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Overpricing in a Spatial Hedonic Frontier Model: The Case of Ski Lift Tickets in Norway

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A general assumption of the standard hedonic price model is that producers produce outputs/services efficiently, and deviations from this situation are assumed to involve either overcharging or undercharging. Using the profit maximising behaviour, we derive an alternative hedonic model to show when prices are overcharged for services or products with the same characteristics. We argue that price charged by a firm depends on the price charged by the neighbouring firms giving rise to spatial dependence in prices. Based on this philosophy, we present a spatial-lag frontier hedonic pricing model. This new modelling framework is illustrated using data from Norwegian ski resorts in the winter season of 2014/2015 to examine whether one-day ski lift ticket prices are interrelated with other operators and to what extent the ski lift tickets are overcharged, if any.

Keywords: Hedonic price model; spatial econometrics; stochastic frontier; alpine skiing; Norway.

JEL Classification: C31, L11, Z30

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Introduction

If the output market is competitive, a profit maximising firm produces output by setting an exogenously given output price equal to its marginal cost (MC). If the output market is non-competitive, a firm uses the marginal revenue equals MC rule. In this case, both price and output are endogenous (decided by the firm) (e.g., Pindyck and Rubinfeld, 2018). In such a case, one can use a demand function to solve the identification problem (endogeneity of price and output). The alternative is to use the reduced form expression of price as a function of exogenous variables. As prices are influenced by the characteristics of output, hedonic price models are used commonly (e.g., Rosen, 1974; Epple, 1987; Papatheodorou *et al.*, 2012).

The hedonic pricing method has many applications in economics, ranging from real estate markets, price of food and wine, studies of the hospitality and tourism sector, environmental issues, etc. (e.g., Chau and Chin, 2003; Malpezzi *et al.*, 2003; Waltert and Schläpfer, 2010; Outreville and Le Fur, 2020; Asche *et al.*, 2021; Han and Bai, 2022). The extensive use of the hedonic pricing framework is not surprising because the concept is easy to use, and it can include several attributes for a product or service offered by a multiplicity of actors with the aim of satisfying customers' demands.

In the standard hedonic price model literature, the researchers use the difference in predicted and observed price to show whether the product/service is overpriced or underpriced. Although one can justify it theoretically, it is unlikely to be the case in practice based on estimation results. That is, the difference in predicted and observed prices may not be overpricing or underpricing of a product/service, because this difference can capture estimation noise and it can be caused by many other factors. Our theoretical model is based on a standard hedonic price model that we justify based on the profit maximising behaviour of firms. This is a reasonable framework for a firm operating in either a competitive or non-competitive market. In our modelling framework, underpricing by firms does not exist, and we are able to disentangle % overcharge (which can be controlled by the firm) from noise (which cannot be controlled by the firm). To disentangle overpricing from noise, we use the stochastic frontier (SF) technique as a tool.[1]

There are many applications in the literature that combine the standard hedonic price model with the stochastic frontier modelling framework. For example, Kumbhakar and Parmeter (2010) introduced a hedonic price model to account for buyers'/sellers' incomplete information. They use a two-tier stochastic frontier (Polachek and Yoon, 1987) model in which a standard hedonic price model

[1]Recent reviews of SF models can be found in, e.g., Kumbhakar *et al.* (2015), Sickles and Zelenyuk (2019) and Kumbhakar *et al.* (2022a, 2022b).

is used to account for incomplete information by the buyers (who are not fully informed of the lowest price available in a market) and the sellers (who are not fully informed about the highest price they could charge). Using the framework, Kumbhakar and Parmeter (2010) and Bonanno *et al.* (2019) assessed whether Italian food manufacturers carrying products with credence attributes in their portfolio were able to obtain higher prices. Although these papers used hedonic models, we do not address consumer/producer ignorance in our paper.[2]

Another issue is that we know from practise that many firms set their prices in response to the prices charged by neighbouring firms. Thus, we expect a spatial pattern in prices, meaning that the price charged by a given firm is linked to prices by other firms.[3] This aspect may create an endogeneity problem/spatial dependency problem, which we deal with by using a spatial hedonic price formulation (e.g., Anselin, 2010).[4]

There are several applications of the spatial hedonic pricing models in the literature. Falk (2008) included a spatial hedonic price model in his analyses of ski lift ticket prices in Austria, but did not report the results from that analysis. Armstrong and Rodriguez (2006) estimated spatial hedonic price functions to examine local and regional accessibility benefits of commuter rail service in Massachusetts. Seo *et al.* (2014) analysed the relationships between housing prices and proximity to light rail and highways in Arizona using a spatial hedonic regression framework. Following Kumbhakar and Parmeter (2010), the hedonic price model of Samaha and Kamakura (2008) also accounts for, through use of the SF framework, that buyers (sellers) are not fully informed of the lowest (highest) price available in the real estate property market. In their study, they combined the SF model and geographically weighted regression, and in that sense used a hedonic price model for cases with incomplete information among the sellers/buyers to account for spatial heterogeneity.

In this paper, we make two main contributions. First, we use a hedonic pricing model, but do not follow the assumption made in the standard hedonic pricing model. Specifically, we assume, based on our theoretical model, that some firms follow the best practice regarding the price and quality they offer, and that firms that deviate from best practice, overcharge. Second, we account for the endogeneity that is supposed to exist between the output prices of a firm and those of neighbouring

[2] One can assume that price overcharge by the seller indicates that consumers are not fully informed about the market (lowest price available).

[3] In this paper, we do not address the theory behind this behaviour. Instead, we explore whether this is the case in our empirical model.

[4] Recent reviews of spatial econometric methods can be found in, e.g., LeSage and Pace (2009), Chi and Zhu (2019), Arbia *et al.* (2021) and Postiglione *et al.* (2022).

firms by specifying and using spatial lags of prices in a hedonic frontier pricing model.

In our empirical application, the spatial-lag hedonic frontier model is estimated using data from Norwegian ski resorts in the winter season of 2014/2015. The focus in the empirical application is to examine what affects one-day ski lift ticket prices and the degree to which the ski lift tickets are overpriced or not. This part of the model is an extension of standard hedonic price models. Note that both features, spatial relationship in prices and overcharging of prices of ski lift, are testable hypotheses. Thus, overcharging of prices in our model can occur either with or without spatial price relationships. This is not possible in a standard hedonic price model.

Hedonic Price Models

Standard hedonic price model

A standard hedonic model for the price of a product or service may be specified as a function of several characteristics or qualities, as follows:

$$\ln Y_i = \alpha + \sum_j \beta_{ij} \ln \mathsf{X}_{ij} + e_i, \tag{1}$$

where Y_i is the price of product or service (in our case a ski resort) i, X_{ij} is a vector of characteristics j associated with the product/service i, α and β_{ij} are parameters and e_i is a random error that is independent and identically distributed with an expected value of zero and constant variance. X_{ij} may be measured in logs or levels.

It is possible to use more flexible forms than the linear form (Cropper *et al.*, 1988). For example, Halvorsen and Pollakowski (1981) used a quadratic Cox–Box transformation and Falk (2008) used a linear spline functional form. $\frac{\partial Y_i}{\partial X_{ij}}$ is the marginal effect of a particular characteristic on price, i.e., the marginal cost of or the consumers' willingness to pay for a particular characteristic of a product/service. This standard hedonic price model (1) can be estimated using OLS. Once (1) is estimated, the estimated coefficients α and β_{ij} can then be used to calculate the predicted price, which can be compared with the observed price. In the standard hedonic price literature, studies have typically used the difference in predicted and observed prices to reveal whether the product/service is overcharged or underpriced (Papatheodorou *et al.*, 2012).

Hedonic frontier price model

Using the price equal MC rule and specifying (log) marginal cost as $\ln \mathrm{MC} = \alpha + \sum_j \beta_{ij} \mathsf{X}_{ij}$ Equation (1) is the $P = \mathrm{MC}$ rule in logarithms, viz.,

$$\ln P = \ln \mathrm{MC} + e, \tag{2}$$

where we added an ad hoc error/noise term in (2). As the noise term e, by definition, is larger or smaller than zero ($e \gtrless 0$), the price can be larger or smaller than the marginal cost ($P \gtrless \mathrm{MC}$). Note that e is an unobserved variable to the firm, e.g., either measurement error in P and/or some unobserved X variables not included in the model. If $P \gtrless \mathrm{MC}$, it is not overpricing because e is not a decision variable to the firm. Thus, in this framework, the use of the terms overpricing or underpricing seems to be misleading.[5]

To include an overpricing component in the model, we assume the firms are operating in a non-competitive market in which price is not exogenous and their objective is to maximize profit π. Profit is defined as

$$\pi = P(Y) \cdot Y - C(W, Y), \tag{3}$$

where W are input prices, $P(Y)$ is the inverse demand function with $\frac{dP}{dY} \leq 0$, and $C(W, Y)$ is the cost function derived from competitive input markets.

The first-order condition (FOC) of (3) with respect to Y gives

$$\frac{d\pi}{dY} = P + Y\frac{dP}{dY} - \frac{dC}{dY} = 0, \tag{4}$$

where $\frac{dC}{dY}$ is the MC. It implies

$$P - \mathrm{MC} = -\frac{dP}{dY}Y. \tag{5}$$

As $\frac{dP}{dY} \leq 0$, $P \geq \mathrm{MC}$. If $P > \mathrm{MC}$, the excess can be viewed as a markup or overcharging. We define it formally later. Given that the estimating model is usually expressed in logarithms, we rewrite the FOC in (5) as

$$\frac{P - \mathrm{MC}}{P} = -\frac{Y}{P} \cdot \frac{dP}{dY} \equiv \epsilon, \tag{6}$$

where $\epsilon = \frac{d \ln P}{d \ln Y}$ is the (inverse) demand elasticity. Then, it follows that

$$\begin{aligned} 1 - \frac{\mathrm{MC}}{P} &= \epsilon \\ \Rightarrow P &= \mathrm{MC} \cdot \frac{1}{1 - \epsilon}. \end{aligned} \tag{7}$$

Note that $P \geq \mathrm{MC}$, because $\frac{1}{1-\epsilon} \geq 1$. By taking logarithms of both sides of the last part of (7) we obtain

$$\ln P = \ln \mathrm{MC} + u, \tag{8}$$

[5]This is partly an issue related to the efficient market hypothesis research in finance. In that field, any test of market efficiency assumes an equilibrium model that defines normal security returns. However, if market efficiency is rejected, this could either be because of an incorrect equilibrium model has been assumed (e.g., a regression model with omitted variables or measurement error), or because the market is truly inefficient (Campbell *et al.*, 1997).

where $u = \ln(\frac{1}{1-\epsilon})$. Thus, u is related to price overcharge and it is always zero or positive, which can be interpreted as the % overcharge as follows:

$$\begin{aligned}\%\text{ overcharge} &= \frac{P - \text{MC}}{P} = 1 - \frac{\text{MC}}{P} \\ &= 1 - e^{-u} = 1 - \left(1 - u + \frac{u^2}{2} - \cdots\right) \approx u. \end{aligned} \tag{9}$$

If we now assume, as a generalisation, that $\ln \text{MC} = \alpha + \sum_j \beta_{ij}\mathsf{X}_{ij}$ in (8), and substitute it into (1), we obtain

$$\ln Y_i = \alpha + \sum_j \beta_{ij}\mathsf{X}_{ij} + u_i + e_i, \tag{10}$$

which we name the hedonic frontier price model with price overcharge. This model disentangles % overcharge (that can be controlled by the firm) from noise (which cannot be controlled by the firm). This generalised model, in a similar way to the standard hedonic price model, can also include several quality characteristics.

The basic concept of our modelling framework is also outlined graphically in Fig. 1, which presents simple examples of a standard hedonic pricing model and a hedonic frontier pricing model. As already mentioned, the general assumption of the standard hedonic price model is that producers set price by equating price with MC (which can be viewed as the price frontier), and deviations from this frontier are assumed to involve either overpricing or underpricing, as illustrated in the left graph of Fig. 1. With the hedonic frontier pricing model, the frontier is only reached by the some firms that are not overcharging, and all other firms for

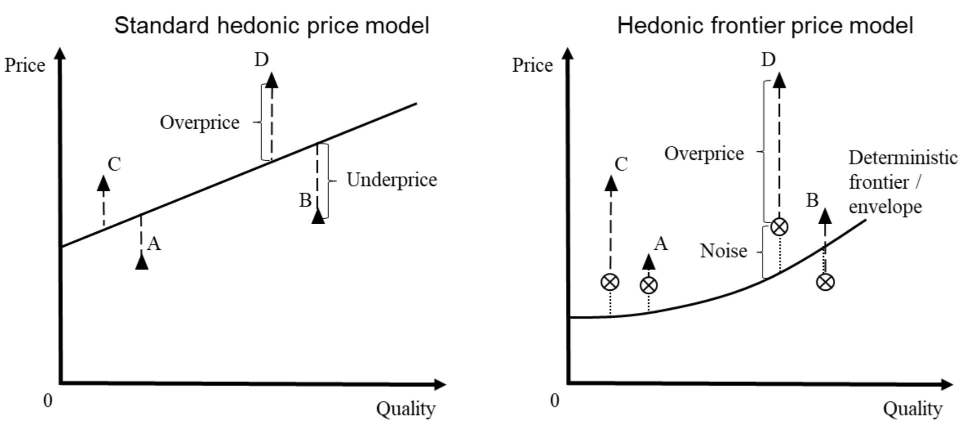

Fig. 1. Outline of standard hedonic price model and hedonic frontier price model for prediction of the “reasonable” price depending on quality. The symbol ▲ indicates quality–price values and ⊗ indicates the stochastic hedonic frontier.

which prices are away from the frontier, after controlling for noise in the data, are overcharging/overpricing. The greater the distance of price from the frontier, after controlling for noise, the larger is the overcharging.[6]

Spatial-lag hedonic frontier price model

Equation (10) can be extended in several ways to account for spatial dependence. Spatial dependence, as is the analysis of spillovers, is a special case of cross-sectional dependence. The structure of the correlation or covariance between random variables at different locations is derived from a specific ordering, determined by the relative position (distance) of the observations in geographical space. This framework typically requires a specialised set of techniques, including spatial-lag models (SLM), spatial autoregressive models (SAR), spatial cross-regressive models (SLX), or spatial error models (SEM) (e.g., Anselin, 2010; Arbia *et al.*, 2021).

In this study, we extend the model in (10) by including a spatial-lag model (SLM)/spatial autoregressive model (SAR) (Anselin, 1988; LeSage and Pace, 2009) that contains the price of neighbouring firms. More specifically, in the empirical application, we use the following spatial-lag hedonic frontier pricing model:

$$Y_i = \alpha + \rho \mathsf{W}_i' \mathsf{Y} + \sum_j \beta_{ij} \mathsf{X}_{ij} + u_i + v_i. \tag{11}$$

Compared with Equation (10), the model in (11) includes one additional component, i.e., the component $\rho \mathsf{W}_i' \mathsf{Y}$, which captures the spatial dependence in ticket prices between the spatially connected firms. W_i' is the spatial weights matrix (W_i' being the ith row of it) and ρ is the coefficient for the spatially lagged variable. A non-zero ρ coefficient indicates a spatial lagged ticket price effect.

Estimation

We estimate Equation (11) in two steps. In step 1, we estimate the spatial hedonic price model

$$Y_i = \alpha + \rho \mathsf{W}_i \mathsf{Y} + \sum_j \beta_{ij} \mathsf{X}_{ij} + e_i \tag{12}$$

This model was estimated using a generalised spatial two-stage least-squares estimator (Kelejian and Prucha, 2010; Drukker *et al.*, 2013), using the procedure "spregress" in Stata 17. With the introduction of the spatial lag of the dependent

[6]Note that in an SF model the probability of a firm being fully efficient is zero. That is, in our hedonic model, there will always be overcharging. This is also consistent with the model in (10) in which $u \geq 0$. Although we allow $u = 0$ as a theoretical possibility, empirically $u > 0$, which is the case in (10).

variable, the interpretation of the regression coefficient estimates differs from the interpretation of the coefficient estimates from a standard regression model. If $\rho = 0$ (which can be econometrically tested) then the model in (12) is identical to the model in (10). A change in the independent variables for a given firm affects not only the dependent variable/price for this firm but also the dependent variable/price of the neighbouring firms. Then, from the estimated spatial model, we find the direct impact of an independent variable for a given firm on the own firm's dependent variable/price and the price effect on other firms is called an indirect impact. The sum of the direct and indirect impacts is termed the average total impact.

From step 1, we obtain $\hat{e}_i$, which is used in step 2. For this we write

$$\hat{e}_i = u_i - E(u_i) + v_i. \tag{13}$$

In this step, we assume u_i to be truncated-normal, i.e., distributed as $N^+(\mu, \sigma_u^2)$ (Kumbhakar *et al.*, 2015). Furthermore, the noise term v_i is assumed to be i.i.d. $N(0, \sigma_v^2)$. Using these distributional assumptions, we estimate Equation (13) using the standard cross-sectional stochastic frontier (SF) technique. This model was estimated using a maximum likelihood estimator, using the "sfcross" procedure (Belotti *et al.*, 2013) in Stata 17. Estimates from this model provide the remaining parameters (σ_u^2, σ_v^2, and μ). We then use the method of Jondrow et al. (1982) to obtain estimates of the overcharging components $\hat{u}_i$. These estimates provide the degree of overcharging in terms of percentages for each firm.

Empirical Application — One-Day Ski Lift Ticket Prices in Norway

As an empirical application, we estimate our spatial-lag hedonic frontier price model using data for Norwegian ski resorts in the winter season of 2014/2015, which is the same data used by Malasevska (2018).

A brief survey of the literature

The hedonic pricing framework has been used for the Alpine skiing industry to reveal which ski resort characteristics are important and to what extent for skiers, as well as to investigate whether ski resorts overcharge or underprice. Mulligan and Llinares (2003) examined the effect of a detachable chairlift on ski lift prices among 344 ski resorts in the US. Falk (2008) analysed how supply-related factors affect ski lift ticket prices and ranked 84 ski resorts in Austria according to their quality characteristics. Borsky and Raschky (2009) investigated individuals' willingness to pay (WTP) for risky sports activities by examining ski resorts in Austria. Falk (2011) analysed international ski lift ticket price differences in medium- and large-sized ski resorts in France, Austria, and Switzerland. Alessandrini (2013) estimated skiers' evaluation of the different characteristics of 19 ski resorts in Italy. Fonner and Berrens (2014) investigated the relationship between lift ticket prices and the physical characteristics and amenities offered by 181 ski areas in the US. Wolff (2014) combined hedonic pricing with a non-parametric and principal component analysis to identify the price–quality relationship of 168 ski resorts in France. Rosson and Zirulia (2018) identified the relative importance of different attributes in the determination of ski lift ticket prices in the Dolomites. Malasevska (2018) used the hedonic price method to examine what affected one-day ski lift ticket prices in Norway. Malasevska (2018) included ski lift ticket prices at the nearest ski resort as an independent variable. However, this step may have introduced an endogeneity problem.

Data

The data used in this study were collected during the winter season of 2014/2015 from the webpages of each ski resort, from comparative ski lift operators, as well as from questionnaires sent to ski resort representatives. The data are the same as those used in Malasevska (2018). The sample consists of 83 ski resorts, representing approximately 43% of all ski resorts (which include all the largest ski resorts) in Norway. Figure 2 shows where these 83 ski resorts are located in Norway.

In addition to the dependent ticket price variable, 15 independent quality characteristic variables were specified and applied in the analysis. These 15 independent

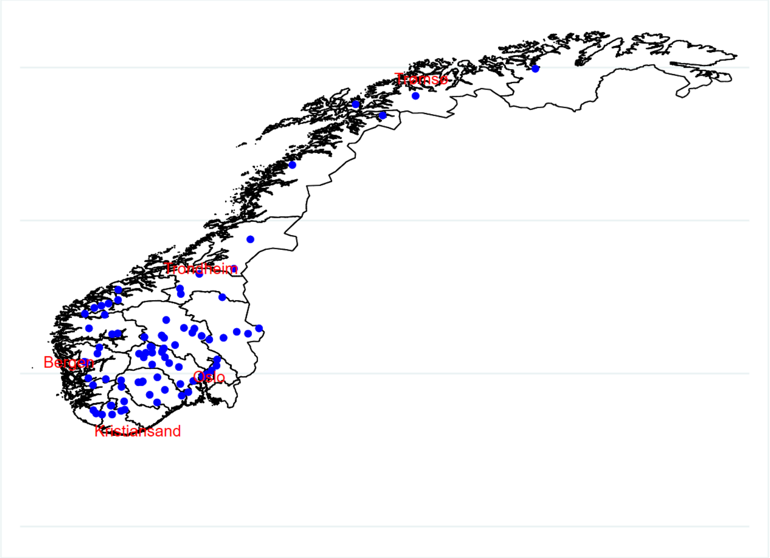

Fig. 2. Map of Norway, showing location (blue points) of the ski resorts.

Table 1. Variable description.

Variable	Description
PRICE	Single-day lift ticket price for adults. ln (natural logarithm) values used in the regression.
RISS	Percentage of intermediate ski slopes (for more confident skiers and snowboarders and known as RED runs).
RCL	Percentage of chair lifts and gondolas in the total number of ski lifts.
KM	Total length of ski slopes (km). ln values used in the regression.
DROP	Vertical drop (m) measured as the distance in altitude between the top and base of a ski resort.
BASEALT	Base altitude of the ski resort (m). ln values used in the regression.
SNOWFALL	Last five years average amount of snowfall in a season (cm). ln values used in the regression.
PARKS	Number of terrain parks—specially designed outdoor areas containing half-pipes, jumps, and metal features such as rails and boxes. ln values used in the regression.
SKINORWAY	Travel distance (km) to the nearest ski resort in Norway. ln values used in the regression.
SKISWEDEN	Travel distance (km) to the nearest large Swedish ski resort (one of the 10 largest Swedish ski resorts by the total length of slopes, according to information from http://www.skiresort.info). ln values used in the regression.
AIRPORT	Travel distance (km) to the nearest international airport (travelling by car). ln values used in the regression.
DENSWE	Travel distance (km) to the nearest large urban area (one of the 10 largest cities by population) in Denmark or Sweden (travelling by car). ln values used in the regression.
PRICENEAR	Price at the nearest ski resort in Norway (NOK). ln values used in the regression.
SEVERAL	Dummy variable to identify two or more ski resorts within a 50-km radius.
WEST	Dummy variable to identify a ski resort located in Western Norway.
SMALLCAPACITY	Dummy variable to identify a ski resort with a total ski lift capacity lower than 3000 persons per hour.

quality characteristic variables represent both internal and external supply-related factors. Table 1 provides a description of the variables used, while Table 2 includes the descriptive statistics associated with these variables.

For each of the 83 ski resorts, we also collected their GPS coordinates. Based on these coordinates, we constructed the inverse distance weighting matrix W, where the spillover effects are proportional to the inverse of the distance between ski resorts.

Table 2. Descriptive statistics.

	Mean	Std. Dev.	Min	Max	Median
PRICE (NOK)	339.20	43.39	200	430	345
RISS (%)	32.21	16.38	0	68.75	29.41
RCL (%)	9.92	13.96	0	50.00	0
KM (km)	13.35	12.78	0.85	75	10
DROP (m)	399.30	203.85	125	1010	360
BASEALT (m)	482.23	255.86	60	965	484
SNOWFALL (cm)	409.33	301.32	68.95	1246.90	268.24
PARKS	1.24	0.91	0	5	1
SKINORWAY (km)	52.31	65.30	2.00	434	36
SKISWEDEN (km)	428.35	189.04	27.50	966	410
AIRPORT (km)	158.55	84.14	15	594	160
DENSWE (km)	536.96	253.76	263.00	1446	479
PRICENEAR (NOK)	342.45	38.59	250	405	345
SEVERAL	0.39	0.49	0	1	0
WEST	0.25	0.44	0	1	0
SMALLCAPACITY	0.29	0.46	0	1	0

Note: $N = 83$.

Results

Table 3 shows the parameter estimates of the spatial-lag hedonic frontier pricing model for daily lift tickets for the sample of 83 ski resorts.

The assumption that the coefficient of the spatially lagged variable (ρ) equals zero (Moran test) was rejected, implying that daily ticket prices for a given ski resort are influenced by daily ticket prices at neighbouring ski resorts.

Overall, the fit of the model is good and explains approximately 78.8% of the variation in the ski resort lift ticket prices. This is higher than that in Malasevska (2018) (73.7%) with the same data using a standard hedonic pricing model.

In the spatial-lag model, the coefficients do not have a direct interpretation. That is, they do not represent marginal effects. The marginal effects can be decomposed into direct, indirect, and overall effects. Of the 15 independent quality characteristic variables included in the study, 12 are significant at the 1%, 5%, or 10% level. We also observed that the main impacts of the independent quality characteristic variables on the dependent ticket price variable are direct. The indirect effects are quite small, and almost 50% of them are statistically insignificant. However, the estimated ρ is statistically significant.

The percentage of intermediate ski slopes (RISS), the total length of ski slopes (KM), the vertical drop (DROP), the base altitude (BASEALT), and the number of snow parks (PARKS) have positive and statistically significant effects. The sign of

Table 3. Estimated coefficients and the associated direct, indirect, and average total impacts.

Coefficient for	Model coeff	Direct impact	Indirect impact	Average total impact
RISS	0.001**	0.001**	−0.00003*	0.001**
RCL	−0.0004	−0.0004	0.00001	−0.0004
KM	0.031*	0.031*	−0.0008	0.030*
DROP	0.0002***	0.0002***	−0.00001**	0.0002***
BASEALT	0.036**	0.036**	−0.001	0.035**
SNOWFALL	−0.033*	−0.033*	0.0009	−0.032*
PARKS	0.102***	0.102***	−0.0027**	0.099***
SKINORWAY	−0.057***	−0.057***	0.0015*	−0.055***
SKISWEDEN	0.059***	0.059***	−0.0016**	0.058***
AIRPORT	−0.007	−0.007	0.0002	−0.007
DENSWE	−0.114***	−0.114***	0.003*	−0.111***
PRICENEAR	0.167***	0.167***	−0.0045**	0.163***
SEVERAL	−0.008	−0.008	0.0002	−0.007
WEST	−0.081***	−0.081***	0.0022*	−0.078***
SMALLCAPACITY	−0.072***	−0.072***	0.0019**	−0.07***
CONSTANT	5.34***			
Weighting matrix PRICE (i.e., ρ)	−0.0339***			
Pseudo R^2	0.788			

Note: *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

these effects is intuitive. For example, if a ski resort increases the total length of ski slopes (KM) by 100% (doubles the total length), it leads to an increase in ticket prices of 3.1%, on average, ceteris paribus. Furthermore, if a ski resort increases PARKS by 100% (a doubling of the number of ski parks), it leads to an increase in the ticket price of 10.2%, on average, ceteris paribus. Malasevska (2018) used the same data, but a standard hedonic price model, and found that the variables KM and BASEALT had a positive and increasing effect on ski lift ticket prices, but in that study, these relationships were not statistically significant. Fonner and Berrens (2014) obtained the same result as us of a positive and significant effect of an increase in the base altitude of ski resorts. Although Malasevska (2018) found that snow conditions did not directly affect lift ticket prices, we found that the average yearly snowfall (SNOWFALL) has a significant negative effect on lift ticket prices. Fonner and Berrens (2014) also found that snowfall had a negative effect on lift ticket prices, but their findings were not significant. The negative effect of snowfall on price seems counter intuitive. However, one explanation could be that a lack of or insufficient snowfall makes a ski resort dependent on artificial snow production

(Bark *et al.*, 2010). That leads to higher ski lift prices to cover additional costs of snow-making at higher temperatures. Ski resorts with a total lift capacity of fewer than 3,000 persons per hour (SMALLCAPACITY) have significantly lower prices (7.2% lower) than ski resorts with greater ski lift capacity, which is expected and consistent with Malasevska (2018).

The distance to the nearest large ski resort in Sweden (SKISWEDEN) has a positive and significant effect, indicating that ski resorts close to large Swedish ski resorts tend to have lower prices. The distance between two Norwegian ski resorts (SKINORWAY) has a significant, but negative effect on ski lift prices, consistent with the findings of Malasevska (2018). The dummy variable SEVERAL, which takes the value one if there are more than two ski resorts in a 50 km radius, and zero otherwise, was not statistically significant. The lift ticket price at the nearest ski resort (PRICENEAR) has a significant and positive impact. Our findings indicate that, if prices at the nearest ski resort increase by 10%, there is an average increase in lift ticket prices of 1.7% for the investigated ski resort. Travel distance to the nearest international airport (AIRPORT) has a negative but insignificant effect. However, travel distance to the nearest large urban area in Sweden or Denmark (DENSWE) significantly and negatively affects prices. Finally, the results also show that ski resorts located in Western Norway (WEST) have significantly lower prices (8.1% lower) than ski resorts in the rest of Norway.

The distributions of the estimated overcharging/overpricing component u_i in our model (Equations (12) and (13)) are plotted in Fig. 3. The ski resorts with prices

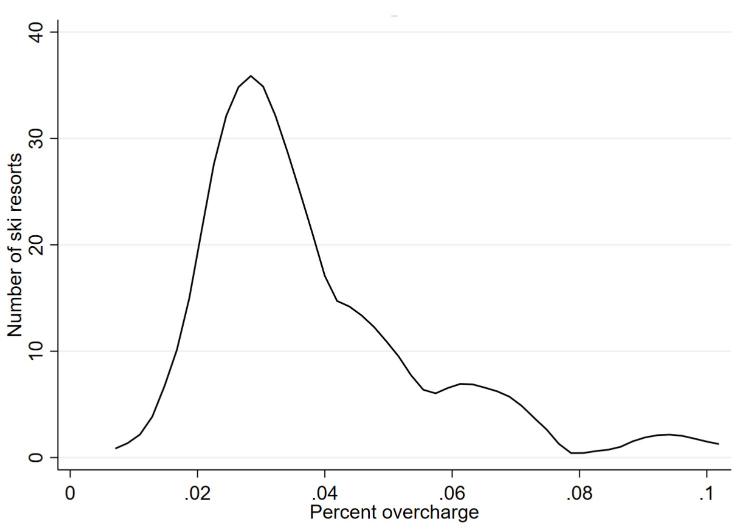

Fig. 3. Density plot of overcharging.

Table 4. Mean values of some variables for the following two groups: ski resorts that are overcharged by less than 6.6%; ski resorts that overcharged by more than 6.6%.

	Overcharge less than 6.6% $N = 75$	Overcharge more than 6.6% $N = 8$	Two-sample t test
PRICE (NOK)	336.59	363.75	*
RISS (%)	31.91	35.01	
RCL (%)	9.93	9.82	
KM (km)	14.11	6.21	*
DROP (m)	400.93	384.00	
BASEALT (m)	492.33	387.50	
SNOWFALL (cm)	395.66	537.51	
PARKS	1.27	1	*
SMALLCAPACITY	0.27	0.50	*

Note: *, **, and *** denote statistically significant differences at the 10%, 5%, and 1% levels, respectively.

closest to the most efficient resort in terms of price (indicating no overcharge) overcharged by 1.7%, whereas the ski resort with the highest degree of overpricing overcharged by 9.7%. The average overcharge in the sample was 3.8%. Looking at the right tail of the distribution in Fig. 3, the price overcharged at the 90th percentile was 6.6%.

To learn more about the ski resorts that overcharged the most, in Table 4, we present descriptive statistics for two groups: the group of ski resorts that overcharged by less than the 90th percentile (i.e., less than 6.6%) and the group of ski resorts that overcharged by more than the 90th percentile. While there is no clear statistically significant differences between these two groups, we observe that the most overcharging group (that overcharged by more than 6.6%), on average have the highest one-day ski lift ticket price, less kilometres of ski slopes, fewer terrain parks, and less ski lift capacity.

Concluding Comments

Pricing is a strategic choice for (almost) all commercial companies, and a range of pricing models exist in the literature. One frequently used approach to estimate the price for a service or product, and to identify what characteristics contribute to and limit the overall price, is the hedonic pricing model. In this study, we introduced an alternative hedonic pricing model, and we named it the spatial-lag frontier hedonic pricing model. This model was derived from the profit maximising behaviour of firms and we estimated it using the stochastic frontier (SF) technique, which was originally developed to measure efficiency in production (Kumbhakar *et al.*, 2022a, 2022b).

Using the spatial-lag frontier hedonic pricing model, we estimate the "best buy" function (after controlling for data noise) and compare prices for all products/services not on the "best buy" function. In addition, we allowed for endogeneity by including prices charged by neighbours in the same business. This new modelling framework was illustrated using data for the winter season of 2014/2015 for Norwegian ski resorts, to examine what affected one-day ski lift ticket prices and the degree to which the ski lift tickets are overcharged or not.

Our model disentangles noise from price overcharging by the firm, where noise can both capture unobserved variables and measurement error in price. Still, we know that in our empirical example, and in probably most other empirical studies in the literature, omitted variables will often influence the empirical estimates. Thus, in future research, there is a need for relevant and reliable rich data sets for applied research. An extension of the model presented here would be to use panel data, which would provide more reliable estimates, and also the possibility to examine the development of overpricing for a company, sector or region.

The framework presented in this study is to analyse reasonable pricing and to what extent different attributes influence the pricing can also be applied to many other similar cases, where there exists a "best practice" minimum (maximum) and the observed counterpart of the variable in question is above (below) the "best practice" minimum (maximum).

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References

Alessandrini, S (2013). Quality of ski resorts and competition between the Emilian Apennines and Altipiani Trentini. An estimate of the hedonic price. *Review of Economic Analysis*, 5, 229–240.

Anselin, L (1988). *Spatial Econometrics: Methods and Models*, Vol. 4, New York: Springer Science & Business Media.

Anselin, L (2010). Thirty years of spatial econometrics. *Papers in Regional Science*, 89, 3–25.

Arbia, G, G Espa and D Giuliani (2021). *Spatial Microeconometrics*, UK: Routledge.

Armstrong, RJ and DA Rodriguez (2006). An evaluation of the accessibility benefits of commuter rail in eastern Massachusetts using spatial hedonic price functions. *Transportation*, 33, 21–43.

Asche, F, J Bronnmann and AL Cojocaru (2021). The value of responsibly farmed fish: A hedonic price study of ASC-certified whitefish. *Ecological Economics*, 188, 107135.

Bark, RH, B Colby and F Dominguez (2010). Snow days? Snowmaking adaptation and the future of low latitude, high elevation skiing in Arizona, US. *Climatic Change*, 102, 467–491.

Belotti, F, S Daidone, G Ilardi and V Atella (2013). Stochastic frontier analysis using Stata. *The Stata Journal*, 13, 719–758.

Bonanno, A, F Bimbo, M Costanigro, A Oude Lansink and R Viscecchia (2019). Credence attributes and the quest for a higher price–a hedonic stochastic frontier approach. *European Review of Agricultural Economics*, 46, 163–192.

Borsky, S and PA Raschky (2009). The hedonics of hedonism-estimating the value of risk-taking activities. *Kyklos* 62, 210–225.

Campbell, JY, AY Lo and MacKinlay (1997). *The Econometrics of Financial Markets*, 2nd edn., Princeton, NJ: Princeton University Press.

Chau, KW and T Chin (2003). A critical review of literature on the hedonic price model. *International Journal for Housing Science and Its Applications*, 27, 145–165.

Chi, G and J Zhu (2019). *Spatial Regression Models for the Social Sciences*, New York: SAGE publications.

Cropper, ML, LB Deck and KE McConnell (1988). On the choice of functional form for hedonic price functions. *The Review of Economics and Statistics*, 70, 668–675.

Drukker, DM, P Egger and IR Prucha (2013). On two-step estimation of a spatial autoregressive model with autoregressive disturbances and endogenous regressors. *Econometric Reviews*, 32, 686–733.

Epple, D (1987). Hedonic prices and implicit markets: Estimating demand and supply functions for differentiated products. *Journal of Political Economy*, 95, 59–80.

Falk, M (2008). A hedonic price model for ski lift tickets. *Tourism Management*, 29, 1172–1184.

Falk, M (2011). International price differences in ski lift tickets. *Swiss Journal of Economics and Statistics*, 147, 303–336.

Fonner, RC and RP Berrens (2014). A hedonic pricing model of lift tickets for US alpine ski areas: Examining the influence of crowding. *Tourism Economics*, 20, 1215–1233.

Halvorsen, R and HO Pollakowski (1981). Choice of functional form for hedonic price equations. *Journal of Urban Economics*, 10, 37–49.

Han, W and B Bai (2022). Pricing research in hospitality and tourism and marketing literature: A systematic review and research agenda. *International Journal of Contemporary Hospitality Management*, 34, 1717–1738.

Jondrow, J, C K Lovell, IS Materov and P Schmidt (1982). On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics*, 19, 233–238.

Kelejian, HH and IR Prucha (2010). Specification and estimation of spatial autoregressive models with autoregressive and heteroskedastic disturbances. *Journal of Econometrics*, 157, 53–67.

Kumbhakar, SC and CF Parmeter (2010). Estimation of hedonic price functions with incomplete information. *Empirical Economics*, 39, 1–25.

Kumbhakar, SC, CF Parmeter and V Zelenyuk (2022a). Stochastic frontier analysis: Foundations and advances I. In *Handbook of Production Economics*, SC Ray, RG Chambers and SC Kumbhakar (eds.), Vol. 1, pp. 331–370. New York: Springer.

Kumbhakar, SC, CF Parmeter and V Zelenyuk (2022b). Stochastic frontier analysis: Foundations and advances II. In *Handbook of Production Economics*, SC Ray, RG Chambers and SC Kumbhakar (eds.), Vol. 1, pp. 371–408. New York: Springer.

Kumbhakar, SC, H Wang and AP Horncastle (2015). *A Practitioner's Guide to Stochastic Frontier Analysis using Stata*, UK: Cambridge University Press.

LeSage, J and RK Pace (2009). *Introduction to Spatial Econometrics*, US: Chapman and Hall/CRC.

Malasevska, I (2018). A hedonic price analysis of ski lift tickets in Norway. *Scandinavian Journal of Hospitality and Tourism*, 18, 132–148.

Malpezzi, S *et al.* (2003). Hedonic pricing models: A selective and applied review. *Housing Economics and Public Policy*, 1, 67–89.

Mulligan, JG and E Llinares (2003). Market segmentation and the diffusion of quality-enhancing innovations: The case of downhill skiing. *Review of Economics and Statistics,* 85, 493–501.

Outreville, J-F and E Le Fur (2020). Hedonic price functions and wine price determinants: A review of empirical research. *Journal of Agricultural & Food Industrial Organization*, 18, 20190028.

Papatheodorou, A, Z Lei and A Apostolakis (2012). Hedonic price analysis, In *Handbook of Research Methods in Tourism*, UK: Edward Elgar Publishing.

Pindyck, RS and DL Rubinfeld (2018). *Microeconomics*, UK: Pearson Education.

Polachek, SW and BJ Yoon (1987). A two-tiered earnings frontier estimation of employer and employee information in the labor market. *The Review of Economics and Statistics,* 296–302.

Postiglione, P, R Benedetti and F Piersimoni (2022). *Spatial Econometric Methods in Agricultural Economics Using R*, US: CRC Press.

Rosen, S (1974). Hedonic prices and implicit markets: Product differentiation in pure competition. *Journal of Political Economy*, 82, 34–55.

Rosson, S and L Zirulia (2018). A hedonic price model for ski lift tickets in the Dolomites. *Worldwide Hospitality and Tourism Themes*, 10, 222–235.

Samaha, SA and WA Kamakura (2008). Assessing the market value of real estate property with a geographically weighted stochastic frontier model. *Real Estate Economics*, 36, 717–751.

Seo, K, A Golub and M Kuby (2014). Combined impacts of highways and light rail transit on residential property values: A spatial hedonic price model for Phoenix, Arizona, *Journal of Transport Geography*, 41, 53–62.

Sickles, RC and V Zelenyuk (2019). *Measurement of Productivity and Efficiency — Theory and Practice*, UK: Cambridge University Press.

Waltert, F and F Schläpfer (2010). Landscape amenities and local development: A review of migration, regional economic and hedonic pricing studies. *Ecological Economics*, 70, 141–152.

Wolff, F-C (2014). Lift ticket prices and quality in French ski resorts: Insights from a non-parametric analysis. *European Journal of Operational Research*, 237, 1155–1164.