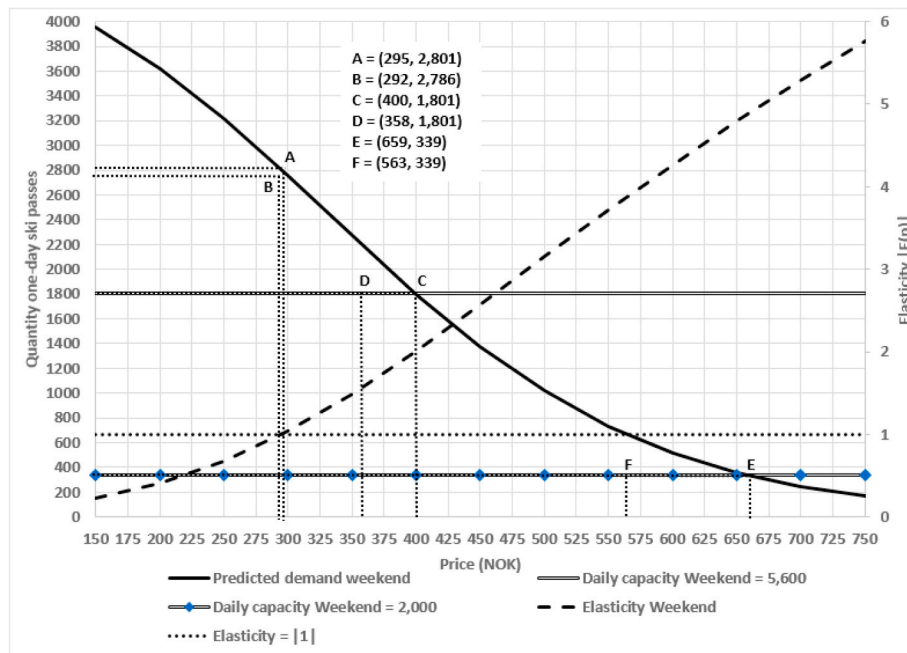
Fig. 7. Predicted demand, capacities, and optimal prices. Weekend. A: No constraint and without diversion. B:No constraint and with diversion. C: Daily capacity = 5600 and without diversion, D: Daily capacity = 5600 and with diversion, E: Daily capacity = 2000 and without diversion, F: Daily capacity = 2000 and with diversion.
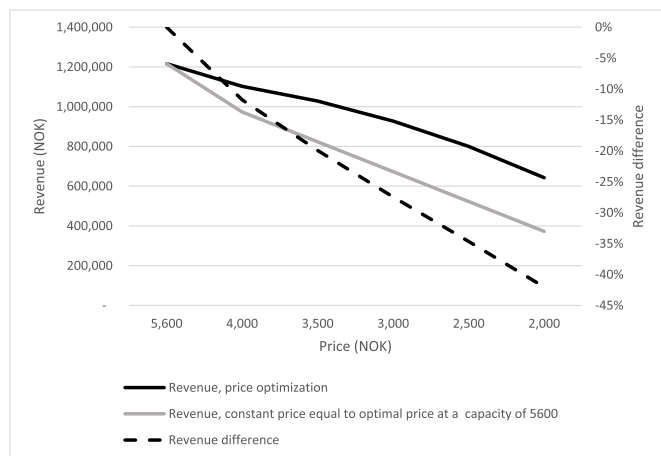

Fig. 8. Revenue with and without price optimization, at different capacity levels, and with demand shifting.
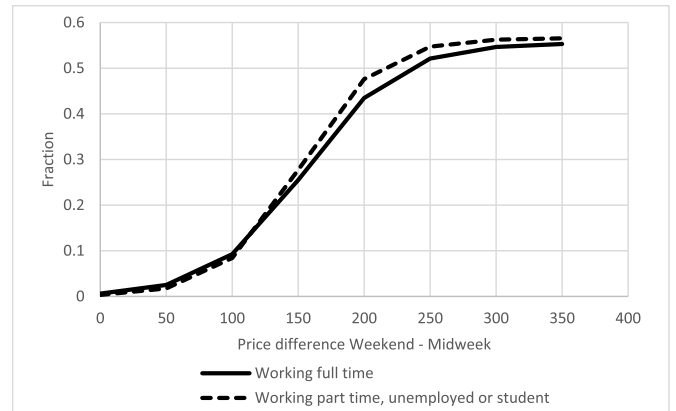

Fig. 9. Predicted demand-shift values using the logit function. Subset: Working full time and not working full time.

Table 6
The results of the price optimization for different subsets of the skier criteria.

|	Optimal price					
	Without diversion		With diversion		Diversion	
	Midweek	Weekend	Midweek	Weekend	Number	Percent
Total	263	295	270	292	48	2.8
Working full time	277	306	283	302	36	2.9
Not working full time	233	267	238	263	12	2.2
Accommodation						
- Home	273	292	276	290	10	1.4
- Own cabin/apartment	238	303	257	296	24	5.1
- Hotel or rental apartment/cabin	270	290	274	288	12	2.2
Distance ski resort ≤70 km	264	288	268	285	11	1.7
Distance ski resort >70 km	265	298	272	294	37	3.3
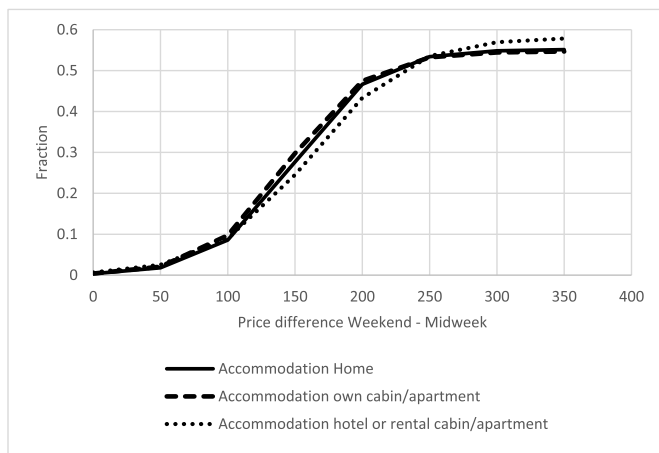
Fig. 10. Predicted demand-shift values using the logit function. Subset: Accommodation.
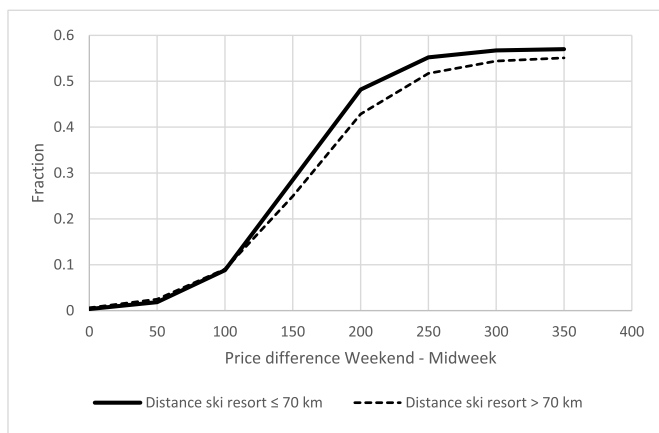

Fig. 11. Predicted demand-shift values using the logit function. Subset: Distance.

runout price, a price at which demand exactly equals available capacity.

6. Conclusion, discussion and implications

The purpose of this study was to test a price optimization model for the alpine skiing industry, which took into account demand shifting from peak periods to off-peak periods and capacity constraints. The analysis was based on a survey conducted at one of the largest ski resorts in Norway and interviews with the resort manager. The reported willingness to pay for ski experiences can differ from the actual willingness to pay since there are no commitments in such a study. Hence, studies based on stated, not revealed, observations have their limitations. The model we used assumed that the incremental cost per additional skier is close to zero, so the resort's price optimization problem is to maximize total contribution by maximizing revenue. This assumption has also been used in earlier studies on the alpine skiing industry (see Haugom & Malasevska, 2018) and can be defended by the fact that the initial capacities are set with high fixed costs, and one extra skier will have little effect on the total costs. This cost structure is quite typical in the tourism industry in general. An example is amusement parks, where the incremental costs are close to zero per additional visitor, based on the argument that the fixed costs are relatively high, and low demand does not stop the attractions (Phillips, 2005).

In general, our model can be used in different industries to increase their profit as long as demand is varying and predictable, the capacity is relatively fixed, the incremental cost is near zero, and there is no storage

problem. Many services exhibit all these criteria and have successfully implemented price differentiation (Haugom & Malasevska, 2018). However, as mentioned in Section 2, as per our knowledge, there are no studies on optimal price differentiation, considering both demand shifting at various price levels and capacity constraints. The current study fills this gap and our analytical framework can be used by ski resorts and other firms in the service industry worldwide.

In our analysis of demand shifting by intra-weekly price differentiation, we divided the week into two periods: midweek (Monday–Thursday) and weekend (Friday–Sunday), where weekends are the peak period. Our findings indicate that small changes in price differences between midweek and weekend, when the price differences initially are either low or high, have a marginal impact on the number of skiers shifting demand from weekends to midweek. Changes in-between have a large impact, which gives the demand shifting curve its S-shape. Our findings also indicate that no matter how high the price difference is, there will not be more than 56% of skiers shifting from weekends to midweek days. This maximum diversion value indicates that approximately half of the skiers will ski on the weekends regardless of the price difference, and their decision is based on factors other than the price. These findings are consistent with previous research (Haugom & Malasevska, 2019) that approximately 50% of the skiers will increase their skiing activity on midweek days to take advantage of the reduced price in this period compared with the ski pass price on the weekend.

Our results from the price optimization model show that capacity constraints will significantly impact the intra-weekly price differentiation. In a hypothetical situation with no capacity constraints, the optimal prices are only affected by price sensitivity and demand shifting. In this case, the optimal weekend price is only 8% higher than the optimal midweek price. The importance of capacity constraints for price differentiation is due to the fact that the market's size is initially much larger on the weekends than on midweek days. Hence, capacity utilization is higher on the weekends, and the resort must set a runout price on an earlier capacity stage than on midweek days. The runout price is higher than the optimal price without full capacity utilization and will affect the demand shifting and optimal prices in the off-peak period.

The actual capacity at the resort in a normal season is 5600 daily visitors. Incorporating this capacity level in our model gives low capacity utilization midweek, and over 100% on weekends, using the optimal prices without any constraints. The runout price on the weekend must then be set 23% higher than the optimal price without a capacity constraint. The corresponding optimal price on midweek days will be 36% lower than the weekend price.

Our results show that the intra-week optimal price difference will increase with reduced capacity as long as the midweek capacity is not fully utilized. At 100% capacity utilization in both periods, further reductions in the capacity limit will decrease the price differences. Furthermore, the optimal prices in both periods will increase as long as it is necessary to set a runout price in at least one of the periods.

Ski resorts worldwide face significant challenges because of COVID-19 as governments impose limits on ski resort capacity. According to our optimization model, the resorts should, therefore, increase their prices. If they keep their prices unchanged, they risk large revenue losses. The ski resort was instructed in the 2020/21-season to reduce its daily capacity from 5600 to 4000 daily skiers. According to our model, this will increase optimal prices by 13% midweek and 14% on weekends, but the total revenue will still fall by 9% due to fewer skiers on the weekends. If the resort decides not to do anything with its prices, they risk a much larger fall in revenue, as shown in Fig. 7.

Our analysis focused on how customers responded to different prices, and we used the survey data to estimate a model to optimize prices. In these pandemic times, it is possible that customers will accept higher prices due to capacity restrictions, which will in some way guarantee them more secure skiing. Future research should examine further possible differences in short- and long-term effects on customer acceptance. In the long term, consumers may change their behaviour due to

updated expectations of future prices based on the price currently offered (Phillips, 2005). Another long-term effect is when a pricing tactic makes buyers angry because it is perceived as 'unfair' (Phillips, 2005). Both effects can be considered when the ski resort makes its pricing decisions for the season. If high prices can harm the ski resort's reputation and, for example, reduce the participation of new and young skiers, a tactic for the resort can be to bear more of the loss due to the pandemic situation itself and instead ensure greater future demand. It is possible to incorporate customers' expectations of future prices in our model mathematically, and future research may focus on that topic.

CRediT authorship contribution statement

Per Kristian Alnes: Conceptualization, Investigation, Methodology, Formal analysis, Visualization, Writing – original draft, Funding acquisition. **Iveta Malasevska:** Conceptualization, Investigation, Validation, Writing – review & editing. **Ørjan Mydland:** Writing – review & editing. **Erik Haugom:** Conceptualization, Investigation, Data curation, Validation, Writing – review & editing, Funding acquisition, Project administration.

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