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Detecting Collusion in Spatially Differentiated Markets*

Matthias Firgo† and Agnes Kügler‡

Abstract

The empirical literature on mergers, market power and collusion in differentiated markets has mainly focused on methods relying on output and/or panel data. In contrast to this literature we suggest a novel approach that allows for the detection of collusive behavior among a group of firms making use of information on the spatial structure of horizontally differentiated products. By estimating best response functions using a spatial econometrics approach, we focus on differences in the strategic interaction in pricing between different groups of firms as well as on differences in price levels. We apply our method to the market for ski lift tickets using a unique data set on ticket prices and detailed resort-specific characteristics covering all ski resorts in Austria. We show that prices of ski resorts forming alliances are higher and increase with the size and towards the spatial center of an alliance. Strategic interaction in pricing is higher within than outside alliances. All results are in line with the findings of theoretical models on collusion in horizontally differentiated markets.

Keywords: tacit collusion, strategic alliances, spatial differentiation, ski lift ticket prices;

JEL Classification: C21, D43, L11, L41, L83, R32

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1 Introduction

In many retail markets consumers choose from a supply of varieties which are scattered in geographic or product space. Thus, when making their product choice, consumers have to consider different transportation costs (monetary, temporal, deviation from most preferred variety). Even when offering otherwise homogeneous products, spatially differentiated firms gain local market power because consumers prefer supply close to their own location to reduce transportation costs. As a consequence, irrespective of the total number of firms in the entire market, a single firm directly competes for consumers only with a limited number of neighboring firms. Competition is localized and reduced to local oligopolies in which firms interact strategically. Mergers, collusion and the cooperation of firms within strategic alliances may increase the firms' market power and therefore equilibrium prices. However, in horizontally differentiated markets this is only true if the size of the segment in the product or geographical market space served by the firms concerned is increased by such cooperation as demonstrated theoretically by Levy and Reitzes (1992) and Giraud-Heraud et al. (2003), and empirically by Pennerstorfer and Weiss (2013).

Measuring market power in oligopolistic markets in order to evaluate the impact of mergers, strategic alliances or collusion has been focused on by researchers and policy makers for many years. Concentration indices have been used to monitor market power concentration, e.g. the Lerner Index and the Herfindahl-Hirschman Index (HHI). The latter is suggested by the Federal Energy Regulatory Commission (2008) as well as by the horizontal merger guidelines of the U.S. Department of Justice and the Federal Trade Commission (2013). However, these indices are known to involve some severe disadvantages in general (see e.g. Tremblay and Tremblay, 2012), and in particular in markets with localized competition because they are calculated at the aggregate market level which may be a poor proxy to measure local market power (Levy and Reitzes, 1992). As a result, structural models estimating demand systems have been employed to evaluate mergers or market power in differentiated markets (Baker and Bresnahan, 1985, Berry et al., 1995, Nevo, 2000, 2001, and Pinkse and Slade, 2004, among others). Indeed, the dependency on output or demand data as well as on time series, which often raises problems in empirical studies (as pointed out by e.g. Kim and Singal, 1993 or Pennerstorfer and Weiss, 2013), is a major limitation associated with such structural models.[1]

In this paper we suggest a novel approach to bypass the problems associated with missing data on output/demand in detecting collusion by making use of information on the spatial structure of horizontally differentiated markets. Further, our approach does not rely on the availability of panel data. It can be applied to topics of (tacit) collusion, but also provides a tool for ex-post merger evaluation in spatial markets. Instead of focusing on price levels only, we investigate differences between groups of nearby firms in their strategic price setting behavior by estimating best response functions using a spatial econometrics approach. This allows us to illustrate the impact of strategic alliances and to detect collusive behavior of firms in differentiated markets on prices also in the framework of a cross-section and without output data. It is important to note that our approach does not provide a tool for screening a market for collusion. However, if there are grounds for suspicion that a group of firms is colluding, our method allows a detection of (tacit) collusion by comparing the group's strategic pricing behavior with that of outsiders.

We apply our approach to the market for ski lift tickets in Austria that is characterized by an increasing number of local alliances among nearby ski resorts. We use a unique data set covering all ski resorts in Austria for the 2011/12 winter season. Within an alliance of nearby ski resorts, alliance mem-

[1] One exception is Thomadsen (2005), who estimates a model of demand and supply without data on output.

bers typically legally sell exclusive common multi-day ski lift tickets that are valid in all resorts of the alliance. The exclusive provision of common single-day tickets, however, was prohibited in an antitrust lawsuit in 2003. Still, our results indicate that strategic interaction in pricing of single-day tickets within groups of ski resorts forming alliances is higher than between other resorts, that alliances resorts significantly overcharge compared to non-alliance ski resorts, and that prices are higher at the geographical center than at the fringe of an alliance, ceteris paribus. All our results are consistent with theoretical models (Levy and Reitzes, 1992; Giraud-Heraud et al., 2003) that analyze multiproduct firm behavior or collusion in differentiated markets. Thus, we conclude that allowing ski resorts to form alliances selling exclusive common multi-day ski lift tickets seems to lead to collusive behavior in pricing of single-day tickets. In contrast to a number of studies on airline alliances (e.g. Brueckner and Whalen, 2000, Brueckner, 2001, 2003, Brueckner and Pels, 2005, Bilotkach, 2007, Ito and Lee, 2007, Armantier and Richard, 2008, Gayle, 2008, Bilotkach and Hüschelrath, 2011, and Brueckner et al., 2011) analyzing markets characterized by a hub and spokes structure, our results have important implications for cooperation in markets with a linear (Hotelling, 1929) or circular (Salop, 1979) spatial structure that describes the majority of conventional retail markets.

2 Models of cooperation and collusion in spatially differentiated markets

The main reasons for firms to cooperate strategically are similar to those of merging firms. First, cooperation can be associated with an increase in technical efficiency in the case of increasing returns to scale and/or due to knowledge transfer. Second, firms may increase the quality of their products through cooperation. This, for instance, has been the major argument for the antitrust immunity of strategic alliances in the airline industry. Third, cooperation may aim at increasing the market power of the firms involved.

At the horizontal level and in markets with differentiated products, collusive cooperation – similar to a merger – may or may not have a direct impact on prices, depending (among other factors) on the locations of the products supplied by the cooperating firms in the market space. If competition is localized and takes place between neighboring firms (in terms of the geographical area and/or in terms of the product space), a merger, an alliance or a cartel of neighboring firms results in a situation in which stand-alone firms face competition with a multiproduct firm (i.e. the post-merger firm, the alliance or the cartel, respectively). Levy and Reitzes (1992) and Giraud-Heraud et al. (2003) analyze instances of this kind in the framework of the Salop (1979) circular city model. Levy and Reitzes (1992) restrict their analysis to a merger of two neighboring firms. Giraud-Heraud et al. (2003) generalize the model to an arbitrary number of similar adjacent products offered by a multiproduct firm.

[Figure 1 about here]

Figure 1 illustrates the model by Giraud-Heraud et al. (2003), which can also be used in the context of collusion or a post-merger market without loss of generality. A horizontally/spatially differentiated product is offered by a total of N equidistantly distributed firms. Out of these, $n > 2$ adjacent firms cooperate and collude on prices. In Figure 1 this group of firms is denoted by M. Each of the remaining $q = N - n$ adjacent firms represents an independent stand-alone firm that fully competes on prices.[2] The group of stand-alone firms is denoted by F in Figure 1. While each stand-alone firm maximizes its individual profit, the group of cooperating firms maximizes the joint profits of its n members. Under the assumption of fixed locations and inelastic demand

[2]The model by Levy and Reitzes (1992) corresponds to the case of $n = 2$.

Giraud-Heraud et al. (2003) compute equilibrium prices, demand and profits for the alliance of cooperating firms and the individual stand-alone firms in a simultaneous Betrand game. Due to a reduction in competition all firms in the market charge higher prices compared to the benchmark case of $n = 1$, which corresponds to the standard Salop (1979) model. In Giraud-Heraud et al. (2003) the equilibrium price for the product of alliance firm $i (i = 1, ..., n)$ is given by

$$p_i^* = f\left(N_{(-)}, n_{(+)}, i_{(+/-)}\right), \tag{1}$$

and for the product of stand-alone firm $k (k = 1, ..., q)$ by

$$p_{n+k}^* = f\left(N_{(-)}, n_{(+)}, k_{(+/-)}\right), \tag{2}$$

with $p_i^* > p_{n+k}^*, \forall i, k$.

Hypothesis 1a: *Prices of cooperating firms are higher than prices of stand-alone firms, ceteris paribus.*
Hypothesis 1b: *The higher the prices of cooperating firms, the higher the number of cooperating firms, ceteris paribus.*

In case of $n > 2$ prices of firms differ depending on their position within the group of cooperating firms (i). Thus, Giraud-Heraud et al. (2003) demonstrate that the cooperating alliance sets prices for their members as a function of their exposure to outside competition: the closer the position of a member to the market boundary of the alliance and thus the closer to a competitive environment, the lower its price; the closer the firm is located to the center (m) of the alliance, the more it is shielded from outside competition and the higher its price. Conversely, equilibrium prices of stand-alone firms decrease towards the center (f) of the market segment served by this group of firms. The closer a stand-alone firm is located to the boundary of the alliance the less competitive its environment and the higher its price. The distribution of equilibrium prices is illustrated in Figure 2 and leads to our second hypothesis.

[Figure 2 about here]

Hypothesis 2a:: *Prices within the group of cooperating firms are higher at the geographical center than at the periphery of this group.*
Hypothesis 2b:: *Prices of stand-alone firms are higher the closer they are to a group of cooperating firms.*

The best response functions in Giraud-Heraud et al. (2003) expose further differences in pricing between cooperating and stand-alone firms. In their model the slope of the best response function between two cooperating neighbors is twice the slope of the best response function between a cooperating firm and an adjacent stand-alone firm and between two stand-alone firms. In a Salop model a price increase of an individual firm directly affects its own demand and that of the two adjacent firms. The impact of a price change of one alliance member is internalized in the profitability of other members of the alliance. While such a price change shifts demand between adjacent alliance members, it does not affect demand faced by the inner alliance members (firms 2 to $n-1$ in Figure 1) but only affects the two firms (1 and n in Figure 1) at the fringe of the alliance. By increasing prices, a stand-alone firm loses consumers to both neighboring firms (two other stand-alone firms or one alliance member and one independent firm). Conversely, a peripheral alliance firm loses consumers to one 'real' competitor (the adjacent stand-alone firm) only. As a consequence, the response to a price change within an alliance is stronger than outside the alliance since stand-alone firms are more concerned about the trade-off between a price increase (decrease) and the loss (gain) of consumers with respect to profit.

Hypothesis 3: *Best response functions within a group of cooperating firms are different from best response functions outside the group. Strategic interaction in pricing among cooperating firms is more intense than outside their group.*

At first glance our first hypothesis contradicts the empirical results found for the airline industry. Brueckner and Whalen (2000) and Brueckner (2003), for instance, estimate price reducing net effects of international airline alliances between 17% and 30%. On the one hand, alliances result in lower fares and higher traffic in the interline city-pair markets where the connection to a destination would require the services of different carriers. On the other hand, the formation of an alliance implies a loss of competition in the interhub markets that connect the hub cities of the allying partners and tends to raise fares in these markets. Empirically, Brueckner and Whalen (2000) and Brueckner (2003) find that the decrease in prices due to the former effect outweighs the price increase due to the latter consequence of international airline alliances. However, in contrast to the airline market that is characterized by a hub and spokes network (Brueckner, 2001))[3], most retail markets are characterized by a Salop (1979) type of market structure. While there might be an increase in efficiency due to cooperation for technological reasons, the presence of alliances is associated with a softening in competition because only the price increasing effect analogous to the interhub market exists in such Salop (1979) type of markets.

In section 4 we present our estimation strategy to test the hypothesis presented above using data from Austrian ski regions. In the theoretical model of

[3]Brueckner (2001) analyzes the effects of international airline alliances on traffic levels, fares, and welfare in a theoretical model.

Giraud-Heraud et al. (2003) firms offer a spatially differentiated but otherwise homogeneous product. To test our hypotheses in the empirical setup chosen the inclusion of quality attributes is necessary. Therefore, we add a variety of control variables in the estimations presented in section 5.

3 The market of ski resorts in Austria

3.1 The history of alliances

Cooperation among ski resorts occurs mainly via legally approved alliances. From the 1970s on, chairlifts and cable cars allowing the transport of a higher number of skiers at faster speed have successively replaced traditional t-bar lifts. As the advanced technologies enabled skiers to ride greater distances within one day of skiing, ski resorts were extended continuously. Additionally, resorts that were (geographically) separated from each other have been linked by lifts and cable cars to form so-called ski carousels. These mergers of ski resorts resulted in an increase in quality due to an increased variety in landscape and sporting amenities. They also raised the consumer and producer surplus due to an increased demand and increasing returns to scale. Today, most of the well-known ski resorts across Europe are ski carousels, e.g. Les Trois Valles (France), Verbier (Switzerland), Kitzbühel (Austria) or Sellaronda (Italy).

In the late 1980s a group of physically unconnected nearby ski resorts in Austria introduced a new way of cooperation. Ski lift tickets bought in one of the resorts were mutually accepted by other group members. In the year 2000, 22 municipalities in that area accounting for 270 ski lifts officially founded the company "Ski Amade" based on a written contract including agreements on cooperation and revenue-sharing. The cooperation on ski lift tickets resulted in an exclusive supply of common tickets and prohibited the selling of individual tickets for the individual resorts within Ski amade.[4]

[4]Seven of the smallest resorts were exempted from the common ticket policy. However,

The case of "Ski Amade" was investigated by the Austrian Competition Authority (BWB) in 2003/2004 (see the Austrian Competition Authority (BWB), 2003, 2004). BWB decided that the agreements on tickets violated Austrian antitrust-laws. The lawsuit resulted in a compromise agreement. According to the agreement "Ski Amade" was legally obliged to remove agreements on pricing and selling of common single-day tickets from the contract. Thus, since the winter season 2004/05 all members of "Ski Amade" have been selling individual single-day ski lift tickets but have been selling exclusive common tickets for validity periods extending to one and a half days or more. Within the last decade the number of similar alliances among physically unconnected ski resorts in the tradition of "Ski Amade" has increased dramatically. In the winter season of 2011/12 almost one out of two ski resorts in Austria was part of an alliance of this kind, i.e. alliance members sell individual single-day tickets and common multi-day tickets. During the same period of time prices for ski lift tickets have increased sharply. The average annual price increases amounted to about twice the annual inflation rates (see Austrian Consumers' Association (VKI), 2010, 2012, 2013).

3.2 Data

Whether alliances of this kind are having an effect on the prices of single-day tickets is investigated by using a unique data set containing all ski resorts in Austria for the winter season 2011/12. The data were collected by combining information available at several online databases. The websites www.bergfex.at and www.tiscover.at offer price information on ski lift tickets, as well as detailed information on the characteristics of each ski resort. These characteristics cover the number of different types of ski-lifts available (cable car, chairlift, t-bar), the total length of slopes by category (easy, medium and difficult), as well as information on different amenities such as

prices for their tickets were also set centrally.

ski schools.These data are combined with data on lift capacities provided by the website www.skiresorts.info and with data on the snow levels of the previous two winter seasons (2009/10 and 2010/11) obtained from the website www.schneehoehen.de. Capacities are used as a proxy for the costs of a ski resort and snow levels allow us to include information on the quality and reliability of snow conditions. We also include a number of demand side variables such as regional GDP per capita, as well as data on tourism and on the local hotel industry provided by Statistics Austria.

In addition, we use the geographic coordinates of each base station to calculate the exact positions of each ski resort and measure the distance between resorts in ArcGIS using the routing tool WIGeoNetwork.[5] The distance measured relates to the driving time by car (in minutes) between base stations of different resorts on the road network. This allows us to generate more detailed and realistic distance measures as compared to Euclidean distances or driving distance in road kilometers. Neither of the latter two sufficiently captures distance experienced by customers in Alpine regions. Further, we calculate the driving time to the nearest city with a population of at least 100,000 inhabitants for each resort to control for regional differences in the demand for single-day ski lift tickets.

When investigating single-day tickets, a ski carousel, unlike an alliance, is treated as one ski resort, and thus as one observation since it can be used within one day due to the direct physical connections (lifts) between the different parts of the resort. As many resorts and all ski carousels consist of several base stations, distances to other ski resorts and to cities are calculated based on the station that is closest to the respective site the resort is paired with. Thus, the distance between ski resorts i and j is equal to the smallest distance between any pair of base stations of i and j.

Table 1 presents some descriptive statistics for the variables used in the

[5]See https://www.arcgis.com and http://www.wigeogis.com for company details.

econometric analysis below. In total, we observe 285 physically unconnected ski resorts in Austria. The price for a single-day ticket is about 28 EUR on average with prices ranging from 7 EUR to 45.5 EUR. In total, almost half (46%) of the resorts are associated with an *Alliance*.[6] The mean number of slope kilometers (*Slopekm*) is around 28 km per resort. However, looking at the minimum (0.5 km) and maximum (283 km) of *Slopekm* it becomes obvious that size varies substantially. As a decrease in the day-trippers' marginal willingness to pay for an additional slope kilometer can be expected, we use the log of total slope kilometers as an explanatory variable for our estimations. The variable *Capacity* indicates the maximum number of passengers that can be carried per hour, which, given the differences in the number of ski-lifts available, also varies highly among resorts and is also transformed to its logs in the estimations. *ShareDrag* reflects the share of t-bar (drag) lifts in the total number of lifts. This category of lifts is slow, uncomfortable and associated with low capacities. Therefore, it is considered as a proxy for inferior technology (compared to chair lifts and cable cars).

[Table 1 about here]

The maximum (minimum) altitude of the summit ($SealevelMax$) of a ski resort is at 3,440 (403) meters, with the mean summit at 1,710 meters above sea level. The variable $SnowValley$ contains the average maximum snow level of the previous two winter seasons at the bottom (in the valley) of a resort. $SealevelMax$ and $SnowValley$ are included as proxies for the snow quality of a ski resort. $SealevelMax$ additionally serves as an indicator for the attractiveness of the scenery. *DistCity* measures the driving time a ski resort is located from the nearest Austrian city with at least 100,000 inhabitants and can be interpreted as a proxy for differences in demand for single-day tickets. The latter variable as well as the variables on altitude and snow levels are also

[6]Note that alliance membership does not imply that resorts of the same alliance set the same price for their single-day tickets.

transformed to logs. Besides the expected diminishing marginal willingness to pay, all variables that are transformed to logs show a log-linear correlation with prices. Therefore, we refrain from transforming prices to logs and use linear prices as our dependent variable.

Around 70% of the resorts have access to snowmaking technologies such as snow cannons or snow lances (indicated by $ArtificialSnow$). Since reliable snow conditions and a long season are essential for the survival of a ski resort (Falk, 2013), many resorts produce artificial snow, at least for the lower parts of their slopes. We expect this variable to be an important proxy for differences in costs. The availability of a ski school ($SkiSchool$) may increase parents' willingness to pay for their own ski-lift tickets. Differences in the willingness to pay may also stem from differences in the type of clients targeted. To control for such differences we include the share of tourist overnight stays in luxury accommodation (4 and 5 star) at the municipality level ($ShareLux$). If a ski resort has base stations in several municipalities, we calculate the average share weighted by the number of stations per municipality.[7] Further, we include the driving time to the nearest ski resort of similar size ($DistNextSim$) to control for a resort's degree of spatial differentiation. As resorts of the same alliance are not necessarily genuine competitors, we ignore members of the same alliance in constructing this variable.[8] GPD is the log of the gross regional product per capita at current prices on a NUTS-3 level to control for differences in income and price levels in different regions of Austria.

[7]Note that we also estimated our models using alternative measures of differences in touristic demand, such as the number of overnight stays in the municipalities covered by the resort, the number of overnight stays per bed as an indicator for capacity utilization of the local hotel industry, as well as the average number of overnight stays per arrival as an indicator for the relevance of single-day tickets for total revenues of the ski-resort. However, our main results are very robust to the choice of these variables.

[8]'Similar size' indicates that a pair of ski resorts belongs to the same category based on the number of slope kilometers: micro ($0 < SlopeKm < 5$), small ($5 \leq SlopeKm < 20$), medium ($20 \leq SlopeKm < 50$), big ($50 \leq SlopeKm < 100$), giant ($SlopeKm > 100$); Alternatively, we included other measures such as the distance to the nearest resort irrespective of the category and/or alliance, and the number of (similar) ski resorts within 30/45/60/75/90 minutes' driving time. Surprisingly, however, none of these measures were significant in any of the specifications (see the discussion in Section 5).

Table 5 in the appendix provides details on all 23 alliances observed.[9] The largest alliance in terms of the number of members as well as size measured by the number of total slope kilometers is "Ski Amade", located in Salzburg and consisting of 17 ski resorts that amount to 6% of all resorts. Those 6% cover more than 240 ski-lifts and about 760 slope kilometers.[10] The next largest ski alliances in terms of members are "3-Taeler Skipass Vorarlberg" with 11 members, "Murtaler Schiberge" and "Skihit Osttirol" with 8 members each, and "Allgaeu-Tirol Skicard" ("Vitales Land") with 7 members. Big alliances do not necessarily consist of large ski resorts only but include small resorts as well. Further, not all large ski resorts are part of an alliance: 38% of the ski resorts in the fourth quartile of slope kilometers are not affiliated with any alliance. The locations and the sizes of ski resorts are shown in Figure 3. The diameters of the circles in Figure 3 reflect the resorts' number of slope kilometers. Most of the (bigger) ski regions are located in the western parts of Austria, which is the mountainous part of the country. A light circle indicates that a resort is part of an alliance, dark circles reflect stand-alone resorts. Each ski resort mapped in Figure 3 accounts for one observation in our empirical analysis.

[Figure 3 about here]

[9]Note that we exclude two supra-regional alliances – Salzburg Super Ski Card and Kitzbuehler Alpen Allstarcard. The effects of these alliances are captured by considering more local alliances that are nested within them.

[10]The number of total slope kilometers of an alliance is based on the sum of slope kilometers of the individual alliance members in line with our online data sources and may thus differ from the numbers published by the websites of the alliances.

4 Econometric models and identification strategy

We estimate equilibrium prices of single-day ski lift tickets using the simple linear model

$$y = X\beta + u, \tag{3}$$

in which y is the vector of prices, X is a matrix containing information on alliances membership and on nearby resorts' alliance membership, a set of ski resort characteristics, demand side variables, as well as a constant. β is the vector of coefficients to be estimated and u is a random error term that captures unobserved cost and demand variables and that is assumed to be heteroskedastic or spatially correlated.[11]

Equation (3) allows us to test Hypotheses 1a and 1b as well as 2a and 2b on differences in equilibrium prices between alliance members and stand-alone resorts. In order to test Hypothesis 3 (best response functions within the alliance are different from best response functions outside the alliance) best response functions have to be estimated rather than equilibrium prices as denoted in (3). The best response functions of ski resorts can be denoted as

$$y = \rho W y + \rho_A W_A y + X\beta + u, \tag{4}$$

where W and W_A are spatial weights matrices in which element $w_{ij} \neq 0$ if ski resort j is a neighbor of ski resort i that is relevant in determining the price of i and where $w_{A_{ij}} = w_{ij}$ if i and j are members of the same alliance, and $w_{A_{ij}} = 0$

[11] The errors are regionally clustered (by NUTS-3 region). Using more local spatial units to form clusters, for example districts, increases the number of clusters but implies the problem that different base stations of ski resorts may belong to different districts and thus increases the challenge of assigning a ski resort to a certain cluster. This also applies to clustering regions at the NUTS-3 level, albeit to a much lesser extent. Additionally, in many regions the number of resorts per cluster drops substantially if more local clusters are used. To control for heteroskedasticiy of unknown form we also estimated our models using robust instead of clustered errors but this modification did not affect the main results of the paper.

otherwise. ρ and ρ_A are the slope parameters of the best response functions to be estimated. ρ_A corresponds to the difference in the slope between same-alliance resorts and all other resorts according to Hypothesis 3 in Section 2. Thus, ρ_A can be interpreted as the marginal effect of the strategic interaction within an alliance in addition to ρ. Recall that the higher the slope parameters ρ and ρ_A the higher the strategic interaction in pricing. If an alliance colludes the slope of best response functions within the alliance $(\rho + \rho_A)$ should be larger than the slope outside the alliance (ρ) according to Hypothesis 3. Any $\rho_A > 0$ identifies collusive behavior among alliance members.

Prices for ski lift tickets are typically set before the start of the winter season and remain fixed throughout the season. Thus, our approach of modeling pricing decisions in a static Bertrand game seems justified. While ski resorts probably earn higher revenues on multi-day tickets we argue that single-day and multi-day tickets can be regarded as different markets, as multi-day tickets mainly involve touristic stays while single-day tickets are mainly sold to day-trippers. Thus, prices for multi-day tickets can be assumed to have little influence on prices and quantities of single-day tickets.

While unobservable local characteristics by nature rely on the geographical location of ski resorts, the intensity of competition, as opposed to homogeneous products, is not necessarily determined by geographical proximity only, but also by similarity in characteristics and quality attributes of different resorts. Imagine a valley hosting four ski resorts, two big resorts of similar size at each end of the valley, and two very small resorts each located right next to one of the two big resorts. The big (small) resorts are likely to care more about the pricing decision of the other big (small) resort, even though it is further away than the adjacent small (big) neighbor. Therefore, to account for the fact that distance and quality jointly determine consumer choice, we construct the spatial weights matrix W in a similar functional form as previously used to model elements of non-physical distance (Pinkse and Slade, 2004; Pofahl and

Richards, 2009; Richards et al., 2010; Rincke, 2010). The elements of matrix W are constructed by

$$w_{ij} = \frac{1}{1 + \sqrt{(d_{ij})^2 + (s_i - s_j)^2}}. \tag{5}$$

where (d_{ij}) is the driving time between resorts i and j and where s is the total length of slopes of a ski resort in kilometers. The intensity of interaction between resorts decreases with the increase of distance that separates them and increases with their similarity in terms of size. To facilitate the interpretation of the slope parameters ρ and ρ_A we row normalize W and W_A so Wy and $W_A y$ reflect the spatially and similarity weighted average prices of neighboring ski resorts.

Some authors, most prominently Manski (1993), have stressed the importance of exogenous weights in order to identify the interaction between economic agents through matrices such as W. The inclusion of non-spatial elements such as similarity in size may thus raise questions about the exogeneity of the spatial weights in W. However, we provide two arguments in favor of our approach: First, the size of ski resorts is mainly exogenously determined by the topography of the landscape, as well as the altitude and magnitude of the mountain or mountain range hosting a ski resort. Second, the necessity of adding similarity to geographical distance in modeling strategic interaction between ski resorts becomes obvious when comparing the Moran scatter plots in Figures 4 and 5. Figure 4 shows the correlation between prices (y) and neighbors' prices (Wy), Figure 5 plots the same relation for y and My, where M is a purely distance-based weights matrix with $m_{ij} = 1/d_{ij}^2$ if $d_{ij} \leq 75$ minutes of driving time and $m_{ij} = 0$ otherwise[12]. The substantially lower

[12]We choose 75 minutes of driving time as a cut-off distance because at this distance each observation has at least one neighbor. This way we avoid all-zero rows and columns while not restricting a ski resort's number of neighbors as in a spatial weights matrix based on k-nearest neighbors (with $k \geq 1$). In W we also set $w_{ij} = 0$ if $d_{ij} > 75$ or if $1/\left(1 + \sqrt{(d_{ij})^2 + (s_i - s_j)^2}\right) < \gamma$ where γ is the smallest row-maximum in W. This again

correlation in Figure 5 illustrates the obvious loss of information when purely relying on spatial distance in defining neighborhood relations and their weights (see Rincke (2010) for a similar discussion).[13]

[Figure 4 + Figure 5 about here]

Equation (4) implies – similarly to the theoretical foundation in Giraud-Heraud et al. (2003), which leads to Hypothesis 3 – that ski resorts are playing a simultaneous Bertrand game. By definition, prices and rival prices are jointly determined. Thus, Wy and $W_A y$ are endogenous. Under the assumption that W and W_A are known to the researcher, the parameters ρ and ρ_A, and vector β can be estimated either by estimating the reduced form of (4) using nonlinear methods such as maximum likelihood (Kalnins, 2003; McMillen et al., 2007; Richards et al., 2008; Pennerstorfer, 2009) or by estimating (4) directly using instrumental variables (2SLS, GMM) techniques (Pinkse et al., 2002; Kalnins, 2003; Pinkse and Slade, 2004; Fell and Haynie, 2013). Recent papers by Pinkse and Slade (2010) and Gibbons and Overman (2012) persuasively emphasize the advantage of IV-estimation over the maximum likelihood approach because of the strict assumptions on normally distributed and homoskedastic error terms implied in the ML-approach to obtain unbiased and efficient results. GMM on the other hand does not require any assumptions on the distribution of the error terms and is less sensitive to misspecification in spatial models (see also McMillen, 2012).

Indeed the estimation of a spatial lag of the dependent variable, which is required to identify best response functions, imposes challenges in the speci-

ensures that each observation has at least one neighbor, but also accounts for the fact that ski resorts that are neither close in geographical nor in product space are not likely to be rivals at all.

[13] McMillen (2012) finds substantial variation in results depending on the functional form of W and the estimation methods chosen. He thus recommends researchers to use different functional forms of W and different estimators to illustrate the robustness of their results. Therefore, to check the robustness of our results we also estimated equation (4) using matrices based on M and on additional functional forms of the spatial weights matrix (see Section 5).

fication of the empirical model. However, spatial data have the advantage of usually providing a wide set of potential instruments. WX, WZ with $Z \subset X$ or higher orders such as W^2X can be used to instrument Wy. The use of characteristics of neighboring observations as instruments can be considered analogously to the idea of Hausman and Taylor (1981) and is in line with the use of rival product characteristics as instruments (e.g. Berry et al., 1995).

Due to the fact that there is a high degree of variation in the individual (continuous) characteristics of ski resorts even among nearby resorts, we follow the IV-approach rather than the ML-approach because of the high quality of the potential instruments available. However, to check the robustness of our results with respect to the estimation technique chosen – as recommended by McMillen (2012) – we present ML estimation results of our main specification as well.[14]

Table 1 above illustrates a number of individual characteristics of ski resorts that could serve as instruments. Gibbons and Overman (2012) point out several problems associated with using a multitude of instruments and higher order spatial lags because of the high correlation between X, WX, W^2X, etc. Thus, in order to avoid biased and imprecise estimates in the second stage we narrow our set of instruments and use a subset Z of X to instrument Wy and W_Ay in the first stage by using the spatial lags of Z (WZ and W_AZ). In this subset Z we only include continuous variables on the ski resorts' individual characteristics which provides information for all resorts in the sample. This includes the variables $log(SlopeKm)$, $log(SealevelMax)$ and $ShareDrag$. We provide tests for weak identification and underidentification, and for potential violation of the overidentification restrictions for all results based on

[14] Instead of clustering standard errors by NUTS-3 regions our ML estimator allows for spatial autocorrelation in the residuals, which corresponds to the so-called general spatial autocorrelation model (LeSage and Pace, 2009) commonly used in the ML framework. This model extends equation (4) to $y = \rho Wy + \rho_A W_A y + X\beta + u$ with $u = \lambda W + \epsilon$. The reduced form of this system of equations that is estimated is given by $y = (I - \rho W - \rho_A W_A)^{-1} X\beta + (I - \rho W - \rho_A W_A)^{-1} (I - \lambda W)\, \epsilon$.

IV-estimation. The OLS results on price levels in Section 5.1 include a specification that contains WZ and other spatially lagged variables as explanatory variables. The fact that none of these variables are significant supports the exclusion restriction for the chosen instruments.

As we are testing our hypotheses using cross-sectional data we should be particularly concerned about the identification of our parameters of interest because of the possibility of different competing explanations regarding the impact of alliances on prices. Firstly, observed differences in pricing might stem from unobserved differences in cost structures if alliance membership leads to an increase in efficiency. However, a wide range of cost-relevant variables such as a ski resort's capacity, the availability of snow cannons, as well as sea level data that reflect the costs of a reliable of snow coverage, are included in the model. The high R^2 of around 90% in all specifications reflects the high quality of our control variables and provides arguments against a potentially omitted variable bias.

Secondly, alliances might ask for higher prices because their marketing is superior to that of stand-alone resorts. However, as demonstrated in the results of Section 5 we find evidence for higher overcharge rates at the geographical center than at the geographical fringe of an alliance (as proposed in Hypothesis 2a). If marketing techniques were the source of price differences between an alliance and stand-alone resorts, all alliance members and not only those at the center which are shielded from outside competition should benefit from better marketing.

Thirdly, the assumption that alliance membership is exogenous and independent from the price setting behavior may be seen critically. However, we found an insignificant inverse Mills ratio in a two-stage Heckman correction model of equation (3), which supports our assumption. Also, only two variables ($SlopeKm$ and $ShareDrag$) were found to significantly predict alliance membership.[15]

5 Results

5.1 Estimation results of equilibrium prices

According to the hypotheses in Section 2, if alliances collude alliance resorts are expected to show higher prices in general (Hypothesis 1a) which are increasing with the number of alliance members (Hypothesis 1b) and particularly high prices at the geographical center of an alliance (Hypothesis 2a).[16] Stand-alone resorts, on the other hand, are expected to set higher prices, ceteris paribus, if they are close to an alliance (Hypothesis 2b). In this section we test these hypotheses based on OLS estimation results of the model in equation (3). Table 2 summarizes the results of this analysis.

The variable $ShareSameAlliance$ in specifications (2), (3) and (5) includes the spatially and similarity weighted shares (according to W) of a ski resort's neighbors that are part of the same alliance. A value of one (zero) in $ShareSameAlliance$ indicates that all (none of the) neighbors of an alliance resort are part of the same alliance. Similarly, $ShareAllianceFringe$ measures a stand-alone resort's share of neighbors that are members of an alliance. A value of one (zero) in $ShareAllianceFringe$ indicates that a stand-alone resorts is surrounded by alliance resorts only (does not have any neighbors that are part of an alliance). $ShareSameAlliance$ ($ShareAllianceFringe$) is set to zero if a ski resort is not part of an alliance (is an alliance resort) itself. We use $ShareSameAlliance$ to measure the degree of an alliance member's centrality within an alliance. Ski regions being mainly sur-

[15] Both variables are negatively correlated with the probability of being an alliance member. Larger resorts and resorts with a higher share of inferior drag lifts are less likely to be part of an alliance, ceteris paribus. The regression results drawn from this exercise are provided by the authors on request.

[16] Recall that the geographic center refers to the position within the alliance relative to other alliance members (see Figure 1) and not to centrality relative to other factors such as the clustering of consumers around specific locations as in Anderson et al. (1997).

rounded by other alliance members have a central position within the alliance. Similarly, $ShareAllianceFringe$ serves as an indicator for the closeness to alliances for stand-alone resorts. The dummy variable *Alliance* controls for alliance membership and identifies the effect of *ShareSameAlliance* and $ShareAllianceFringe$. Additionally, specification (3) includes the spatial lag of the ski resorts characteristics (WC with $C \subset X$) to capture potential direct effects of the characteristics of neighboring ski resorts on prices.[17]

Specification (1) in Table 2 illustrates that ski resorts that are part of an *Alliance* are expected to charge prices that are on average by 1.90 EUR higher per day. Specifications (2) and (3) reveal that the prices of alliance resorts increase corresponding to the share of same alliance members in the neighborhood. If all neighbors belong to the same alliance, an alliance resort is expected to charge about 4.4 to 4.9 EUR more than an alliance resort that does not have any neighbors associated with the same alliance.[18] With the inclusion of *ShareSameAlliance* the coefficients of *Alliance* turn negative. However, this effect is insignificant in both specifications.

Instead of the dummy variable *Alliance*, specifications (4) and (5) include a variable measuring the number of alliance members within an alliance ($\#AllianceMembers$), which is equal to zero in case of a stand-alone resort. As indicated by specification (4) prices are expected to increase corresponding to the size of an alliance, which is in line with Hypothesis 1b. This effect also holds if the share of other alliance members and the share of fringe firms in the neighborhood are included in specification (5). There is a positive correlation between the two variables $\#AllianceMembers$ and *ShareSameAlliance* (by definition, larger alliances tend to have higher shares of same-alliance

[17] C includes $SealevelMax$, *Slopekm*, *ShareDrag*, *Capacity*, *SkiSchool*, $ArtificialSnow$ and $SnowValley$.

[18] The mean of *ShareSameAlliance* for alliance resorts is 0.63. The mean of $ShareAllianceFringe$ for the group of stand-alone resorts is 0.3. $ShareAllianceFringe = 0$ for about 25% and $ShareAllianceFringe = 1$ for about 2% of all stand-alone resorts, while $ShareSameAlliance = 1$ for about 9% of all alliance resorts.

members than small alliances). This correlation implies that the effect of $ShareSameAlliance$ may be overestimated if $\#AllianceMembers$ is excluded from the set of variables. The size of the coefficient for $ShareSameAlliance$ is reduced if $\#AllianceMembers$ is included in specification (5) but both variables remain significant. The closeness to alliances or rather the level of encirclement should also have an impact on the prices of stand-alone resorts as assumed by Hypothesis 2b. But this cannot be confirmed by $ShareAllianceFringe$, which is insignificant in all specifications.

[Table 2 about here]

The effect of spatial differentiation ($DistNextSim$) on prices remains insignificant in all specifications. This contradicts theory on localized competition in differentiated markets as well as the empirical results found for many spatially differentiated industries. Besides the distance to the nearest similar ski resort (not part of the same alliance) we used a number of alternative proxies to measure the degree of competition (in differentiated markets) such as the distance to the nearest resort in general, or the number of ski resorts within radii of 30, 45, 60, 75 and 90 minutes. However, none of these variables turned out to be significant.[19]

Among the remaining variables capacities, snow levels at the base stations, facilities to produce artificial snow, and the share of (inferior) drag lifts turn out to be the most reliable variables for predicting ticket prices. These variables are significant at least at the 5% level in all specifications. The size of ski resorts in terms of slope kilometers and the maximum altitude of a resort's peaks are significant only in the specifications that do not include spatial lags of the ski resorts' characteristics (WC). All the coefficients of these lags in specification (3) are insignificant.[20] The presence of ski schools does

[19]Estimation results on these alternative measures are available from the authors upon request.

[20]Tables including the results for WC can be provided by the authors upon request.

not significantly influence prices. We also included some demand side variables (*DistCity*, *ShareLux* and *GDP*; see Table 1) to avoid potential omitted variable bias resulting from differences in demand. The contribution of these variables turned out to be rather limited and their inclusion/exclusion did not affect the coefficients for the remaining variables with respect to sign and significance. Thus, the results for these variables are not reported in Table 2 but are available upon request. While the effect of the share of tourist overnight stays in luxury accommodation on prices is weakly significant, the distance to the nearest big city and regional GDP per capita levels are insignificant in all specifications. In a nutshell, our results suggest that supply side variables seem to dominate prices for ski lift tickets.

5.2 Estimation results of best response functions

Testing Hypothesis 3, claiming that strategic interaction in pricing is different within a colluding alliance, requires the estimation of best response functions. For this reason Table 3 provides IV-estimates of ski resorts' best response functions as denoted in equation (4). Specification (1) in Table 3 assumes similar best response functions for all ski resorts and thus restricts $\rho_A = 0$. Specifications (2) and (3) allow us to test Hypotheses 1 to 3 simultaneously. Both specifications contain the demand side variables *DistCity*, *ShareLux* and *GDP* in addition to the variables on ski resorts' characteristics, which are however not reported in Table 3, and the results for these variables are available upon request.

Specification (1) in Table 3 shows that under the restriction of a common single slope parameter for the best response functions of alliance and non-alliance ski resorts, this parameter is equal to 0.21. This means that an average increase in prices of all neighboring resorts by one Euro is associated with an increase of a ski resort's best response price by 0.21 Euros. If the restriction is relaxed and different slope parameters are estimated for alliance members and non-alliance members, the slope is 0.17 [0.12] for non-alliance members and 0.28 [0.24] for alliance members ($Wy + W_A y$) according to specification (2) [(3)]. The fact that $W_A y$ is significantly different from zero and that a test for the equality of the coefficients for Wy and $W_A y$ cannot be rejected supports the findings of the underlying theoretical model and therefore Hypothesis 3. Strategic interaction in pricing within the alliances in general suggests a pricing behavior similar to colluding firms in spatially differentiated markets. Also, the results of the previous section on Hypothesis 2a and 2b are confirmed. The higher the share of neighbors that are part of the same alliance, the higher the prices (Hypothesis 2a). *ShareSameAlliance* is significant at the 5% (1%) level if the number of alliance members is (not) included. The high level of significance of $\#AllianceMembers$ itself again confirms Hypothesis 1b, i.e. prices increase with the size of an alliance. However, the assumption of the presence of an alliance having a positive effect on stand-alone resorts' prices as expected by theory (Hypothesis 2b) is again not confirmed since the coefficient for $ShareAllianceFringe$ is again insignificant.

[Table 3 about here]

The negative coefficient of the dummy variable *Alliance* becomes highly significant once we estimate different slope parameters for alliance and stand-alone resorts. This, however, does not mean that alliance members charge significantly lower prices. Rather, the net effect of alliance membership consists of the parameters of $W_A y$, *Alliance*, *ShareSameAlliance* (and $\#AllianceMembers$). Figure 6 illustrates the distribution of the total effect of alliance membership based on the coefficients of specification (2) for these three variables times the values of the respective variables for alliance members. With a mean of 2.06 and a median of 2.32 this net price effect of alliance membership is positive for more than 95% of alliance members. A t-test on the mean effect being equal to zero is rejected at the 1% significance level. To put it another way, we observe two different effects of an alliance having been formed: an efficiency effect and a market power effect. The former is reflected by the dummy *Alliance*. While we include a number of variables controlling for differences in costs (capacity, snow canons, etc.), the negative sign for *Alliance* may reflect an efficiency increasing effect of alliance membership that lowers costs and therefore reduces prices. However, this effect is clearly outweighed by the market power effect reflected by the coefficients of $W_A y$, *ShareSameAlliance* and $\#AllianceMembers$. Due to the increase in market power alliance members charge higher prices and the net effect on prices is positive.

[Figure 6 about here]

Further, the estimates of best response functions mostly confirm the results for the remaining explanatory variables obtained in the previous section. Capacities, artificial snow, sea level, snow conditions in the valley and the share of inferior (t-bar) drag lifts remain highly significant in all specifications. Additionally, compared to the OLS estimations of equilibrium prices, the intercept of the best response functions is significantly shifted by the presence of ski schools (at least at the 10% significance level), by the share of tourist overnight stays in the luxury segment of the market and by the level of the local GDP per capita. Again, the coefficients of the number of slope kilometers, the distance to the nearest big city, and the distance to the nearest similar ski resort (outside the same alliance) are insignificant. As indicated at the bottom of Table 3 our set of instruments is valid and strong. According to the Hansen J-statistics the null hypothesis of valid (exogenous) instruments that are correctly excluded from the estimation equation cannot be rejected. These test statistics support our exclusion restriction that is based on the insignificance of these variables in the estimation of equilibrium prices (specification (3) in Table 2). The Kleinbergen-Paap LM-tests for underidentification are each rejected at the 1% significance level. The Kleinbergen-Paap F-statistics for weak identification are sufficiently high and thus also indicate strong instruments.

5.3 Checks for robustness

Table 4 demonstrates that the results for differences in price levels and strategic interaction between alliance members and stand-alone resorts are very robust with respect to a different estimation technique (ML) and to different functional forms in specifying the spatial weights matrix, which affects the lag of prices, the calculation of the weighted shares of (same) alliance members in the neighborhood as well as the instruments. Specification (1) in Table 4 estimates the reduced form of equation (4) using a maximum likelihood estimator. While the coefficient of Wy remains unchanged with slightly higher standard errors, the coefficient of $W_A y$ increases to 0.22 and remains significant at the 1% level.

Relying purely on distance (specification (2)) or on similarity only (specification (3)) in calculating the spatial weights matrix instead of considering both dimensions of closeness does not affect the significance of the within-alliance component $W_A y$ in the GMM framework.[21] The slope parameter for strategic interaction outside the alliance (Wy) is significant at a 1% level (insignificant) in case of a purely similarity (distance-) based spatial weights matrix. Constructing W based on shorter radii such as 60 or 45 minutes of driving time (specifications (4) and (5) in Table 4) instead of 75 minutes again does only affect the coefficient for Wy, which becomes insignificant in case of 60 minutes, but again does not affect the significance of $W_A y$. The size of this within-component of the slope parameter for alliance resorts increases from 0.12 to about 0.17-0.18.

[Table 4 about here]

[21] In the similarity-based matrix S we also set $s_{ij} = 0$ if $d_{ij} > 75$ or if $1/\left(1+\sqrt{(s_i-s_j)^2}\right) < \gamma$ where γ is the smallest row-maximum in S.

The spatial structure of prices within alliances, however, does not show a similar robustness with respect to these different modifications. The variable *ShareSameAlliance* remains significant at a 5% level for the case of a similarity-based neighborhood matrix (S) but is insignificant when applying the ML estimator and when using shorter cut-off radii or the purely distance based matrix (M), respectively. This weak robustness, however, does not necessarily imply that the result does not hold. It is more likely that some of the modifications of the spatial weights matrix in Table 4 result in a loss of information and efficiency. As can be seen at the bottom of Table 4, the LM test for underidentification is only significant at the 5% level in case of a cut-off distance of 60 or 45 minutes and for the purely distance-based weights matrix, while it is significant at the 1% level for W used in the main results of Table 3. Also the F statistics for weak identification – although it still remains relatively high – drops substantially in the specifications using smaller radii for determining the weights in W.

The shorter cut-off radii in specifications (4) and (5) of Table 4 provide additional robustness checks with respect to changes in the sample. Due to the shorter radii a few observations that do not have (same-alliance) neighbors within the respective cut-off distance are dropped. As for the main results in all specifications of Table 4 the Hansen J-statistics indicate that the overidentification restrictions on our set of instruments are satisfied.

It might be the case that $W_A y$ does not capture the interaction between alliance members, but rather reflects the fact that alliance members are often closer neighbors than other resorts. To identify the price setting behavior between members of the same alliance it is crucial to make sure that the results are not driven by structural differences in the neighborhood of alliances and independent ski regions. One point in favor of our model is that the variable measuring the distance (in driving minutes) to the nearest resort irrespective of the category and/or alliance membership is insignificant in all specifications. Furthermore, the null hypothesis that the similarity- and distance-based weights of both groups, alliance members and independent ski resorts, have equal means in the spatial weights matrix W cannot be rejected by a two-sample t-test.[22] Again, this result supports the chosen identification strategy of the alliances' best response to other alliance members.

6 Discussion and conclusions

In this paper we propose a novel approach to identify collusive behavior in spatially differentiated markets that makes use of the spatial structure of the market and does thus not rely on output or panel data. We adopt the results of a theoretical model by Giraud-Heraud et al. (2003), which analyzes pricing in a Salop (1979) type of market space and in the presence of a multiproduct firm with an arbitrary number of products and an arbitrary number of fringe firms to the case of collusion. A group of colluding firms in spatial markets maximizes joint profits and thus sets prices the same way a multiproduct firm does. We use a unique data set containing the characteristics and locations of all ski resorts in Austria to test our approach empirically. Our results indicate that allowing ski resorts to form alliances to sell exclusive common multi-day ski lift tickets seems to lead to a softening in competition with respect to the price setting of single-day tickets that alliance members are legally obliged to sell individually for their own resorts. Our results provide evidence that prices of alliance members are generally higher, increase with their size and towards the geographical center of an alliance, and (by estimating best response functions) we show that strategic interaction in pricing is more intense within alliances than outside alliances, ceteris paribus. These findings are in line with

[22]A two sided t-test accepts the null of equal mean spatial weights $\overline{w_i}$ of alliances and of stand-alone firms to their neighboring resorts within a driving distance of 75 minutes at a significance level of 1%. The same holds when solely the average of the distance-based weights $\overline{m_i} = (1/J)\sum_j (1/d_{ij}^2)$ are used to carry out this t-test. More details on these tests are available upon request.

the predictions of theoretical models (Levy and Reitzes, 1992; Giraud-Heraud et al., 2003) that analyze the pricing behavior of colluding firms in horizontally differentiated markets.

Further, we do not find a significant relation between the degree of spatial differentiation and equilibrium prices. We test a number of different variables such as the distance to the nearest (similar) ski resort (outside the same alliance) or the number of (similar) ski resorts (outside the same alliance) within several cut-off radii, but none of them show any significant effect on price levels. These findings contradict theory on competition in differentiated markets as well as the findings of a broad empirical literature. Clemenz and Gugler (2006) interpret a negative relation between the station density and prices of gasoline stations as sufficient evidence against collusion. Analogously, it may be concluded that not finding a significant relation between the density of ski resorts and prices provides additional evidence for a lack of competition in this market. In line with previous research on Austrian ski resorts (Falk, 2008) we find that besides alliances, mainly capacity and snow levels, the share of lifts with inferior technology, the possibility to produce artificial snow and the altitude of top stations drive prices for ski lift tickets. We also add a number of demand side variables that turned out to be of little relevance in modeling prices.

Thus, our results challenge the legal compromise obtained between the biggest and oldest alliance ("Ski Amade") and the Austrian Competition Authority (BWB) in 2003/2004. According to this compromise an alliance of physically unconnected nearby ski resorts is allowed to sell exclusive common multi-day ski lift tickets whereas each alliance member is obliged to sell an individual single-day ticket for its own resort. According to our results, consumers staying in a region for several days of skiing might be better off buying several single-day tickets for different alliance members if alliances were prohibited, than buying the actual corresponding multi-day ticket of the existing alliance. Further, to calculate the net welfare effects of the alliances, of course, information on quantities of tickets for different periods of validity would be required. Indeed, these aspects should be subject to further research.

Our results seem to contradict the findings for airline alliances (e.g. Brueckner and Whalen, 2000; Brueckner, 2001), which usually observe positive net benefits associated with the cooperation of airlines serving different hub and spokes markets. These net benefits result from two countervailing effects, with a price decreasing effect on the interline city-pair markets (connections which require different carriers) outweighing the loss of competition in the interhub markets (which connect the hub cities of the partners). However, the industry focused on in the present paper is not characterized by hub and spokes networks, but rather by a linear (Hotelling, 1929) or circular (Salop, 1979) city type of market. Thus, following the terminology of Brueckner (2001), the effect of alliances is reduced to the price-increasing effect found for interhub markets.

In contrast to the market structure of the airline industry, which has received a lot of attention in the literature but is characterized by a very specific spatial market structure, the approach to detect anti-competitive behavior in price setting suggested in this paper can be applied to a number of different industries provided that a group of firms is suspected of collusion. Relevant markets are characterized by localized competition with fixed consumer locations and high relocation costs for firms. Such market conditions can be found in many different retail and wholesale industries, such as food or gasoline markets, and entertainment or tourism services such as theaters, hotels and theme parks. We hope that our contribution spurs further research in this direction.

While in this paper we suggest that our approach enables tracking down collusive behavior in spatially differentiated markets with cross-sectional data, the availability of panel data and the possibility to use a difference-in-difference approach would simplify the detection of the causal effect of cooperation and collusion. This, however, requires further research. Specifically, the choice of an appropriate reference group should be well-considered if the diff-in-diff approach is applied to spatial markets. Particularly in the case of ski resorts setting prices that remain unchanged throughout the season only once before the start of the winter season, the formation of an alliance may also affect prices of nearby "non-treated" resorts. Our approach circumvents this problem by explicitly focusing on the spatial structure of price patterns. Thus, one way to ensure that the price setting of the control group is not affected by the behavior of alliance members in a difference-in-difference approach is that of choosing similar ski resorts in countries further away (e.g. France in our case) as reference and/or by using propensity score matching. Also synthetic control methods could be applied to compare prices of individual alliance resorts before and after forming or joining an alliance. Further, it may be worth analyzing the market with respect to potential heterogeneity in pricing of different alliances. Specifically, the question of what drives the extent to which market power can be exploited in different groups of alliances could be investigated by applying spatial quantile regression methods.

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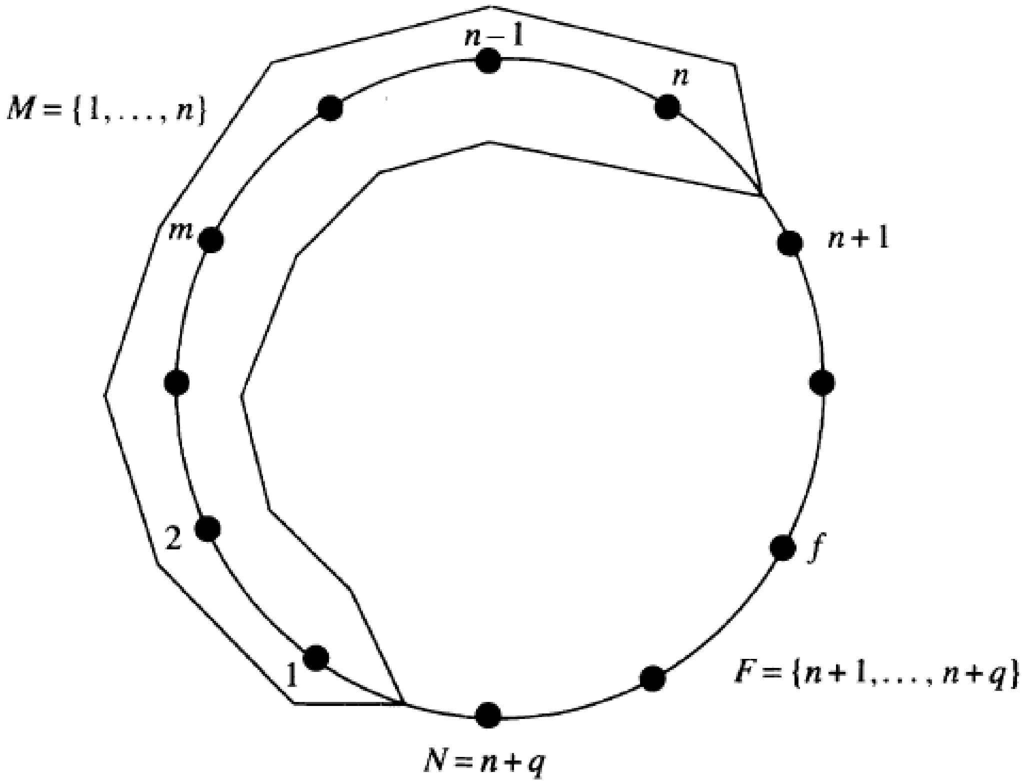
Appendix

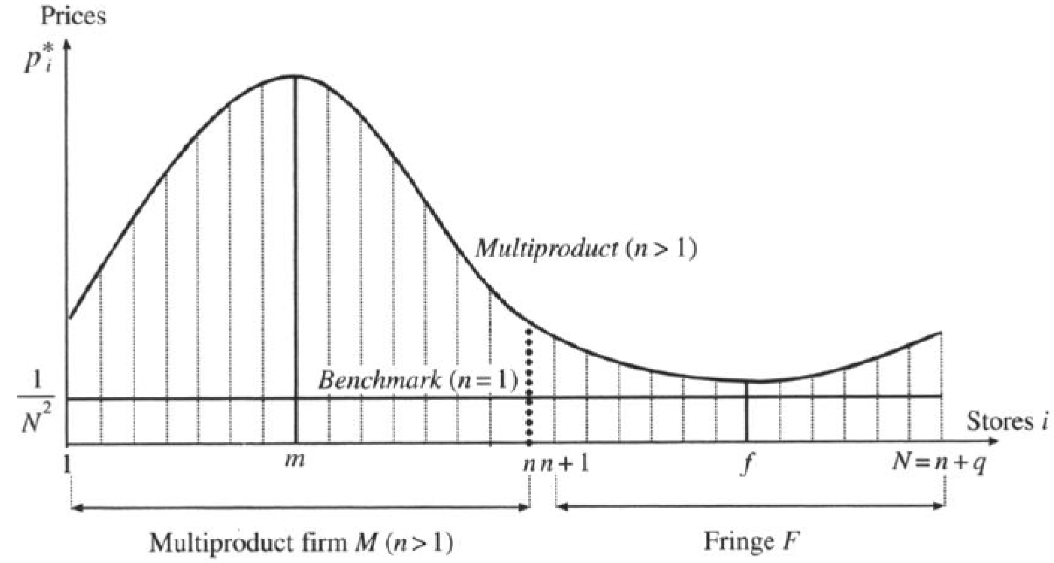
[Table 5 about here]

Figure 1: A circular city model with a multiproduct and stand-alone firms



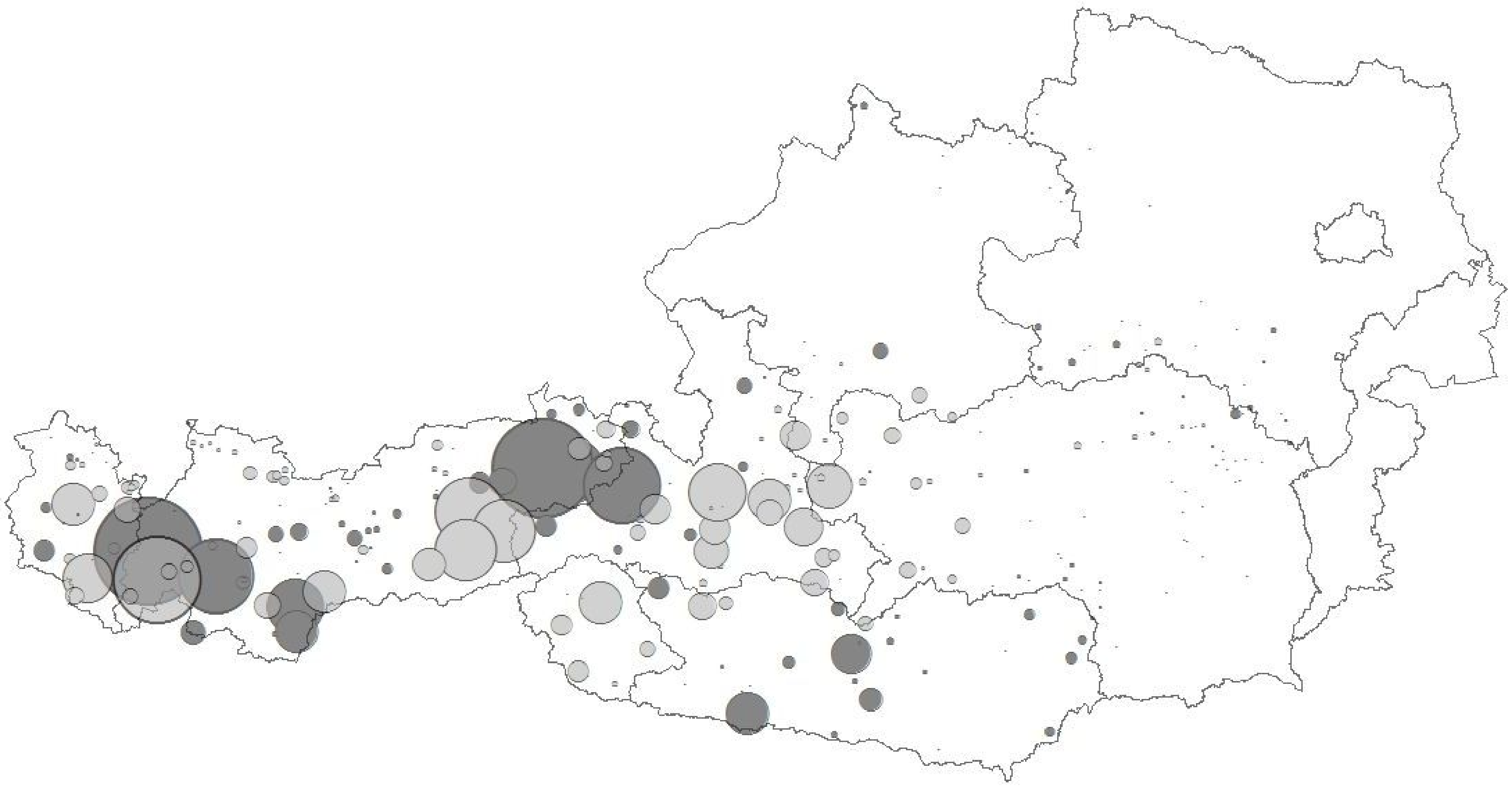
Source: Giraud-Heraud et al. (2003)

Figure 2: Typical shape for equilibrium prices with $n > 2$



Source: Giraud-Heraud et al. (2003)

Figure 3: Size and Locations of Ski Resorts and Alliances



Dark gray: stand-alone resorts; Light gray: alliance resorts; Size of circles: total slope kilometers

Figure 4: Moran scatterplot of y and Wy

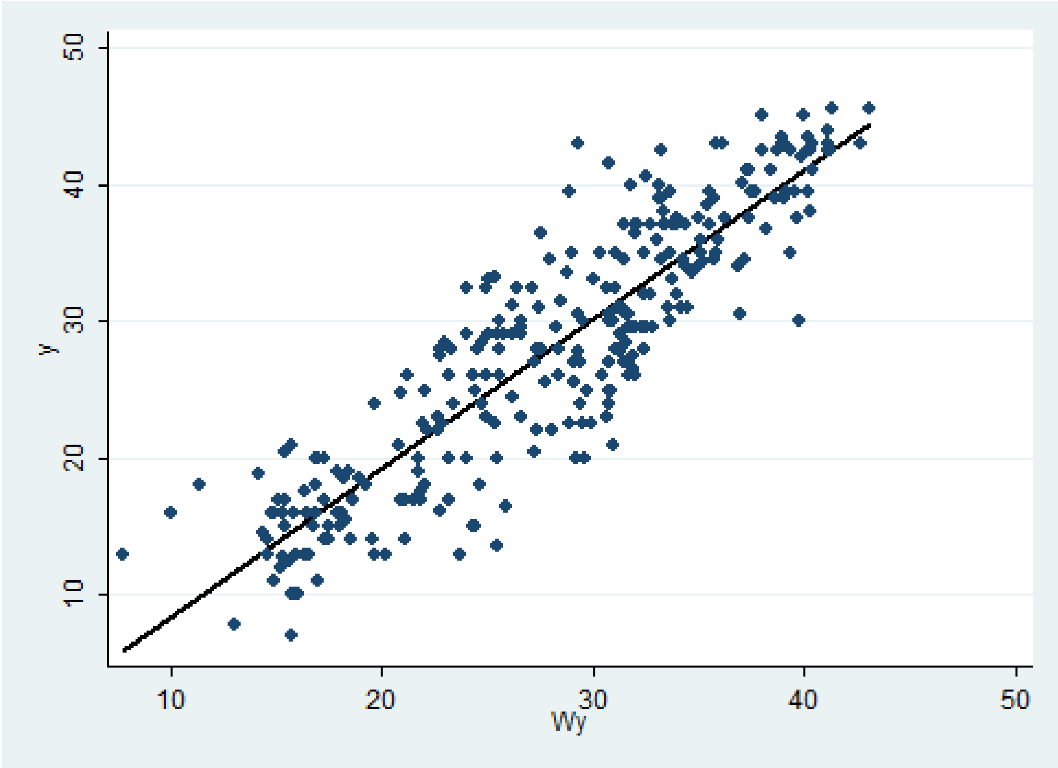


Figure 5: Moran scatterplot of y and My

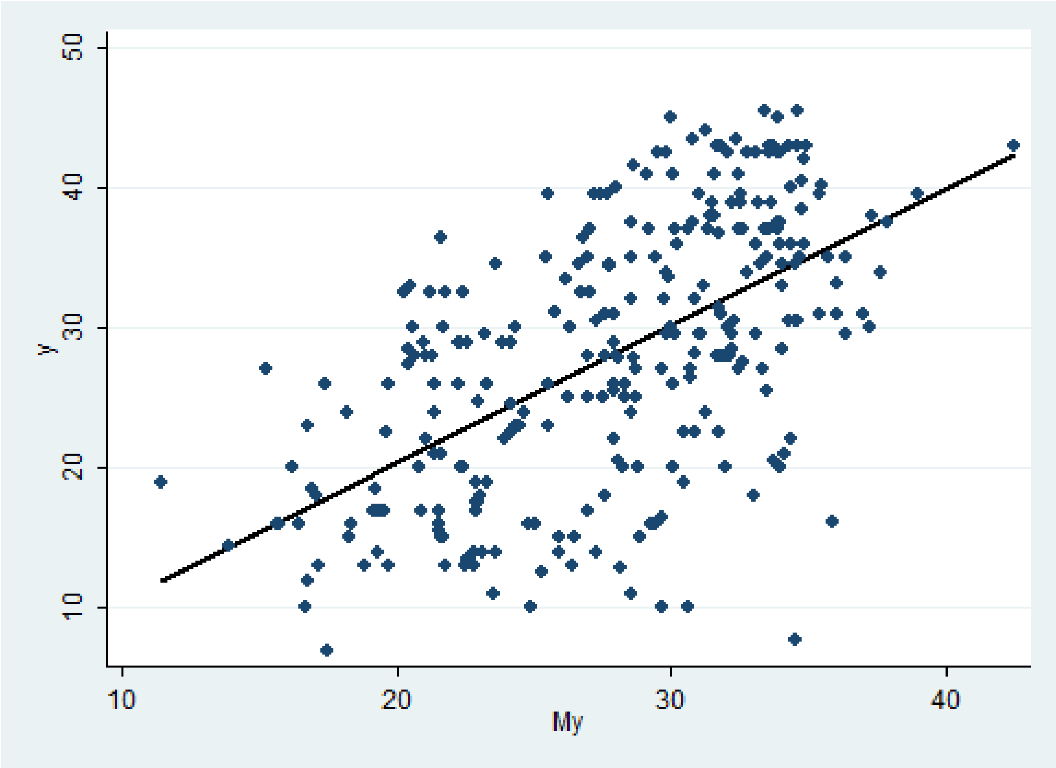
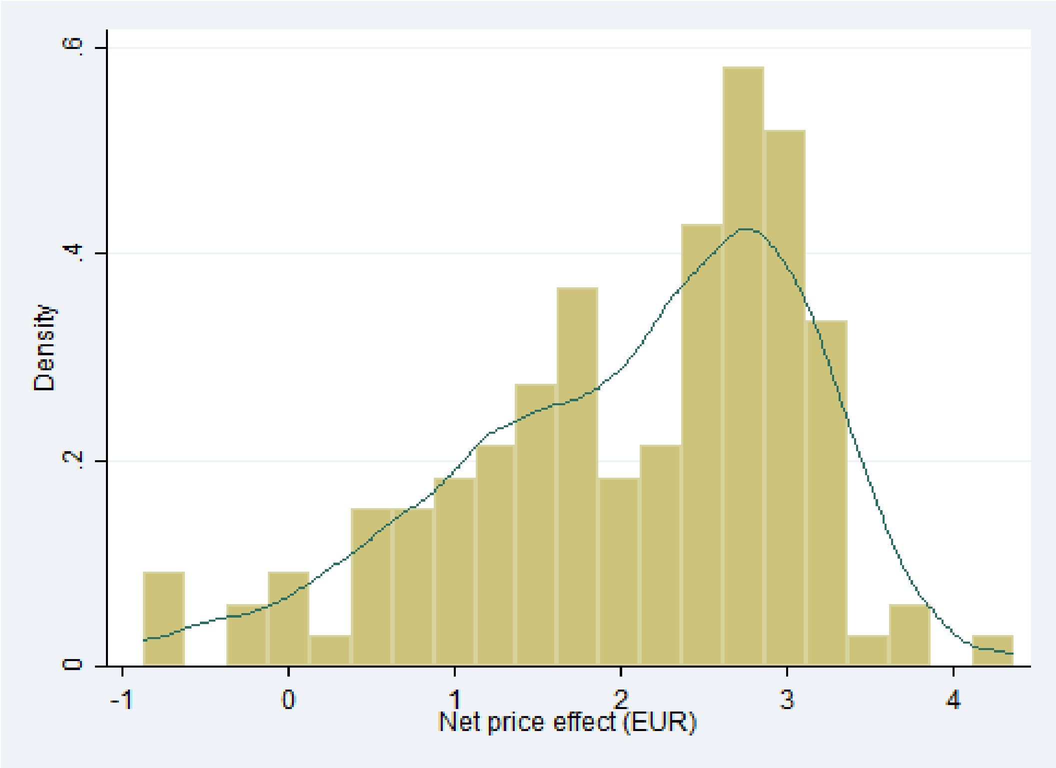


Figure 6: Distribution of net price effects of alliance membership



Histogram (bars) and kernel density estimation (line) based on specification (2) in Table 3;

Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Price	28.035	9.500	7	45.5	285
Alliance	0.46		0	1	285
SealevelMax	1709.758	572.621	403	3440	285
Slopekm	27.858	42.723	0.5	283	285
ShareDrag	70.615	27.242	0	100	285
Capacity	12800.744	19588.657	350	136494.5	251
SkiSchool	0.926		0	1	285
ArtificialSnow	0.726		0	1	285
SnowValley	67.629	30.448	10	265	178
DistCity	86.101	38.304	14.16	194.5	285
ShareLux	18.5	21.576	0	93.853	201
DistNextSim	39.802	22.282	3.04	104.86	285
GDP	31040.207	6202.682	19099.166	44712.125	285

Table 2: OLS regression results of price levels

	(1)	(2)	(3)	(4)	(5)
Alliance	1.902***	-0.534	-0.519		
	(3.44)	(-0.66)	(-0.48)		
#AllianceMembers				0.263***	0.201**
				(5.05)	(2.22)
ShareSameAlliance		4.853***	4.411**		2.026*
		(4.19)	(2.60)		(1.86)
ShareAllianceFringe		0.967	0.609		1.255
		(0.83)	(0.52)		(1.27)
log(*DistNextSim*)	0.174	-0.00476	-0.111	0.124	0.0288
	(0.36)	(-0.01)	(-0.25)	(0.26)	(0.06)
log(*SlopeKm*)	1.468**	1.491**	0.344	1.522***	1.473**
	(2.75)	(2.55)	(0.48)	(2.84)	(2.55)
log(*Capacity*)	2.344***	2.329***	2.517***	2.250***	2.296***
	(6.98)	(6.84)	(6.72)	(6.68)	(6.70)
ArtificialSnow	1.386**	1.615**	1.473**	1.446**	1.565**
	(2.27)	(2.60)	(2.53)	(2.59)	(2.66)
log(*SealevelMax*)	4.069***	3.764***	2.569	4.140***	3.913***
	(2.84)	(2.81)	(1.31)	(3.00)	(2.91)
log(*SnowValley*)	1.026**	1.045**	1.048**	0.842*	0.885**
	(2.43)	(2.66)	(2.24)	(1.92)	(2.07)
ShareDrag	-0.0739***	-0.0735***	-0.0760***	-0.0737***	-0.0724***
	(-7.56)	(-7.68)	(-7.36)	(-7.01)	(-7.19)
SkiSchool	0.573	0.515	0.660	0.753	0.631
	(0.71)	(0.65)	(0.77)	(1.00)	(0.82)
Constant	-22.11*	-9.273	-10.99	-24.07*	-14.03
	(-1.82)	(-0.70)	(-0.46)	(-2.02)	(-1.11)
Demand variables	Yes	Yes	Yes	Yes	Yes
WC	No	No	Yes	No	No
N	285	285	285	285	285
R^2	0.895	0.900	0.907	0.902	0.903

t-statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$;

Standard errors clustered by NUTS-3 regions;

Demand variables include *DistCity*, *ShareLux* and *GDP*;

WC = spatial lag of ski resorts characteristics with $C \subset X$;

Including dummy variables for missing values in *Capacity*, *SnowValley* and *ShareLux*;

Table 3: GMM Results of best response functions in prices

	(1)	(2)	(3)
Wy	0.209***	0.165**	0.122*
	(2.85)	(2.17)	(1.70)
$Waay$		0.115***	0.121***
		(2.79)	(2.94)
$Alliance$	-0.773	-3.529***	-4.450***
	(-1.03)	(-2.70)	(-3.24)
$\#AllianceMembers$			0.185***
			(3.22)
$ShareSameAlliance$	3.799***	2.814***	1.757**
	(3.80)	(3.40)	(1.99)
$ShareAllianceFringe$	-0.233	0.461	0.426
	(-0.24)	(0.45)	(0.44)
$log(DistNextSim)$	-0.202	-0.229	-0.260
	(-0.58)	(-0.70)	(-0.79)
$log(SlopeKm)$	0.500	0.451	0.762**
	(0.93)	(1.10)	(1.97)
$log(Capacity)$	2.361***	2.355***	2.281***
	(7.92)	(8.51)	(8.22)
$ArtificialSnow$	1.717***	1.715***	1.724***
	(3.20)	(3.41)	(3.62)
$log(SealevelMax)$	3.976***	4.156***	4.268***
	(4.55)	(5.00)	(5.01)
$log(SnowValley)$	1.334***	1.491***	1.268***
	(3.65)	(4.71)	(3.70)
$ShareDrag$	-0.0743***	-0.0784***	-0.0771***
	(-9.51)	(-13.05)	(-10.56)
$SkiSchool$	0.888	1.007*	1.139**
	(1.45)	(1.73)	(2.00)
$Constant$	-15.47	-15.18	-17.96*
	(-1.56)	(-1.57)	(-1.76)
Demand Variables	Yes	Yes	Yes
N	285	285	285
R^2	0.905	0.910	0.912
Hansen J-stat.	1.241	1.803	1.745
p-value	0.538	0.772	0.783
F-stat. for weak id.	163.4	103.0	117.0
LM test for underid.	15.97	16.21	15.82
p-value	0.001	0.006	0.007

t statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$;
Standard errors clustered by NUTS-3 regions;
Demand variables include $DistCity$, $ShareLux$ and GDP;
Including dummy variables for missing values in $Capacity$, $SnowValley$ and $ShareLux$;

Table 4: Robustness checks for best response functions in prices

	(1)	(2)	(3)	(4)	(5)
Estimator	ML reduced form	GMM	GMM	GMM	GMM
Weights Matrix	W	S	M	W_{60min}	W_{45min}
Wy	0.165*	0.222***	0.0564	0.0171	0.118***
	(1.91)	(2.71)	(1.17)	(0.25)	(2.61)
$W_A y$	0.222***	0.115***	0.216***	0.181***	0.170***
	(3.93)	(2.93)	(5.63)	(3.95)	(4.43)
$Alliance$	-5.866***	-3.018**	-4.992***	-4.904***	-3.953***
	(-3.37)	(-2.42)	(-3.49)	(-3.14)	(-2.74)
$ShareSameAlliance$	1.578	1.758**	-0.125	1.592	0.927
	(1.05)	(1.98)	(-0.16)	(1.53)	(1.02)
$ShareAllianceFringe$	0.852	0.0201	-0.881	0.148	0.216
	(0.74)	(0.02)	(-1.24)	(0.17)	(0.40)
Ski resorts char.	Yes	Yes	Yes	Yes	Yes
Demand variables	Yes	Yes	Yes	Yes	Yes
N	285	285	285	284	271
R^2	0.914	0.910	0.911	0.907	0.914
Hansen J-stat.		2.676	1.305	2.335	4.307
p-value		0.613	0.860	0.674	0.366
F-stat. for weak id.		73.07	89.44	50.83	51.81
LM-test for underid.		16.09	11.29	11.97	12.68
p-value		0.007	0.046	0.035	0.027

t statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$;
ML: Spatial Error based on W; GMM: Standard errors clustered by NUTS-3 regions;
W_{60min} (W_{45min}) spatial weights matrix based on 60 (45) minutes cut-off distance;
M (S) spatial weights matrix based on distance (similarity) only based on equation (5);
Ski resorts characteristics include all variables reported in Table 3;
Demand variables include $DistCity$, $ShareLux$ and GDP;
Including dummy variables for missing values in $Capacity$,
$SnowValley$ and $ShareLux$;

Table 5: Summary statistics of alliances

		Slope kilometers	
Name of Alliance	No. of members	total	per member
Ski Amade	17	759.8	44.7
Zillertaler SuperSkipass	5	613.0	122.6
Skihit Osttirol	8	384.0	48.0
Silvretta Skipass	4	343.0	85.7
3Taeler Skipass Vorarlberg	11	300.0	27.3
Lungo	5	250.0	50.0
Skipass Montafon	5	209.0	41.8
Murtaler Schiberge	8	190.0	23.7
Schneewinkel Tirol	5	171.0	34.2
Stubaier Superskipass	4	149.0	37.2
Tiroler Top Snow Card	6	147.0	24.5
Skiverbund Dachstein West	6	138.0	23.0
Zell am See Kaprun	3	138.0	46.0
Pitz Regio Card	3	131.0	43.7
Schneebaerenland	5	119.0	23.8
Kleinwalsertal	4	88.8	22.2
Allgaeu Tirol Skicard	7	72.0	10.3
Hinterstoder Wurzeralm	2	62.0	31.0
Romantic Card Steiermark	6	57.0	9.5
Achensee	5	57.0	11.4
Schiland Voralpen	5	52.5	10.5
Seefeld	3	37.0	12.3
Schi & Langlaufregion Joglland	4	15.5	3.9