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Norwegian Competition Authority

Rapport 5/2018

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Substitution Between Online Distribution Channels: Evidence from the Oslo Hotel Market*

Arthur Cazaubiel† Morgane Cure† Bjørn Olav Johansen‡ Thibaud Vergé†‡

August 1, 2018

Abstract

Using an exhaustive database of bookings in one large chain of hotels active in Oslo (2013-2016), we estimate a nested-logit demand model that allows us to evaluate substitution patterns between online distribution channels. Making use of the chains' decision to delist from Expedia's platform, we can then compare simulated and actual effects of such an event on prices and market shares and identify ways to improve on simulated counterfactual outcomes.

JEL Classification : D22, D43, L11, L81

Keywords: Multi-channel distribution, Pricing, Structural demand estimation, Online substitution.

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*We are grateful to Philippe Choné, Lukasz Grzybowski, Vincente Lagos, Joao Montez, Franck Verboven, Wenche Wang as well as to participants at seminars and conferences (BECCLE, CREST, CRESSE 2018, Telecom ParisTech, University of Florida Competition Policy Initiative) for valuable comments and discussions. Bjørn Olav Johansen and Thibaud Vergé are grateful to the Norwegian Competition Authority for financial support. The views expressed in this paper are those of the authors only.

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1 Introduction

Retail e-commerce sales have been rapidly growing over the last 20-25 years. According to Statista, online sales will reach 2.8 trillion US dollars worldwide in 2018, having almost doubled in the last three years. In some markets such as music, books or travel, a large majority of sales are now made online rather than offline. Even groceries are now more commonly bought online.

The rapid growth of online retailing has led economists and competition agencies to look at the importance and impact of multi-channel distribution, and at the degree of substitution between online and offline sales.[1] Among others, Gentzkow (2007) and Pozzi (2013) analyze the cannibalization effects of online distribution on offline sales. Gentzkow (2007) shows that the introduction of a digital version of the *Washington Post* reduced sales of the print edition, while Pozzi (2013) concludes that the introduction of an online shopping service by a large US grocery retailer had a limited cannibalization effect on brick-and-mortar sales and increased total revenues. In addition to this issue of within-firm cannibalization, an important question is to identify whether online retailing has led consumers to benefit from increased competition, i.e., to focus on across-firm substitution (see for example Prince (2007), Duch-Brown et al. (2017) and Ellison and Fisher Ellison (2018)).

Substitution between online and offline distribution is also an important issue for competition authorities. In merger control, delineating product markets is essential to assess the competitive impact of mergers and this now frequently involves identifying whether online sales should be part of the same relevant market as offline sales.[2] The role of online sales and the interaction between brick-and-mortar, click-and-mortar, and pure online players has also been a major issue when revising the European rules applicable to vertical agreements.[3] Many cases involving restraints related to online sales have been evaluated by competition agencies in

[1]For a review of the early literature, see Lieber and Syverson (2012).

[2]See for example recent cases in traditional retailing [e.g., FNAC/Darty (France, 2017)], mobile payments [e.g., Telefonica UK/Vodafone UK/Everything Everywhere (European Commission, 2012)] or sales of books [e.g., Ahold/Flevo (European Commission, 2012)].

[3]See Commission Regulation 330/2010 of 20 April 2010 on the application of Article 101(3) of the Treaty on the Functioning of the European Union to categories of vertical agreements and concerted practices, *Official Journal of the European Union*, L102, pp. 1-7, and *Guidelines on Vertical Restraints*, Commission Notice, C(2010) 2365.

the last 10 to 15 years: restriction of online sales in selective distribution networks [e.g., Pierre Fabre (France, 2007 and CJEU, 2011)], dual pricing or resale price maintenance [e.g., BSH (Germany, 2013) and United Navigation (UK, 2015)], exclusive territories or geo-blocking [e.g., Sector inquiry into e-commerce (European Commission, 2016)].[4]

More recently, the policy debate has shifted to the impact of specific types of vertical restraints in online retailing, restraints usually related to the role of third-party platforms. Recent cases have involved restrictions imposed by manufacturers on online retailers with respect to the use of third-party platforms [e.g., Coty (Germany, 2014 and CJUE, 2017) or Adidas and Asics (Germany, 2014)], and by platforms on suppliers with respect to pricing, such as price parity (or MFN) clauses [e.g., eBooks (European Commission, 2017), Amazon (UK and Germany, 2013)].

Throughout Europe, platform price parity clauses have been the subject of several investigations in the market for online booking platforms/online travel agencies (OTAs). In Germany, the Bundeskartellamt prohibited price parity clauses imposed by HRS (December 2013) and Booking (December 2015). In April 2015, the French, Italian and Swedish competition agencies simultaneously accepted commitments offered by Booking to remove any availability requirements from their contracts and to switch from wide to narrow price parity clauses.[5] Although it did not formally offer commitments to the competition agencies, Expedia announced similar changes to its contracts throughout Europe.[6,7]

The question of market definition has been an important part of the debate, with agencies ultimately concluding that the hotels' direct sales do not belong to the same market as sales made through OTAs. Authorities have indeed taken the view that OTAs offer a bundle of services that includes search and comparison

[4]For a detailed review of competition issues and cases in Europe, see Friederiszick and Glowicka (2016).

[5]See Decision of 15 April 2015 by the Swedish Competition Authority in Case 596/2013.

[6]The French (2015), Austrian (2016) and Italian (2017) parliaments have since voted in favor of legislation prohibiting any form of price parity (or price control by the platforms) for hotel room bookings.

[7]In October 2015, the Swiss Competition Commission prohibited the use of wide price parity clauses by Booking, Expedia and HRS but allowed them to adopt narrow price parity clauses. In September 2016, the Australian Competition and Consumer Commission accepted commitments offered by Expedia and Booking to amend the price and availability parity clauses in their contracts and to switch from wide to narrow price parity clauses.

as well as the possibility to book online, whereas hotels' websites only offer the opportunity to book. They also concluded that hotels view OTAs more as a complement than as a substitute to their own direct sales.

The issue of substitution between online channels also has important theoretical implications when considering the effects of price parity clauses. Boik and Corts (2016) (in a context with a monopolist supplier) and Johnson (2017) (with competing suppliers) both show that when suppliers sell through competing platforms, price parity clauses lead to higher commissions and thus higher final prices. However, their results rely on the assumptions that the platform commissions either are linear tariffs (i.e., a fixed price per sale) or based on revenue-sharing. Once these assumptions are relaxed, the effects of price parity clauses may well be different. For example, Rey and Vergé (2016) show that with non-linear commissions, price parity clauses do not affect final prices, and that they only affect the division of profits. Johansen and Vergé (2017) consider linear commissions but assume that suppliers can also reach final consumers directly. In such a setting, price parity clauses have an ambiguous effect on commissions, final prices, and suppliers' profits. In particular, when inter-brand competition (i.e., competition between suppliers) is sufficiently fierce, price parity clauses may well lead to lower commissions and prices, while simultaneously increasing suppliers' and platforms' profits. However, their result relies on the assumption that it is a viable option for a supplier to delist from one of the platforms: This requires that, when delisting from a platform, a sufficiently big share of the recaptured sales are indeed recaptured through the direct channel and not exclusively through the rival platforms.[8]

In this paper, we use an exhaustive database of bookings in 13 Oslo hotels (all belonging to the same chain) to evaluate the degree of substitution between online distribution channels, including the two largest online OTAs (Booking and Expedia) and the chain's own online distribution channel. We can then try to check whether selling directly constitutes a credible alternative to selling through OTAs. Contrary to recent papers that have focused on the effects of price parity clauses

[8] See also Edelman and Wright (2015), Wang and Wright (2016) and Wang and Wright (2017) who show that, despite reducing the risk of free-riding by platforms ("showrooming"), price parity clauses usually lead to higher prices or inefficient investment. However, in their search setting, delisting from a platform is never a profitable strategy for suppliers: Because all sales are made through the most efficient platform in equilibrium, a supplier would lose all of its consumers by not listing on this platform.

in this industry by using scrapped price data from metasearch engines (see, e.g., Hunold et al. (2018), Mantovani et al. (2017) and de Nijs and Larrieu (2018)), we use a large dataset of actual bookings and use it to estimate a nested logit demand model that allows us to evaluate substitution patterns between online distribution channels. Our results suggest that, while a substantial share of consumers seem to be loyal to the OTAs, and would switch to the other hotels (i.e., our "outside good") in case of the hotel chain's decision to delist from a platform (or after a substantial price increase by the hotel chain on the same platform), the chain's direct sales channel appears to be a credible alternative to the OTAs. Among the consumers that would continue to book a room at the same hotel (after the hotel's decision to delist from one of the OTAs), a majority would indeed book directly from the hotel rather than from the competing OTA.

Making use of the chain's decision to delist from Expedia's platform, we can then compare simulated and actual effects of such an event on prices and market shares. In that sense, we try to contribute to the debate on the effectiveness of structural IO models initiated by Peters (2006), Angrist and Pischke (2010) and Nevo and Whinston (2010).[9] Comparing the simulated and observed outcomes, we observe important discrepancies in terms of prices and market shares. Following Peters (2006), we thus try to identify sources for these differences and see how to improve the counterfactual simulation. Accounting for changes in the product characteristics slightly changes the simulated outcome. But the most important effect seems to come from a change of pricing behaviour by the hotel chain during the period. Our analysis indeed suggests that while the chain took control of the hotels' pricing strategy in the last few years of the sample period, the individual hotel resorts had more independence in the early period.

The rest of the paper is organized as follows. After presenting our dataset and the specific context in which the 13 hotels operated during the sample period (Section 2), we proceed to the estimation of our nested logit demand model and derive substitution patterns between online distribution channels (Section 3). We then use the estimated demand parameters and a structural pricing model to obtain per-channel marginal costs (Section 4). We then perform a counterfactual analysis and compute equilibrium prices and market shares assuming that all hotels

[9]For recent evidence on the accuracy of merger simulation methods, see among others, Weinberg (2011), Weinberg and Hosken (2013), Björnerstedt and Verboven (2016) and Miller and Weinberg (2017).

decide to stop selling through one channel. Taking advantage of the hotels' decision to delist from Expedia in 2013, we then compare the simulated outcome to the observed data (Section 5). Section 6 concludes.

2 Data and Context

2.1 Data

We use an exhaustive dataset of all bookings made over almost four years in 13 hotels located around Oslo (Norway).[10] These hotels all belong to one of the leading hotel chains active in Norway.

Our initial dataset includes more than 1.2 million observations (i.e., bookings). This dataset has been directly extracted from the hotel chain's information system. It includes all bookings made by consumers through all distribution channels between January 2013 and November 2016. For each booking, we observe:

- The booking date as well as the arrival and departure dates. This allows us to compute the length of stay as well as advance purchase (i.e., how many days prior to arrival the room has been booked).
- The room type (e.g., standard, superior, junior suite, ...).
- The number of guests.
- The channel through which the room was booked.
- The price paid by the consumer as well as the rate code associated with the tariff.

We use our exhaustive dataset and existing information on the number of rooms at each hotel to compute occupancy rates at any point in time. Specifically, we compute the variable $OR_{h,t,x}$, which is the occupancy rate at hotel h at date t, as seen at date $t - x$ (i.e., x days in advance). As x becomes smaller and we get closer to the date t, we thus expect the occupancy rate $OR_{h,t,x}$ to increase. More formally, $OR_{h,t,x}$ is the number of bookings made at date $t - x$ and earlier, for all stays that include a night at date t, divided by the total number of rooms at

[10] Our hotels are located either in the municipality of Oslo or close to the city boundaries, with the exception of two airport hotels (at Oslo-Gardermoen Airport).

the hotel. We compute these occupancy rates for all values of x between 0 and 30 (i.e., we compute the occupancy rate daily up to one month before arrival). The ratio $1 - OR_{h,t,x}$ thus indicates which proportion of the rooms (for a stay at date t) were still available x days in advance.

Although we use the full dataset to compute occupancy rates, we carry out our econometric analysis on a subset of bookings that we consider to be homogeneous enough. We restrict attention to bookings made for one or two guests, for one room only, for no more than a week and exclusively for standard or superior rooms (thus excluding business rooms or suites). In addition, we only consider bookings made at most 30 days prior to arrival. As a first step, this helps to ensure that the bookings we observe for a specific date are mostly made under the same regime (i.e., either during or after the boycott described in section 2.2). Yet, for the first 30 nights after the boycott started, and for the first 30 nights after it ended, we still observe that some of the reservations (for a specific night) were made during the boycott, while the rest of the reservations (for the same night) were made either before or after the boycott. Thus, to ensure that all bookings are made under the same regime, we want to exclude all reservations made for any of the 30 first nights after the boycott had started, and all reservations made during the boycott, but for an arrival date that falls after the hotel has started listing again on Expedia. This whole selection process eliminates about 28 % of the observations, leaving us with 885,249 observations.

Table 1: Share of bookings made through the offline and online channels

Channel	Number of bookings	Share of bookings
Offline	767,489	86.7%
Online	117,760	13.3%
Direct Online (DON)	*55,746*	*47.3%*
Booking (BOO)	*47,762*	*40.6%*
Expedia (EXP)	*14,252*	*12.1%*
Total	885,249	100.0%

Finally, we are only interested in the substitution between online sales channels, and more specifically between the chain's own booking platform (which we refer to as the direct online channel) and the two largest online travel agencies, namely Booking and Expedia. As shown in Table 1, the three online channels account for about 13 % of all bookings in our dataset between January 2013 and November 2016. Although we use information from bookings made through other channels[11] as instruments in our demand estimation, we essentially focus on the 117,760 online bookings. Table 1 also shows that, among online bookings, the direct channel accounts for nearly half of the sales, Booking accounts for about 40 % whereas Expedia represents just over 12 % of all online bookings. Expedia's low market share is to a large extent explained by the long period during which our 13 hotels decided not to list their rooms on Expedia (see section 2.2).

Table 2: Summary statistics of booking characteristics

Channel	Booking	Direct	Expedia	Offline
Price (NOK)	1,123	1,024	1,279	1,074
Advance	9.2	9.6	8.0	7.3
Nights	1.7	1.5	1.5	1.5
Persons	1.4	1.3	1.3	1.2
Superior room	6%	10%	10%	13%
Week-end	34%	31%	31%	22%
Occupancy rate	85%	80%	86%	80%

Table 2 presents some summary statistics of booking characteristics (for all online and offline bookings). Overall, it appears that online prices are lower on the hotels' own websites (about 100 NOK $\sim$ 13$) than on Booking or Expedia (offline prices are somewhere in between). Consumers tend to book earlier online than offline (conditionally on booking less than a month prior to arrival). Given that most bookings are made relatively late (just over one week before arrival on average), it is not surprising that the occupancy rate as seen at the date of the booking (i.e., proportion of rooms already booked) is relatively high, between 80% and 86% on average. We also observe that online bookings include weekend nights more often than offline bookings. This should not be surprising, as our dataset includes corporate rates, and booking made using these corporate tariffs are all part of the offline bookings. Finally, rooms are booked for one to two nights and for 1.3 persons on average.

[11]Although other bookings are made through different types of booking channels such as travel agencies or B2B contracts, we refer to such bookings as made "offline."

We also collected some hotel characteristics, and this additional data includes:

- Number of rooms.
- Precise hotel location (as well as distance from city center and Oslo-Gardermoen Airport).
- Star rating as well as existence of specific amenities (bar, restaurant, fitness and/or wellness center).
- Consumer reviews have been scrapped from TripAdvisor. For our 13 hotels, these reviews have been collected daily for the whole period. Each day, we observe for each hotel the last five ratings (on a 1-to-5 scale), the current average rating and the total number of reviews to date.

Table 3: Summary statistics of hotel characteristics

	Mean	Median	Min	Max
Number of rooms	195	164	103	435
Star rating	3.3	3	3	4
Last TripAdvisor Rating (1-5 scale)	3.8	3.8	3.4	4.3
Bar	0.62	–	0	1
Restaurant	0.54	–	0	1
Fitness/Wellness	0.38	–	0	1
Distance to city center (km)	7.6	1.0	0.5	36.2
Distance to airport (km)	33.5	36.9	4.4	37.8

Table 3 presents summary statistics of the hotel characteristics. Our sample includes only 3 and 4-star hotels (the majority are 3-star hotels) that are relatively large (about 200 rooms on average, all above 100 rooms). Hotels located in the city center tend to be smaller and centrally located, whereas the two hotels located in the vicinity of Oslo-Gardermoen Airport are the largest (both with more than 200 rooms).

2.2 Context: Delisting From Expedia

During the year 2012, several large hotel chains active in Norway decided not to renew their agreements with Expedia following disputes over the terms of these contracts (most prominently the issues of rate parity and commission fees). First Hotels was the first chain to pull out its inventory from Expedia's platforms and was soon followed by some of the other leading chains such as Nordic Choice, Rica Hotels (later acquired by Scandic), Scandic Hotels and Thon Hotels. By the end of 2013, some of these chains had signed new contracts with Expedia and had started listing again on Expedia's various platforms. Nordic Choice (the largest chain in Scandinavia with more than 160 hotels) reported that Expedia had accepted to cut its commission rate to less than 15%, a level similar to Booking's commission rate (reported to be around 15% on average in Europe) and to drop the price parity requirement.[12]

The chain that owns the 13 hotels in our dataset cut its ties with Expedia at the end of 2012, and its inventory stopped appearing on Expedia's platforms as of January 1, 2013. The "boycott" ended in 2015, after almost 3 years, when the hotels started listing again on Expedia's platforms in September and October 2015. Our almost four years of observations thus cover this boycott period (from January 2013 to September/October 2015) as well as a period during which the hotels were listing on Expedia's platforms (from September/October 2015 to November 2016).

For the first month of the dataset (January 2013) none of the 13 hotels are listing on Expedia. However, at the end of the boycott we observe that the different hotels start listing again on Expedia's platforms on different dates. We therefore identify for each hotel the date for which we start observing bookings made through Expedia, and then we use this date as the end of the boycott for that hotel.[13]

As mentioned in the previous section, to ensure that all bookings are made under the same regime, we exclude from our sample all bookings with an arrival date in January 2013 (first month of our dataset), as well as all bookings with an arrival date within the first month after each hotel's decision to list again on Expedia. This helps to ensure that all the bookings we observe for a given arrival date are comparable. For example, for a given hotel, if the boycott ended on September 10, 2015, we consider two separate periods for that hotel: The boycott period, which includes all bookings with an arrival date between February

[12]See press reports at NewsinEnglish.no and Hotel News Now.

[13]Formally, we require that all least three bookings are made during the week through Expedia to consider that the hotel is listing again. We check evolution of each hotels' sales through Expedia between July and November 2015, and this methods seems to perfectly identify the boycott end.

1, 2013 and September 9, 2015, and the post-boycott period, which includes all bookings between October 10, 2015 and November 30, 2016. Table 4 shows the date (formally week) that we identify as the end of the boycott for each of the 13 hotels.

Table 4: Identifying the end of the boycott period

Hotel	End of Boycott
Hotel 1	October 29, 2015
Hotel 2	September 10, 2015
Hotel 3	September 10, 2015
Hotel 4	October 15, 2015
Hotel 5	October 15, 2015
Hotel 6	October 15, 2015
Hotel 7	October 8, 2015
Hotel 8	October 15, 2015
Hotel 9	December 24, 2015
Hotel 10	October 22, 2015
Hotel 11	January 8, 2016
Hotel 12	October 15, 2015
Hotel 13	December 24, 2015

This long boycott period (33-34 months out of 47 months for which we have data) explains Expedia's low market share (about 12 % of the online bookings). Now that we have precisely identified the boycott period, we can compute markets shares (restricting attention to our three online distribution channels) for the boycott and post-boycott periods separately. Table 5 shows each channel's market share during the two periods. Note that we cannot infer from these numbers which distribution channels (if any) were affected by Expedia's return after the boycott, as the market shares do not tell us anything about the underlying volumes. In the next sections, we propose to carefully analyze substitution patterns between these three distribution channels.

Table 5: Online distribution market share for each channel

Channel	Boycott	Post-boycott
Direct Online (DON)	47 %	42 %
Booking (BOO)	53 %	31 %
Expedia (EXP)	–	27 %

3 Demand Estimation

In this section, we focus on the final period of our dataset, during which hotels all list on Expedia (as well as on Booking and on their own website). Using a nested logit demand model, we first estimate demand on all three online channels during that period and evaluate substitution patterns between online channels. Using a standard structural approach, we estimate hotels' marginal costs, before simulating the effects on prices and quantities of hotels delisting from Expedia's platforms. We conclude by comparing our counterfactual prices and quantities with price and quantities observed during the boycott period.

3.1 Specification

We consider a one-level nested logit demand in which nests are constructed by distinguishing two categories of hotels: the 7 hotels that are located in the city center (i.e., less than 1 kilometer from the center of Oslo) belong to the first nest, while the 6 hotels located farther away (i.e., more than a kilometer from the city center) belong to the second nest.

Consumer i's conditional indirect utility when buying product j in nest g at time t (i.e., for a stay starting in week t) is thus given by:

$$u_{ijt} = \underbrace{X'_{jt}\beta - \alpha p_{jt} + \xi_{jt}}_{\equiv \delta_{jt}} + \zeta_{igt} + (1 - \sigma_g)\varepsilon_{ijt}, \tag{1}$$

where product j is the combination of a hotel and a distribution channel, i.e., $j = (h, c)$. The first part of the function, δ_{jt}, is the mean utility for product j at time t. The mean utility depends on observed characteristics that are included in the vector X_{jt}, which consists of booking characteristics (type of room, advance booking (in days), proportion of weekend travelers, occupancy rate at the time of booking, etc.), hotel characteristics that may be time-invariant (distance from the city center or Oslo-Gardermoen airport, star rating, restaurant, bar, wellness/fitness center) or not (TripAdvisor ratings). The mean utility also depends on the price of product j at time t, p_{jt}, and on unobserved time effects, ξ_{jt}, which for example could be that consumers are gradually getting used to booking their hotel rooms online. For the outside good, we normalize this mean utility to zero, i.e., $\delta_{0t} = 0$ for all t.

The second-part consists of the individual-specific deviation from the mean-utility. It consists of two random terms: ε_{ijt} is an individual-specific unobserved preference for product j at time t, while ζ_{igt} is an individual-specific common unobserved preference for all products in nest g. Finally, we allow the nesting parameter to vary across nests, i.e., we allow $\sigma_{\text{Center}} \neq \sigma_{\text{Periphery}}$.

If the random terms have distributions that give rise to the nested logit form, the market share system can then be inverted (see, e.g., Berry (1994)) to obtain the following equation for product j in nest g:

$$\ln\left(\frac{s_{jt}}{s_{0t}}\right) = X'_{jt}\beta - \alpha p_{jt} + \sigma_g \ln\left(\frac{s_{jt}}{s_{gt}}\right) + \xi_{jt}, \tag{2}$$

where s_{jt} is the market share of product j at time t, s_{0t} is the overall market share of the outside goods, and s_{gt} is the overall market share of the products in nest g. To compute the outside good's market share, we adopt the following strategy: starting with monthly data for the total number of hotel rooms booked in Oslo[14], we divide by four to obtain the total number of rooms booked on average each week for that particular month. We then multiply by the share of online bookings observed each week for our thirteen hotels, to estimate the total size of the online booking market for rooms in Oslo in that particular week. Finally, we multiply by the proportion of three or four-star hotels in Oslo, i.e., 70%. In Appendix A, we confirm that our results are robust to variations in the outside goods' market share by varying this last multiplier (share of three and four star hotels) between 50% and 90%.

[14]We use the number of guest nights by month and county for hotels and similar establishments as published by Statistics Norway (*Statistik Sentralbyrå*): https://www.ssb.no/en/overnatting.

3.2 Instruments

The exercise relies on our ability to consistently estimate equation (2). Unfortunately, prices and market shares are endogenously determined and likely to be correlated with product-specific demand shocks that are included in the error terms. Three types of instruments are commonly used to solve such endogeneity problems in demand model estimations: marginal cost shifters, characteristics of rivals' products, and prices in other markets.[15]

Cost shifters are a first common set of instruments. The idea is that costs affect the prices charged to consumers (thus marginal cost shifters and prices are correlated), and that they are uncorrelated with (unobserved) demand shocks. We have therefore collected hourly wages in Norway between 2012 and 2016, and use them as one set of instruments (weighted by the number of rooms to account for hotel size).[16]

We then follow Bresnahan (1987) and assume that demand for a given product (i.e, a hotel in a specific channel) depends not only on the product's own characteristics but also on the characteristics of competing products. However, these characteristics are not likely to be correlated with unobserved demand shocks, because hotels cannot quickly adjust their characteristics (such as star rating and amenities) in response to short-term shifts in demand. We thus use as instruments TripdAvisor ratings of competing hotels in the same market, which are characteristics that change over time. More specifically, we consider, at any point in time, the average across the twelve competing hotels of the average rating for each hotel (for all reviews), the average rating of the last five reviews, and the total number of reviews.

Finally, following Hausman (1996) and Nevo (2001), we instrument the price of a specific product with the average price of other products sold by the same seller. In our case, a seller corresponds to a specific hotel, and we thus use the average price of rooms sold offline to instrument online prices. Prices in different distribution channels are likely to be correlated because they are directly affected by common demand and cost shocks. Moreover, the exclusion condition requires that prices set offline do not affect demand in the online channels. This condition

[15] See for example Bresnahan (1987) and Hausman (1996).

[16] These are seasonally adjusted average total earnings paid per employed person per hour, including overtime pay and regularly recurring cash supplements (reported on a quarterly basis). The data has been collected from OECD statistics: https://stats.oecd.org/.

is likely to hold because offline prices essentially consist of walk-in prices, B-2-B contracted tariffs, and offers to travel agents.

Overall, we thus use three different sets of instrumental variables which vary between hotels and over time:

- Cost shifters: Hourly wage multiplied by number of rooms [quarterly].
- Characteristics of competing hotels in the same market: TripAdvisor ratings [daily].
- Supplier's prices in other markets for the same good: Offline prices [daily].

3.3 Results

In the following, we combine the three types of instruments and estimate three different models. First, we estimate a simple multinomial logit model by constraining the nesting parameters to be equal to zero (i.e., $\sigma_{\text{Center}} = \sigma_{\text{Periphery}} = 0$). We then estimate a standard one-level nested logit constraining the two nesting parameters to take the same value (i.e., $\sigma_{\text{Center}} = \sigma_{\text{Periphery}}$). Finally, we estimate the differentiated nested logit model[17] given by equation (2), where the two nesting parameters can take different values. When we estimate the models, for each hotel we restrict attention to the period during which the hotel was listing rooms on Expedia's platforms. Results of these estimations are given in Table 6.

The results confirm that the simple logit model is not well-suited, because our nesting parameters are significantly different from zero. However, our results differ slightly depending on whether we allow the nesting parameters to vary across nests or not. In our model, we allow consumers to choose the geographic area (i.e., city center or periphery) before selecting the hotel and the online distribution channel and observe that products are close substitutes within each nest, especially for centrally located hotels.

We can then compute own-price and cross-price elasticities of demand for each product j and date t. Table 7 reports the average elasticities for products sold through the same distribution channel (i.e., average elasticities for the thirteen hotels in our sample).

[17] See e.g., Brenkers and Verboven (2006).

Table 6: Demand model estimation

	Differentiated nested logit			Logit	Nested logit
α	0.0024***	0.0028***	0.0023***	0.0038***	0.0023***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
σ					0.421***
					(0.06)
$\sigma_{\text{Periphery}}$	-0.1162	0.1227	0.1785		
	(0.14)	(0.11)	(0.09)		
σ_{Center}	0.239***	0.377***	0.433***		
	(0.09)	(0.08)	(0.06)		
Instruments:					
Competitor characteristics	X	X	X	X	X
Cost shifter		X	X	X	X
Prices in other market			X	X	X
F-Stat:					
p_{jt}	21.6	41.2	47.3	47.3	47.3
$\ln(s_{jt}/s_{gt})$					47.2
$\ln(s_{jt}/s_{gt})_{\text{Periphery}}$	23.7	24.0	21.0		
$\ln(s_{jt}/s_{gt})_{\text{Center}}$	119.0	139.3	123.7		
APF-Stat:					
p_{jt}	17.8	18.2	25.3	47.3	21.7
$\ln(s_{jt}/s_{gt})$					22.1
$\ln(s_{jt}/s_{gt})_{\text{Periphery}}$	19.5	21.3	18.5		
$\ln(s_{jt}/s_{gt})_{\text{Center}}$	44.1	41.4	43.8		
N	1,923	1,923	1,923	1,923	1,923

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Notes: F-Stat refer to standard F-tests, as reported by most linear IV regression software packages. APF-Stat refer to Angrist and Pischke (2008) modified F-statistic that corrects for the presence of multiple endogenous regressors. See also Michel and Weiergraeber (2010) for more applications.

All own-price elasticities are negative and relatively large in absolute value. Consumers are thus quite price-sensitive and react to price changes by switching channel and/or hotel. Cross-price elasticities are very small, especially across products that are not in the same nest, suggesting that consumers tend to switch to hotels outside our sample (other brands) rather than within our sample. In addition, it suggests that hotel location is a major factor in the consumers' decision

Table 7: Elasticities estimates

	Logit		Nested logit			Differentiated nested logit		
Channel	ε_{jj}	ε_{kj}	ε_{jj}	ε_{kj}	ε_{kj}	ε_{jj}	ε_{kj}	ε_{kj}
Nest		$g_j \neq g_k$		$g_j = g_k$	$g_j \neq g_k$		$g_j = g_k$	$g_j \neq g_k$
Booking	-4.73	0.007	-5.26	0.12	0.004	-4.60	0.08	0.004
Direct	-4.16	0.008	-4.60	0.14	0.005	-4.02	0.10	0.005
Expedia	-4.84	0.006	-5.41	0.11	0.004	-4.73	0.08	0.004

process; they almost never substitute between hotels that belong to different nests.

We then estimate elasticities of substitution between channels, that is, we compute the impact on total sales for the 13 hotels of an identical price increase for all 13 hotels in a given distribution channel. For example, we compute the relative change in sales on Booking (for all 13 hotels) when all hotels increase the price on their direct channel by 1%. Results for these "aggregate elasticities" at the channel level are presented in Table 8.

Table 8: Aggregate elasticities estimates

	Nested logit			Differentiated nested logit		
Channel	Booking	Direct	Expedia	Booking	Direct	Expedia
Booking	-4.25	0.62	0.71	-3.96	0.50	0.57
Direct	0.93	-3.62	0.97	0.77	-3.39	0.80
Expedia	0.62	0.56	-4.51	0.49	0.45	-4.19

Note: When all hotels increase their prices by 1% on Booking, total sales for the 13 hotels through Booking decrease by 3.96% while total direct online sales for the 13 hotels increase by 0.50%.

We first observe that, in absolute value, own-price elasticities tend to be higher for OTAs (3.96 for Booking and 4.19 for Expedia) than for direct sales (3.39). This suggests that when all hotels increase their prices on a channel, they are likely to lose more sales if they raise prices on the OTAs websites than if they do it on the hotel chain's website.

Moreover, if they raise prices on one OTA, our results suggests that the consumers switching channel but not hotel will split more or less equally between direct sales and the rival OTA. In that sense, "switchers" probably tend to be more loyal to the hotel chain than to the OTAs. When hotels increases their prices on one OTA, they recapture less than 30 % of the lost sales through their own direct channel and the rival OTA. This means that more than 70% of the consumers that stop booking from our 13 hotels through the now more expensive platform, tend to switch to other hotels (probably, but not necessarily, on the same platform). On average, consumers thus seem slightly more loyal to the OTAs than to the hotels.

4 Supply Estimation

We now use the results of the demand estimation together with a structural model of price competition with differentiated products, to recover the hotels' marginal costs for each channel. For each hotel h and each online distribution channel c, we estimate the total marginal cost, $\gamma_{h,c}$, which includes the "production" cost but also the channel-specific distribution costs (including commissions paid to the online travel agencies Expedia and Booking). Among the three demand models, we choose the more precise form, i.e., the nested logit model which allows the nesting coefficients to differ across nests.

Given that all hotels belong to same hotel chain, two possible pricing strategies could be assumed:

- **Decentralized pricing**: Hotels set prices independently. Each hotel thus sets its three prices (one for each online distribution channel) in order to maximize its individual total profit.

- **Centralized pricing**: A single agent (the chain) sets the prices of all 13 hotels, in all three distribution channels, in order to maximize the chain's total profit.

The system of first-order conditions (to solve for the Nash-Bertrand equilibrium or to obtain the profit maximizing prices of the single-agent) is then given by:

$$\mathbf{s}(\mathbf{p}) - \Theta \odot \nabla s\left(\mathbf{p}\right).(\mathbf{p} - \boldsymbol{\gamma}) = 0 \quad \Longleftrightarrow \quad \boldsymbol{\gamma} = \mathbf{p} + \left(\Theta \odot \nabla s\left(\mathbf{p}\right)\right)^{-1}.\mathbf{s}(\mathbf{p}), \qquad (3)$$

where $\mathbf{s}(\mathbf{p})$ represents the vector of market shares, $\mathbf{p}$ and $\boldsymbol{\gamma}$ are the vector of prices and marginal costs, $\nabla s\left(\mathbf{p}\right)$ is the Jacobian matrix of partial derivatives of market shares and Θ is the ownership matrix.[18] The symbol $\odot$ represents the element-by-element matrix product.

In the decentralized pricing case, the ownership matrix is a block matrix (where each block is a 3×3 submatrix) where all the elements of the diagonal blocks are equal to one and all elements of the non-diagonal blocks are equal to zero. In the centralized pricing case, each element of the ownership matrix is equal to one.

In what follows, we only present the results for the centralized pricing case, as this is consistent with the chain's actual pricing behavior. Since late 2015/early 2016, the chain indeed uses a central revenue manager, which sets prices centrally for all hotels. The analysis for decentralized pricing is relegated to Appendix B.

An alternative approach is to impose additional structure on marginal costs. Rather than assuming different marginal costs for different channels, one could simply assume a common marginal cost for all distribution channels. This allows us to additionally estimate the commission rates paid by the hotels to each OTA. In this setting, the system of first-order condition is then given by:

$$(1-\boldsymbol{\tau})\mathbf{s}(\mathbf{p}) - \Theta \odot \nabla s\left(\mathbf{p}\right).((1-\boldsymbol{\tau})\mathbf{p} - \boldsymbol{\gamma}) = 0, \tag{4}$$

where $\boldsymbol{\tau}$ is the vector of commission rates (such that $\tau_c = 0$ for direct sales), and where the vector of marginal costs $\boldsymbol{\gamma}$ is now such that $\gamma_{h,c} = \gamma_h$ for each channel c.[19]

Table 9: Average marginal cost per channel (in NOK)

Structure		No		Yes	
Channel	Price	Marg. Cost	Margin	Marg. Cost	Commission
Direct online	1,176	727	40.7%	727	–
Booking	1,334	887	35.9%	727	14.0%
Expedia	1,366	918	35.0%	727	16.8%

Table 9 reports the average marginal costs (and commission rates) derived, using our estimated demand parameter, from equations (3) and (4) for the centralized pricing case. We first observe that higher prices coincide with higher marginal costs and lower margins, and that selling directly is the cheapest option

[18] See e.g., Berry et al. (1995) or Björnerstedt and Verboven (2016).

[19] Even if the hotel faces specific distribution costs for its online sales, we cannot separately estimate the "production" and distribution cost.

for the hotel. Selling through the OTAs (rather than directly) adds a cost of 160 NOK for Booking and 191 NOK for Expedia on average, that is, about 12 % and 14 % of the prices charged through these two channels.

We obtain similar results when we impose structure on the marginal cost and try to recover the OTAs' commission rates: These commissions (about 14 % for Booking and 17 % for Expedia) seem in line with rates that are regularly mentioned for OTAs; about 15% for Booking (sometimes higher in large cities), and closer to 20 % for Expedia, but with large chains able to negotiate lower rates than independent hotels.

Because hotel pricing really is a dynamic optimization problem, due to the combination of capacity constraints (fixed number of rooms to be sold each day) and anticipated fluctuations in demand over time (seasonality, concerts, sports events, etc), one may worry that our static structural model does not allow us to estimate true marginal costs (and thus commission rates). The worry is that, when computing the marginal cost at each date, we actually capture the true marginal cost as well as the opportunity cost (or option value) of having a room booked a given day rather than closer to the arrival date.

To test the robustness of our estimation, we therefore derive the marginal costs using our system of first-order conditions given by equation (3), but restricting attention (for each hotel) to bookings made less than 5 days before arrival (rather than less than 30 days) and for dates for which at least 10 % of the hotel's rooms are still available at the arrival date. If a hotel still has a sufficient number of rooms available this close to the arrival date, dynamic optimization should be less of an issue, and the optimization problem should be identical to a static pricing problem. Results are presented in Table 10.

Table 10: Average marginal cost per channel (in NOK)

Selection	No		Yes	
Channel	Marg. Cost	Margin	Marg. Cost	Margin
Direct online	727	40.7%	664	43.2%
Booking	887	35.9%	750	39.7%
Expedia	918	35.0%	849	37.2%

As we should have expected, once we restrict attention to late booking for date with late availability of rooms, estimated marginal cost tend to be slightly lower, the difference varying from 63 NOK (for Direct online) to 137 NOK (for Booking). Revenue management thus plays a non-negligible role. However, the difference in marginal cost between the different channels remains of a similar order of magnitude.

5 Simulated vs. Actual Effects of Delisting

In this section, we evaluate the effects of removing one distribution channel on prices charged by hotels on the active channels as well as on the different channels' market share. Given that our dataset includes an actual "boycott" of Expedia by our 13 hotels for a relatively long period of time, we take advantage of the data to compare the predicted outcome to the actual outcome and determine the reasons for the observed differences.

5.1 Counterfactual analysis: removing one distribution channel

To simulate a decision to stop selling through channel d, we artificially increase the marginal costs for all hotels on this channel so that, in equilibrium, sales through this channel are as close to zero as possible. We thus define a coefficient ϕ by which we multiply all marginal costs $\gamma_{h,d,t}$ and the vector of equilibrium prices $\mathbf{p}(\phi)$ solving the following minimization program :

$$\min_{\mathbf{p}} ||\mathbf{s}(\mathbf{p}) - \Theta \odot \nabla s\left(\mathbf{p}\right) . \left(\mathbf{p} - \tilde{\boldsymbol{\gamma}}(\phi)\right)||^2,$$

where $\tilde{\gamma}(\phi)$ represents the modified vector of costs which is such that for all h and t, $\tilde{\gamma}_{h,d,t}(\phi) = \phi\gamma_{h,d,t}$ and $\tilde{\gamma}_{h,c,t}(\phi) = \gamma_{h,c,t}$ for $c \neq d$.

We then compute the corresponding equilibrium market shares $(s_{h,c}(\phi))$ for each product (i.e., each pair hotel × distribution channel) as well as the aggregate market share for each distribution channel $(s_c(\phi))$. Because we observe that sales made through the "delisted" channel drop to extremely low values (i.e., $s_d(\phi)$ close to 0) for relatively low values of ϕ, we simulate the counterfactual equilibrium assuming from now on that $\phi = 3$.

A first important observation is that equilibrium prices are almost unaffected by the delisting decision: indeed, the equilibrium prices are almost unchanged on the chain's website (direct sales) and only about 0.4 % lower through Booking when hotels decides to stop selling through Expedia (see Table 13 below). This may seem extremely low but is not that surprising, because cross-price elasticities are very low.

We then use our structural model to estimate to which competing online channels consumers switch when the hotels stop using one online channel. Although this differs from looking at switching following a small change in price and we also include the chain's pricing reaction (i.e., change of equilibrium through the other channel although quite limited), we refer in what follows to diversion ratios between online distribution channels. Formally, for any channel $c \neq d$, we define the diversion ratio from channel d to channel c:[20]

$$DR_{d\to c} \equiv \frac{\Delta s_c}{|\Delta s_d|} = \frac{s_c(3) - s_c(1)}{|s_d(3) - s_d(1)|} \simeq \frac{s_c(3) - s_c(1)}{s_d(1)}.$$

This diversion ration $DR_{d\to c}$ thus corresponds to the fraction of sales lost by dropping distribution channel d that are recaptured through channel c. These estimated diversion ratios are presented in Table 11.

Table 11: Estimated diversion ratios

Delisting from (d)	Expedia	Direct	Booking
$D_{d\to\text{Direct}}$	15%	-	16%
$D_{d\to\text{Booking}}$	13%	15%	-
$D_{d\to\text{Expedia}}$	-	14%	12%
$D_{d\to\text{Outside option}}$	72%	71%	72%

A first striking result - consistent with the estimated price elasticities of demand - is that, when hotels stop selling through one of the online distribution channels, they lose about 70 % of these consumers, that is, a large share of consumers switch to the outside good (most likely other hotels). This confirms that inter-brand competition (i.e., competition between hotels) is an important factor and that consumers tend to be loyal to OTAs more than to hotels.

When hotels stop listing on one of the two OTAs, they recapture a small majority of these consumers through the direct channel: indeed, among consumers

[20]For consistency, we use estimated market shares even when the hotels use all distribution channels (i.e., $\phi = 1$) rather than actual market shares as observed in the data. However, the differences are extremely limited and diversion ratios are not significantly affected.

who continue to book a room from the hotel chain (i.e., in one of the 13 hotels), about 54 % book to through the chain's website. Consumers that are loyal to the hotel (or at least to the chain) are thus slightly more likely to book directly than to use another OTA. However, when hotels stop selling directly, consumers tend to split almost equally between the two OTAs. It thus appears that, although a significant share of consumers seem to be loyal to OTAs, the direct sales channel is a close substitute to OTAs. Contrary to what has been assumed by some competition authorities, the direct distribution channel (direct online sales) is a credible alternative to OTAs and should thus be considered as operating on the same relevant market as OTAs.

Finally, we compute the simulated impact on consumer surplus as well as on hotels profits and Booking's revenues. These measures are obviously only partial as we only focus on those consumers who - in the absence of delisting - would have booked (online) a room in one of the 13 hotels included in the sample. The impact on hotels' profit is also limited to the impact on the profit generated by online sales, and the impact on Booking's revenue is limited to the revenue generated on sales for the 13 hotels included in the sample. Results from the counterfactual simulation are presented in Table 12. Figures in the first column ("Observed") are the values using the estimated demand parameters and marginal costs and figures in the second column ("Delisting") are the values in our simulated counterfactual scenario where the hotels all stop listing on Expedia. Figures in the last column simply measure the relative change between the two. All values are measured in thousands NOK per week.

Table 12: Welfare effects of delisting from Expedia (average weekly levels)

×*1,000 NOK*	Observed	Delisting	Δ
Consumers	431	343	-20.0%
Hotels	443	363	-18.0%
Booking	37	41	+13.4%

Based on this simulated counterfactual scenario, it appears unsurprisingly that consumers and hotels are harmed by the boycott. A significantly share of consumers switch to other hotels ("outside good") or to a second-best distribution channel and do not benefit from better prices (new equilibrium prices are almost identical to the initial prices). Hotels pay lower commissions (i.e., faces lower marginal costs) because Expedia was the most expensive distribution channel and thus earn higher profits on sales recaptured through the two remaining channels, but the share of consumers lost to rival hotels is too large to compensated by the higher margins. Finally, Booking's revenue increases because it captures some of Expedia's original sales.

5.2 Comparing predicted and actual outcomes

Because our dataset includes an actual boycott of Expedia, we can compare the predicted outcome to the actual outcome and, more importantly, try to determine the reasons for the observed differences. We first compare the predicted and actual effects of the boycott on prices charged by hotels through Booking and their own website. The average predicted and actual prices are reported in Table 13. Because the boycott period is relatively long (January 2013 - September/October 2015), it is possible that demand for the direct channel or one of the OTAs has evolved over time (for example because consumers got accustomed to booking hotel rooms through online platforms). To limit such effects, we propose two comparisons between the predicted outcome (based on about one year of data post-boycott) and the observed outcome: in the first case, we keep the whole boycott period ("Whole period"); while in the second case, we restrict attention to the bookings made for the last year of the boycott only ("Last year").

Table 13: Observed and predicted prices

Channel	Observed		Counterfactual
	Whole period	Last year	
Booking	1,196 (-10.88%)	1,247 (-7.08%)	1,336 (-0.42%)
Direct	1,063 (-10.07%)	1,130 (-4.42%)	1,182 (-0.02%)

Whereas our counterfactual simulation predicts a very small decrease in the prices charged by the hotels on Booking and the chain's website (less than 0.5 %), prices observed for these distribution channels during the actual boycott period (February 2013 - September 2015) were actually about 10 % lower than once hotels started listing again on Expedia (September/October 2015 - November 2016). The predicted prices are thus much higher than the actual prices. The difference is slightly lower once we restrict the observed boycott period to the last year, but even in this case observed prices were about 4 to 7 % lower during this year than they were after the boycott ended.

The same observation can be made for the distribution channels' market shares (conditional on buying online) that are reported in Table 14. The model seems to predict the outside good's market share quite well, but the split of the online sales between Booking and the direct channel is very inaccurately predicted.

Table 14: Comparison on market shares

Channel	Observed		Counterfactual
	Whole period	Last year	
Booking	56%	49%	43%
Direct	44%	51%	57%
Outside Good	95%	94%	96%

The important discrepancies between predicted and observed outcomes do not necessarily mean that our structural model is not well-suited to perform a sensible counterfactual analysis. It does however suggest that it cannot be used without caution to predict the outcome of a delisting decision for example. In the line of Peters (2006), we try to identify possible explanation for these discrepancies and focus on two possible sources: changes in the observed "product characteristics", here characteristics of the different bookings such as type of room or advance booking for example (i.e., changes in the X's) or changes in the pricing strategy (i.e., here the ownership matrix but in general akin to changes in the conduct parameter). In general, when performing counterfactual simulations, all these parameters are assumed to remain constant. However, if they are good reasons to believe that characteristic or pricing behaviour have changed, the simulation will always yield an incorrect outcome if these changes are not accounted for.

We first focus on bookings characteristics. Table 15 reports average characteristics of bookings during the post-boycott period (September/October 2015 - November 2016), that is, during the period that we used to estimate our demand model, as well as the average booking characteristics observed during the boycott period for the whole period and for the last year only.

It appears that booking characteristics were slightly different during the boycott period (whether we focus on the whole period or only on the last year) when compared to the post-boycott period. For example, occupancy rates (at the time

Table 15: Average booking characteristics during and after the boycott period

Control variables	Channel	Post-Boycott	Boycott Whole period	Boycott Last year
Occupancy rate	Booking	75.4%	86.5%	88.3%
	Direct	72.7%	79.6%	83.7%
Days in advance	Booking	9.3	9.5	9.3
	Direct	10.1	11.8	10.8
Superior rooms	Booking	10.1%	7.8%	8.8%
	Direct	14.7%	11.8%	13.5%
Week-end	Booking	34.2%	31.1%	32.2%
	Direct	32.6%	33.7%	28.7%

of booking) were about 10 percentage points higher on average, consumers used to book fewer superior rooms and were booking less often for week-end nights.

Rather than using characteristics of the post-boycott observations to simulate the counterfactual equilibrium, we thus use the actual booking characteristics during the boycott period. Results for these simulations are reported in the second column of Table 16.[21]

Table 16: Simulated and predicted outcomes

		Counterfactual			Observed	
Pricing		Centralized	Centralized	Decentralized	Whole period	Last year
Correction		$\emptyset$	X	X		
Price	Booking	1,336	1,322	1,189	1,196	1,247
	Direct	1,182	1,176	1,041	1,063	1,130
Market share	Booking	43%	46%	46%	56%	49%
	Direct	57%	54%	54%	54%	51%
	Outside Good	96%	96%	95%	95%	94%

Using the product characteristics observed during the boycott (rather than the post-boycott characteristics) improves the accuracy of the simulated results. The

[21] We simulated two different counterfactuals: one using all observations during the boycott period, the second restricting attention to the last year of the boycott period. However, because the results are almost identical - identical market shares and prices that differ only by less than 2 NOK, we only report one set of results (using data for the whole period).

change is nevertheless quite limited and differences in product characteristics cannot be the main explanation for the discrepancies between simulated and observed outcomes.

An additional explanation for these differences may come from a change of pricing strategy. During our exchanges with the data provider, we were told that while all prices are set since late 2015/early 2016 by a central revenue manager located in the head office, they used to be set at each individual hotel before that (subject to guidelines from the revenue department).

It thus appears that the change of pricing policy and the end of the boycott occurred more or less at the same time. We thus decided to run a counterfactual simulation assuming that prices were set by hotels (rather than centrally) during the boycott period.[22] Results for this counterfactual simulation are reported in the third column in Table 16. Changing the pricing policy (from centralized to decentralized pricing) improves considerably the accuracy of the price prediction. It does not affect market shares, but markets were already relatively well predicted, at least if we compare them to the average market share during the last of year of the boycott period. Once we correct our counterfactual analysis for changes in pricing strategy, our structural model (with our nested-logit demand specification based on distance from the city centre) looks like a reasonable model that can be used to perform relevant counterfactual experiments.

6 Conclusion

In this paper, we use an exhaustive dataset of bookings for 13 hotels in Oslo to estimate a (structural) demand model and evaluate the degree of substitution between different online distribution channels. We conclude that, for each online distribution channel (i.e., two large OTAs as well as the chain's own website), the own-price elasticities of demand are relatively large, meaning that consumers tend to be price sensitive. In addition, cross-price elasticities are significantly lower, which suggests that a large share of consumers would rather switch between hotels (and thus to the outside good in our specification) than switch distribution channel. On average, consumers thus seem more loyal to a platform than to the hotels, and inter-brand competition seems fierce enough. However, our analysis

[22] Once again, we formally ran two different simulations but only report one set of results.

also shows that among those consumers who are willing to switch distribution channel following a price increase on one OTAs' platform (around 30 %), a small majority would rather book directly from the hotel than through the competing OTA.

It thus appears that, although a significant share of consumers are loyal to OTAs, the direct sales channel is a close substitute to OTAs. This observation thus seem to contradict most competition agencies' approach that has been to consider that the direct online channel (hotels' websites) and OTAs do not belong to the same relevant market and are not direct competitors.

Our analysis cannot directly be used to evaluate the competitive effects of price parity clauses imposed by OTAs on hotels, as we would first need to estimate a structural model allowing for bargaining between hotels and OTAs over commission rates (to evaluate the impact of price parity clauses on commissions). It suggests, however, that direct sales are a credible alternative to OTAs, because a significant share of consumers would stay loyal to the hotel if the hotel were to stop listing on one of the OTAs (such as Expedia for example). Therefore, from a theoretical point of view, one cannot simply assume that suppliers (hotels in our case) cannot directly and efficiently reach final consumers. It thus cannot be presumed that platform price parity clauses would necessarily harm consumers and/or hotels in this market.

Because our dataset covers a period that includes an actual decision to delist from Expedia's platforms, we have been able to compare the simulated and actual effects of such an event. Given the important discrepancies between the simulated and observed effects on prices and market shares, one may be tempted to conclude that we either did not use the correct demand model, or, pushing it even further, that structural IO models cannot accurately be used to predict outcomes of counterfactual experiments (such as strategic decisions to stop using some distribution channels or, as more commonly used, to evaluate the competitive effects of a potential or notified merger).

We have, however, been able to identify possible reasons for these discrepancies, namely changes in product characteristics and pricing behavior over time. Once we account for these important changes, especially changes in pricing strategy, we observe that the predicted outcome looks much more similar to the observed outcome. We thus believe that structural IO models can be accurately estimated and used to perform sensible counterfactual experiments. But, one needs to proceed with caution and account for all important changes – including strategic decisions by firms – that may affect the simulated outcome.

Appendix

A Robustness checks on the outside good

In this section, we show that our results are not extremely sensitive to the methodology adopted to compute the outside good's market share. Until now, we have decided to estimate, for each week, the number of bookings made online in 3 and 4-star hotels in Oslo. We thus compute the outside good's share based on number of booked made that month in Oslo, divided by four (to obtain weekly values) and multiplied by the share of online bookings (in our sample for that particular week) and by 0.7 (share of 3 and 4-star hotels in Oslo).

We now confirm that results are relatively robust by varying the last multiplier (and thus the outside good's share) between 0.5 and 0.9. Estimates of the nested-logit parameters are displayed in Table A.1 for different values of the multiplier. We observe that estimates remain almost unchanged.

Table A.1: Demand model estimation

	Differentiated nested logit				
Share of 3 and 4 stars hotels	50%	60%	70%	80%	90%
α	0.00232***	0.00232***	0.00232***	0.00232***	0.00232***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\sigma_{\text{Periphery}}$	0.17935	0.17897	0.17854	0.17810	0.17766
	(0.094)	(0.12)	(0.094)	(0.094)	(0.094)
σ_{Center}	0.43275***	0.43277***	0.43278***	0.43277***	0.43276***
	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)
Instruments:					
Competitor characteristics	X	X	X	X	X
Cost shifter	X	X	X	X	X
Prices in other market	X	X	X	X	X
N	1,923	1,923	1,923	1,923	1,923

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

We also compute the estimated diversion ratios (following a decision by all hotels to delist from Expedia) for these different shares of 3 and 4-star hotels (or outside good's market share). Once again, diversion ratios – that we report in

Table A.2 – remain almost unaffected. Results are thus robust to (reasonable) changes in the outside good's market share.

Table A.2: Estimated diversion ratios

Share of 3 and 4-star hotels	50%	60%	70%	80%	90%
$D_{\text{Expedia}\to\text{Direct}}$	14.4%	15.0%	15.3%	15.7%	15.8%
$D_{\text{Expedia}\to\text{Booking}}$	12.6%	12.6%	12.6%	12.6%	12.7%
$D_{\text{Expedia}\to\text{Outside option}}$	73.0%	72.4%	72.0%	71.7%	71.5%

B Decentralized pricing strategy

In this section we report our results under the assumption that prices are set independently by each hotel (i.e., decentralized pricing strategy).

B.1 Estimated marginal costs

Table B.1 reports the estimal marginal costs (and margins). As expected, marginal costs tend to be higher – and thus margins are lower – than in the centralized case (where the chain acts as a "monopolist" and sets all prices so as to maximize total profit). However, the difference between the different marginal costs remains unaffected: selling on Booking (resp., Expedia) is 161 NOK (resp., 191 NOK) more expensive than selling directly, and Expedia remains the most expensive channel.

Table B.1: Average marginal cost per channel (in NOK)

		Decentralized Pricing		Centralized Pricing	
Channel	Price	Marg. Cost	Margin	Marg. Cost	Margin
Direct online	1,175	867	28.5%	727	40.7%
Booking	1,334	1,028	25.1%	887	35.9%
Expedia	1,366	1,058	24.5%	918	35.0%

Although the baseline marginal cost is now higher, estimated OTAs' commission rates are almost unchanged once we add structure to costs and estimate equation (4) instead of equation (3) as reported in Table B.2.

Table B.2: Average marginal cost per channel (in NOK) with structure

Channel	Price	Decentralized Pricing		Centralized Pricing	
		Marg. Cost	Com. rate	Marg. Cost	Com. rate
Direct online	1,175	867	–	727	–
Booking	1,334	836	14.0%	727	14.0%
Expedia	1,366	836	16.6%	727	16.8%

B.2 Counterfactual analysis: removing one distribution channel

In Table B.3 we report the estimated diversions between distribution channels when all hotels decide to drop one online channel under the assumption of decentralized pricing.

Table B.3: Estimated diversion ratios – Decentralized pricing

Delisting from (d)	Expedia	Direct	Booking
$D_{d \to \text{Direct}}$	20%	-	20%
$D_{d \to \text{Booking}}$	14%	16%	-
$D_{d \to \text{Expedia}}$	-	15%	13%
$D_{d \to \text{Outside option}}$	66%	69%	67%

As in the centralized case, when hotels stop selling through one of the online distribution channels, they lose just less than 70 % of these consumers, that is, a large share of consumers switch to the outside good (most likely other hotels). This confirms that inter-brand competition (i.e., competition between hotels) is an important factor and that consumers tend to be loyal to OTAs more than to hotels.

When hotels stop listing on one the two OTAs, they recapture a majority of these consumers through the direct channel, and the share is slightly higher (about 60 %) than under centralized pricing (only 54 %). Even if we assume decentralized pricing, the direct sales channel remains a close substitute to OTAs even though a significant share of consumers seem to be loyal to OTAs.

Finally, we compute the simulated impact on consumer surplus as well as on hotels profits and Booking's revenues and reports the figures in Table B.4. Results are similar to those obtained when assuming the centralized pricing assumption.

Table B.4: Welfare effects of delisting from Expedia (average weekly levels) – Decentralized pricing

$\times$*1,000 NOK*	Observed	Delisting	Δ
Consumers	431	350	-18.5%
Hotels	302	246	-18.3%
Booking	37	41	+13.7%

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