Vertical Integration of Platforms and Product Prominence *

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Abstract

Meta-search platforms (MSPs) help consumers to compare product prices between different sales platforms. MSPs are often integrated with one of the sales platforms, which can give rise to self-preferencing. A case in point is the online hotel booking industry, where the major online travel agencies (OTAs) are integrated with MSPs. Studying web-scraped data from the MSP Kayak, we find indications that for a given hotel, the offers of affiliated OTAs (like Booking.com) are more visible than those of other OTAs with the same price. Moreover, hotels appear to be less prominent in Kayak's search results when the rival OTA Expedia has the lowest price.

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1 Introduction

Online platforms are an essential part of e-commerce. Their emergence promises substantial advantages for consumers, especially in terms of transparency on offers and prices, low search and distribution costs, and better matches between supply and demand. Nowadays, platforms use complex algorithms to present product information to consumers. The way they function is often opaque and the transparency of ranking criteria is the subject of intense policy debates. An important issue is how vertical integration affects the presentation of information on online platforms. Some of the prominent cases in point concern Google Shopping[1] and Amazon's hybrid role as both a marketplace and a seller.[2]

Focusing on online hotel booking, we study whether vertical integration between meta-search platforms (MSPs) and online travel agents (OTAs) affects the meta-search results. While OTAs account for most of the website-based hotel bookings, MSPs enable users to compare the prices of hotels at different OTAs and on the hotel websites. There are significant ownership links, as each of the two major OTAs Booking.com and Expedia is vertically integrated with an MSP (Kayak and Trivago, respectively, cf. Section 5.1 for details).

The relationship between hotels and OTAs has come under scrutiny with the different national policies in Europe regarding the price parity clauses (PPCs)[3] and academic research (cf. Section 2). Much less visible in the debate is another important link in the chain of this industry: meta-search platforms, such as Kayak, gather a large part of the offers from different hotel booking websites and thus enable a price comparison both across hotels and across sales channels for a given hotel. Although possibly somewhat overlooked, meta-search is arguably economically relevant. For instance, according to figures for Germany for 2017, hotel meta-search generated roughly 200 million euros compared to more than 800 million euros for OTAs.[4] Against the expectation that a key promise of price comparison websites is to show consumers the best offers on the market, Booking Holdings' acquisition of the meta-

[1] See European Commission - Case AT.39740 - Google Search (Shopping), 2017, https://eur-lex.europa.eu/legal-content/EN/TXT/?qid=1516198535804&uri=CELEX:52018XC0112(01), last accessed June 22, 2021.

[2] See European Commission - Antitrust: Commission sends Statement of Objections to Amazon for the use of non-public independent seller data and opens second investigation into its e-commerce business practices, 2020, https://ec.europa.eu/commission/presscorner/detail/en/ip_20_2077, last accessed June 22, 2021.

[3] See, for instance, European Competition Network - Report on the monitoring exercise carried out in the online hotel booking sector, 2016, https://ec.europa.eu/competition/ecn/hotel_monitoring_report_en.pdf, last accessed June 22, 2021.

[4] See Bundeskartellamt - Sektoruntersuchung Vergleichsportale (Bericht), 2019, pp. 32-33, https://www.bundeskartellamt.de/SharedDocs/Publikation/DE/Sektoruntersuchungen/Sektoruntersuchung_Vergleichsportale_Bericht.pdf?__blob=publicationFile&v=7, last accessed June 22, 2021.

search platform Kayak in 2013 raised neutrality concerns about the ranking algorithm of sales channels and products on Kayak. Some observers argued that Kayak may have the incentive to promote Booking Holdings OTAs rather than the cheapest ones. Instead, the CEO of Booking Holdings claimed: *"We won't bias Kayak search results."*[5] Moreover, in January 2020, the Australian Competition and Consumer Commission (ACCC) concluded that the meta-search platform Trivago had misled consumers by indicating that its website helped them to identify the cheapest rates available for a given hotel while its ranking algorithm gave preponderant weight to the cost per click paid by the sales channel.[6]

We study the effect of vertical integration between OTAs and MSPs on how the MSPs ranks hotels and sales channels. For this, we use data collected between October 2014 and September 2017 from the meta-search platform Kayak for hotels in Paris. At that time, Kayak already belonged to the Booking Holdings. The data comprises information from about 1,800 Parisian hotels on room availability and prices on up to 22 different sales channels and different time horizons, adding up to 17 million observations. We distinguish the horizontal ranking of sales channels for a given hotel and the vertical ranking of hotels for given reservation and arrival dates (see Figure 1).

The horizontal ranking refers to the positioning of offers from different channels for a given hotel. We study the hypothesis that offers of sales channels that are vertically integrated with the MSP Kayak are more visible. Our analyses indicate that OTAs of Booking Holdings are more often position leaders (i.e., highlighted sales channels on hotel offers) than price leaders (i.e., among the cheapest sales channels). We primarily use linear regressions with fixed effects on the hotel- and request-level and account for prices and popularity measures. These indicate that the OTAs of Booking Holdings have a higher probability than other OTAs of being among the visible providers and of being the highlighted sales channel. These results are mainly driven by the two major OTAs Booking.com and Expedia.

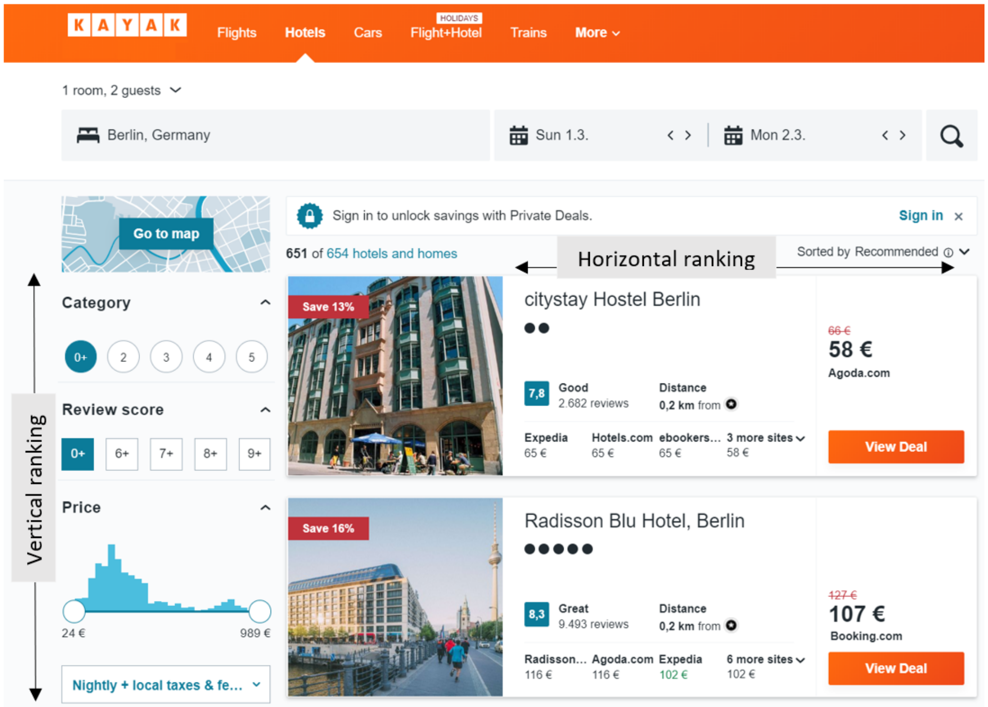
The vertical ranking refers to the positioning of hotels in the search results. We study the hypothesis that hotels which have higher prices on the Booking Holdings channels than on other sales channels are more likely to be ranked worse in the Kayak search results. Our regression analyses indicate that hotels are ranked worse by, on average, about eight positions in the Kayak search results when an OTA of the Expedia Group is the cheapest sales channel.

We contrast this latter finding using data from an MSP that is not integrated with an OTA – Google Hotels. Regarding the vertical ranking, we find that Google Hotels does not

[5] See the article by Dennis Schaal (Skift) - Priceline CEO: We won't bias Kayak search results, 2013, https://skift.com/2013/05/10/priceline-ceo-we-wont-bias-kayak-search-results/, last accessed June 22, 2021.

[6] See ACCC - Trivago misled consumers about hotel room rates, 2020, https://www.accc.gov.au/media-release/trivago-misled-consumers-about-hotel-room-rates, last accessed June 22, 2021.

Figure 1: Kayak rankings



assign a worse position to hotels which are cheaper on OTAs of the Expedia Group.

The rest of the article is structured as follows: Section 2 covers the related literature and Section 3 provides background information on hotel meta-search platforms. In Section 4 the empirical strategy is developed, and Section 5 introduces the data, descriptive statistics, and preliminary evidence. Section 6 is devoted to the econometric results. Section 7 concludes.

2 Related literature

One relevant strand of theoretical literature studies the decisions of intermediaries to bias product presentations by making certain products more prominent than others (Raskovich 2007, Inderst & Ottaviani 2012, Hagiu & Jullien 2011, 2014, De Corniere & Taylor 2014, De Cornière & Taylor 2019, Hunold & Muthers 2017, Shen & Wright 2019). Hagiu & Jullien (2011, 2014) specifically analyze biases in the rankings of search engines. In a setting where customers have heterogeneous search costs and the platform has a per-click payment scheme, Hagiu & Jullien (2011) predict distortions in the ranking in the sense that the less suitable product is displayed first to generate additional revenue from the product providers. De Corniere & Taylor (2014) show that integrated search engines distort search results, but the overall welfare effect is unclear. For instance, the integrated search engine can have a strong incentive to generate demand. Similarly, De Cornière & Taylor (2019) study biased recommendations of intermediaries and show that if the payoff functions of sellers and consumers are conflicting, bias can harm consumers. Hagiu et al. (2020) analyze an intermediary's dual role of being both a reseller and marketplace. They contrast a ban of this practice to other policies which restrict the imitation of products by third parties or steer consumers toward the intermediary's product. Using the example of a streaming platform, Bourreau & Gaudin (2018) and Drugov & Jeon (2019) study incentives to bias recommendations to consumers toward vertically integrated content. We contribute by providing empirical evidence in support of these theories on the potential biases of recommendations.

Related empirical literature highlights the importance of the ranking by intermediaries in the context of online hotel booking. Chen & Yao (2016), De los Santos & Koulayev (2017), Koulayev (2014), Ghose et al. (2012, 2014) study how rankings affect consumer choices and provide estimates of the US-dollar equivalent of a change in a hotel offer's indirect utility for a consumer resulting from a one-position increase in a hotel's ranking (position effect). Ursu (2018) exploits a random variation in the ranking of hotels at the OTA Expedia and also finds significant position effects, albeit of a somewhat lower magnitude. She finds that consumers are more likely to click on an offer that is ranked better to obtain detailed information on it. However, conditional on seeing the detailed information, the ranking position does not influence the booking behavior of consumers.

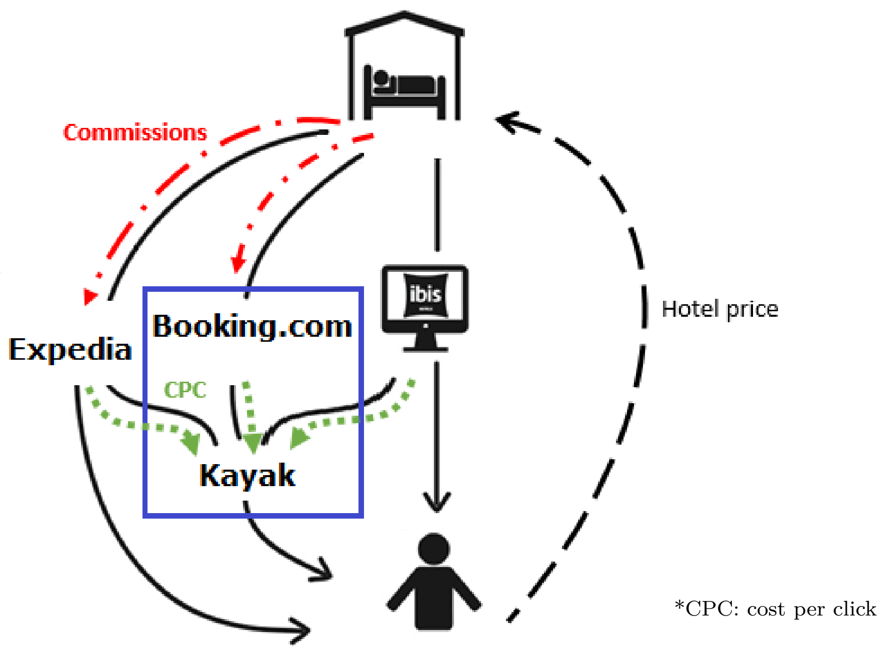
Our work is also related to the recent theoretical literature on the competitive effects of price parity clauses of intermediaries, such as OTAs (Edelman & Wright 2015, Boik & Corts 2016, Johnson 2017, Wang & Wright 2020, Johansen & Vergé 2017, Ronayne et al. 2018, Wals & Schinkel 2018, Mantovani et al. 2018, Hunold et al. 2020). Hunold et al. (2020) show theoretically that OTAs may condition the rankings of hotels in their search results on prices these hotels set elsewhere and thereby achieve the same effects as a price parity clause. Their empirical evidence is consistent with OTAs that condition their rankings on the prices on other channels. We show in the present article that the hotel ranking at an MSP may also depend on the prices of the hotel offer at different OTAs.

Our analysis of meta-search sites' product presentations relates more broadly to the literature on algorithmic bias from recommender systems and targeted advertising. For video-on-demand, Zhang et al. (forthcoming) use a large-scale field experiment to show that the recommender system of a profit-maximizing firm can reduce consumer surplus and welfare. Lambrecht & Tucker (2019) run career ads on Facebook which are intended to be gender neutral. However, they find that these are more often delivered to men. They provide suggestive evidence that it is more expensive to show ads to women, which might explain the allocation as a result of the algorithm's minimizing costs.

3 Industry background

Online hotel booking and meta-search. Hotels can be booked through numerous distribution channels, both offline and online. In the last decade, the latter distinctively gained in popularity (Cazaubiel et al. 2020). Three out of four website-based hotel bookings take place on OTAs according to the European hotel association HOTREC.[7] OTAs pool offers of different hotels and display them through a ranking in response to a user's search request, typically composed of the destination, period, and amount of people travelling. Similar to OTAs, hotel MSPs gather offers of different hotels. In addition, for each hotel, the MSPs display the offers of various online sales channels, typically several OTAs and partly also the hotel's own direct channel (see Figure 2). Thus, MSPs provide a comparison service on a more aggregate (meta-)level than OTAs without actually selling hotel rooms or posting prices themselves (Hunold et al. 2018).

Figure 2: Money flows in the vertical hotel industry



Revenue generation in meta-search. While OTAs generate revenues mainly through booking commissions, the revenues of hotel MSPs are generated by sending referrals to (actual) sales channels and advertising placements on the website.[8] The revenues of MSPs are

[7] See HOTREC - European Hotel Distribution Study 2020, 2020, p. 19, https://www.hotrec.eu/european-hotel-distribution-study-2020/, last accessed June 22, 2021.

[8] See, as an example for Kayak, Booking Holdings Inc. - Annual Report on Form 10-K for the Year Ended December 31, 2019, 2019, https://ir.bookingholdings.com/static-files/92c3d5b6-8f42-4686-afc1-f6bd61b94e06, last accessed June 22, 2021.

realized either once a user clicks on a referral and an advertisement or upon completion of the travel. Advertisers, be they OTAs or hotels, typically make bids for these placements (see Figure 2 in green). These bids can be made dependent on various characteristics, such as the user's location, device, and dates.[9] According to the sector inquiry of the German competition authority (Bundeskartellamt) on comparison websites, the 14 surveyed hotel meta-searchers report that the vast majority of their revenue comes from OTAs and the most frequent remuneration modes are cost per order and cost per click (CPC), the latter being the most important, ranging from a fraction of a cent to several euros per click.[10] However, industry reports suggest a recent trend of OTAs pulling back from MSPs, while hotels are turning to them.[11]

Aggregate revenues and visits of OTAs and MSPs. Almost every hotel meta-search visit by a user results in a redirect to a sales channel.[12] Thus, a presumably large share of bookings originate at hotel meta-search websites. Their relevance is reflected in their revenues and site visits. Hotel meta-searchers report:

- revenues of roughly 200 million euros compared to more than 800 million euros for OTAs (data for 2017 in Germany); and
- 316 million website visits compared to 1.2 billion for OTAs (from November 2016 to October 2017 in Germany).

This resonates well with global website rankings, where multiple hotel meta-search websites are among the Top 50 in the travel category and are shown to be important referrers of the major online travel agents.[13]

Main players and industry concentration. There is a rather high concentration with a few large players, both at the OTA and MSP level. For Germany, in terms of visits and revenues, Trivago has a share of more than 50 percent, followed by Google, TripAdvisor, and Kayak.[14] The surveys by HOTREC between 2013 and 2019 also suggest that these four MSPs

[9] See, as an example, the bidding overview for Hotel ads on Google, where we expect other hotel meta-search websites to work similarly, https://support.google.com/google-ads/answer/9244120, last accessed June 22, 2021.

[10] See p. 33 of Fn. 4.

[11] See the article by Sean O'Neill (Skift) - The Surprising Rise of Hotel Spending on Metasearch Advertising, 2019, https://skift.com/2019/07/25/the-surprising-rise-of-hotel-spending-on-metasearch-advertising/, last accessed June 22, 2021.

[12] This fact and the following numbers are taken from p. 32 and p. 33 of Fn. 4.

[13] See Alexa - Global Top 50 Travel Websites, 2017, http://web.archive.org/web/20170804024015/http://www.alexa.com/topsites/category/Top/Recreation/Travel, last accessed June 22, 2021.

[14] See p. 33 in Fn. 4.

are the most important in Europe.[15] Although there are no figures on MSPs for France, we expect a comparable picture as the general patterns for online hotel bookings are similar.[16]

Vertical integration of online hotel booking and meta-search. The leading OTAs Booking.com and Expedia each acquired a major hotel meta-search platform (Kayak and Trivago, respectively). Both acquisitions took place in 2013 with values of 1.8 billion and 632 million US dollars. They led to a vertical integration of major OTAs and MSPs (see Figure 2 in blue for the Booking Holdings case) in addition to an already present interdependence among OTAs due to other (horizontal) acquisitions by the two major OTAs (also described in Section 5.2).[17]

Interestingly, following the Kayak takeover, the CEO of the parent company of Booking.com argued that Kayak 'will not bias' search results.[18] The sector inquiry by the German competition authority on comparison portals expresses concerns regarding the vertical integration of OTAs and MSPs as this could result in self-preferencing on the hotel meta-search website with respect to its own OTAs and thereby a steering of users.[19] However, the survey among OTAs and MSPs apparently did not reveal such a bias.[20]

In our empirical analysis, we will systematically investigate possible self-preferencing in the (actual) search results of the MSP Kayak by means of a large set of actual website data.

Display of offers on meta-search platforms. MSPs typically use two rankings to organize their websites. The vertical ranking refers to the top-to-bottom order of hotel offers in the search results, which is similar to what OTA websites show. For each hotel offer, MSPs often display some sales channels but hide others. We refer to this as the horizontal ranking. For Kayak (and other MSPs), the horizontal ranking can be further divided into a prominent sales channel, three further visible offers, as well as the remaining offers that are somewhat hidden and denoted by 'x more sites' (see Figure 1).

According to the Bundeskartellamt's sector inquiry, Kayak ranks hotels worse if their

[15] See p. 53 in Fn. 7.

[16] See HOTREC - Hotel Distribution Study France, 2020, https://www.hotrec.eu/wp-content/uploads/2020/07/Addendum-2020_European_Hotel_Distribution_Survey_France.pdf, last accessed June 22, 2021.

[17] See the press releases by Booking.com (https://www.phocuswire.com/Priceline-buys-Kayak-for-1-8-billion) and Expedia (https://www.phocuswire.com/Expedia-pays-632-million-for-majority-stake-in-Trivago-let-the-travel-search-games-begin), last accessed June 22, 2021.

[18] See Fn. 5.

[19] See p. 38 in Fn. 4.

[20] See p. 50 in Fn. 4.

average earning potential is low.[21] The sector inquiry also reveals that meta-search websites make the horizontal ranking of sales channels for one hotel dependent on bids, especially when the prices of the respective hotel are the same. The MSP decides on the prominence of offers based on the expected revenues, which may not coincide with the sales channels having the lowest price.[22]

The hotel meta-searchers in the inquiry further claim that only in 80 percent of the cases is one of the cheapest sales channels the most prominent.[23] This has implications as a significant share of users are reportedly clicking on the prominent spot even though cheaper options exist (thereby steering customers). As a result, there may be tension between a revenue-focused and customer-oriented presentation of hotel and sales channels prices.

The above observations on the prominence of sales channels are in line with that Trivago was found to have breached the Australian Consumer Law for misleading customers. Rather than prominently presenting, as advertised, the cheapest rates for consumers, instead, the rankings were made dependent on the highest cost per click fees paid.[24]

4 Empirical strategy

4.1 Hypotheses

To develop our hypotheses, let us consider a stylized industry with one MSP and several OTAs as well as several hotels. Each OTA and hotel decides which cost per click (CPC) it is willing to pay to the MSP when a user clicks on the respective offer on the meta-search page. Observing the CPCs and the popularity of the different channels, the MSP will decide on the vertical and horizontal rankings.

Non-integration. As a benchmark, let us first consider the case of non-integration, i.e., no ownership links between the MSP and OTA. We consider it plausible that an MSP maximizes a weighted average of short and long-term profits. Short-term profit-maximization would presumably focus on immediate revenues, determined by CPCs and the likelihood of a click (possibly influenced by channel and hotel popularity). Long-term profit-maximization should put more emphasis on repeated visits and thus search quality (consumer surplus).

In the horizontal ranking, the selection of visible sales channels differs between hotels. We would expect more popular channels with higher CPCs to be shown more prominently.

[21] See p. 91 in Fn. 4.
[22] See p. 94 in Fn. 4.
[23] See p. 95 in Fn. 4.
[24] See Fn. 6.

Other things equal, visible sales channels should have lower prices than invisible channels. These conjectures are consistent with statements made by Kayak.[25]

For the vertical ranking, we would expect more popular hotels with more popular sales channels to be shown more prominently. Higher CPC at the hotel-level (for example, for the hotel website) might also lead to a better position of a hotel. This is consistent with statements of Kayak whereby the earning potential of hotels plays a role.[26]

Vertical integration. Let us now consider the case where the MSP is integrated with one OTA. Vertical integration may affect the horizontal and vertical ranking in different ways. Integrated firms may agree on other internal transfer prices (through CPCs) than the typical market prices. For instance, the OTA may pay a higher CPC to the own MSP, knowing that the money remains in the integrated entity. Moreover, irrespective of internal transfer prices, the objective function of the integrated business units (MSP and OTA) may take the joint profit into account. In particular, the integrated MSP may take the booking commissions into account, which the OTA obtains whenever a consumer books a hotel through the OTA website. This may induce the MSP to show the OTA more prominently in the horizontal ranking.

In summary, we expect an MSP to have incentives to favor the integrated OTA in its horizontal and vertical rankings. This may be either because the integrated OTA pays higher CPCs as a result of integration or because the MSP (partially) internalizes the OTA's booking commissions.[27] For the horizontal ranking, the effects of these possible incentives due to integration could arise as follows.

Hypothesis 1 (H1, horizontal ranking)**.** *Other things equal, the affiliated OTAs of a meta-*

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[25] See "How Kayak works," in the version of December 6, 2018, available at https://web.archive.org/web/20181206023556/https://www.kayak.com/company, last accessed June 22, 2021, Kayak states: *"Within a hotel listing, we order our results based on an internal algorithm that balances the prices and our revenue for the results shown. If the cheapest offer is not displayed above the "View Deal" or "Select" button, we highlight it in green in the central section of the listing."* During 2019, another sentence was added stating *"Hotels shown on KAYAK are often available to book on several provider sites, each of which will pay for clicks or bookings that they get via KAYAK."*

[26] See "How Kayak works," in the version of December 6, 2018, available at https://web.archive.org/web/20181206023556/https://www.kayak.com/company, last accessed June 22, 2021, Kayak states: *"In the specific case of hotels, the "Recommended" algorithm is based on a few key factors. The main two rely on the hotel's guest rating and its popularity (in terms of clicks). Hotels shown on KAYAK are often available to book on several provider sites, each of which will pay for clicks or bookings that they get via KAYAK. We also factor the average revenue potential of each hotel into our recommendations."* This was later shortened to *"With hotels, the "Recommended" algorithm is based on a few key factors. We mainly rely on the price, the hotel's guest rating and its popularity (measured in clicks). We also factor in the average revenue potential for KAYAK from each hotel result."*

[27] Other effects of vertical integration may arise from changes in the behavior of other parties, such as the other OTAs, hotels, and possibly other MSPs. We abstract from these here.

search platform have a higher probability of being visible and are more likely to be a position leader in the horizontal ranking.

For the vertical ranking of hotel offers, it is less obvious how incentives to favor an OTA would materialize. An avenue is that the likelihood with which a consumer clicks on the offer of a particular OTA may differ between hotels. For example, the integrated OTA may have the lowest price for hotel X but not for hotel Y, relative to the prices of non-integrated OTAs. Integration may then induce the MSP to show hotel X more prominently in the vertical ranking, which presumably makes it more likely that consumers will click on the offer of the integrated OTA and eventually book the hotel there.

Hypothesis 2 (H2, vertical ranking)**.** *Other things equal, the meta-search platform puts hotels with higher prices on affiliated OTAs sales in a worse vertical position in its search results.*

4.2 Empirical model

Our empirical approach is twofold. First, we investigate how Kayak decides for each hotel offer which sales channels to make prominent (horizontal ranking). Second, we investigate whether Kayak takes the pricing and other factors related to the sales channels into account when deciding which hotels to list first (vertical ranking). Let us describe both approaches in more detail.

Horizontal ranking. To test H1, we estimate the following linear probability model for an offer of sales channel s in hotel h for a request r:

$$Y_{hrs} = X_{hrs}\beta + \beta_{h,r} + \varepsilon_{hrs}. \tag{1}$$

Y_{hrs} is an indicator variable that takes the value one if the sales channel s for hotel h in request r is a position leader and zero otherwise; X_{hrs} are explanatory variables, $\beta_{h,r}$ denotes a hotel – request fixed effect. X_{hrs} includes the log-price of the sales channel, the number of price leader(s) for the offer, the group affiliation of the sales channel, as well as sales channel and hotel popularity that vary across time. The hotel fixed effects take time-invariant hotel characteristics into account, such as the number of stars, amenities, chain affiliation, or location. The group affiliation of the sales channel takes Booking Holdings as the reference category. Therefore, if hypothesis 1 is true, we should observe a negative and significant coefficient associated with other groups, suggesting that sales channels not affiliated with Booking Holdings have a lower probability of being prominent. Although Y_{hrs} is a binary variable, we use a linear probability model (LPM) because this allows us to obtain consistent estimates while including a large number of fixed effects and interaction terms. [28] We report findings of using non-linear models in Appendices E.2 and F.2 and discuss them along with our findings in Section 6.

Vertical ranking. For a given search request, Kayak provides a list of the available hotel offers. From the perspective of pure consumer surplus maximization, we would expect that the rank of a hotel in that list should be better if the hotel's gross match value for the average consumer is higher. This value should increase in the number of stars, the user rating, free breakfast, and so on. Given the gross value, the sales channels' prices should negatively affect the ranking as, other things equal, a higher price should mean a lower net match value for the average consumer. If Kayak cares for its short-term revenues from cost per click fees, it presumably incorporates the likelihood of a click (which might depend negatively on prices and positively on quality) as well as the cost per click fees.

To test H2, we estimate the following linear model for a hotel h in a request r:

$$-R_{hr} = Z_{hr}\kappa + \alpha_h + \gamma_r + \epsilon_{hr}. \tag{2}$$

R_{hr} is the ranking position of a hotel h in the Kayak search results. As a higher value of R reflects a "worse" rank, we multiplied the dependent variable with -1 to allow a similar interpretation as with the horizontal ranking analysis. Z_{hr} includes the minimum log-prices of the sales channels available for this hotel, the group affiliation of the price leader, as well as the average popularity of all sales channels available for this hotel and the hotel popularity that both vary across time. Compared to the horizontal ranking, we additionally control for sales channel availability for the hotel including group availability indicators and the number of sales channels. Hotel (α_h) and request (γ_r) fixed effects are included separately (different to the horizontal ranking analysis). The group affiliation takes the form of several indicators, one for each group, taking the value one if the group is among the price leaders. Therefore, under hypothesis 2, we should observe a negative and statistically significant coefficient associated with the dummy variable of the Expedia Group and/or other OTAs. This would suggest that if a group other than Booking Holdings is among the price leaders, then the hotel is ranked worse in the Kayak search results.

[28] Using the LPM further allows us to easily correct for heteroskedastic standard errors. Moreover, the LPM has a reduced computation time and enables a straightforward interpretation of the implied marginal effects from our parameter estimates. This is especially relevant when we perform interactions with other variables, such as chain affiliation, to explore effect heterogeneity: the interaction term in nonlinear models generally does not identify the partial cross-derivative, as discussed in Ai & Norton (2003).

4.3 Identification

Unobserved demand shocks. A concern could be that a demand shock may impact both the prices of sales channels and the ranking on the MSP. For instance, an increase in demand could lead to a stock-out of cheaper hotels, such that only hotels with a higher price remain in the list of search results and subsequently get a better ranking. We deal with this concern by adding request fixed effects γ_r (or request-hotel fixed effect β_{h_r}) which capture the effects linked to the combination of the booking and arrival date (and thereby also the booking horizon).

Unobserved heterogeneity in hotel popularity. If the MSP expects higher revenues from a hotel, it has an incentive to rank the hotel better – other things equal. Higher revenues can be due to either a higher CPC paid by the hotel (see below) or a higher likelihood of a hotel being clicked on (measured by the click-through-rate, CTR). For instance, if hotels with a lower CTR typically have lower prices on other sales channels affiliated with the MSP, we could get a spurious positive correlation between a bad ranking position and the price markup relative to other channels. We deal with this unobserved heterogeneity across hotels by removing time-constant unobserved heterogeneity between hotels through the inclusion of hotel fixed effects (and even hotel-request fixed effects in the case of the horizontal ranking). We control for temporary deviations in hotel popularity using short-term consumer ratings from TripAdvisor for each hotel.

Unobserved heterogeneity in sales channel popularity. Similar to the argument of unobserved hotel popularity, the MSP should take into account that consumers might have a preference for specific sales channels. The popularity of sales channels could follow seasonal patterns and unobserved trends initiated by marketing activities at the different sales channels. If an OTA affiliated with the MSP is increasingly popular and its popularity is then associated with higher prices, a good ranking position of the OTA could be spuriously correlated with the common ownership of OTA and MSP. To mitigate this concern, we use data about the current relative search volume of each sales channel on Google in France as a measure for the different popularity and associated CTR.

Unobserved channel and hotel-specific CPC. For the rankings, the MSP potentially also takes CPC payments of the different sales channels into account. These might vary between hotels as well as across time and might affect both the pricing across channels and the ranking position of the hotel on the meta-search platform. For instance, when paying a higher CPC for the direct channel, the hotel might increase the direct channel price to account for the higher distribution costs. Better visibility of the direct channel would then be driven by the higher CPC and would drive our 'direct channel' coefficient up in equation 1. It might also distort the price coefficients if the CPC changed the channel-specific prices.

Similarly, it could be that OTAs negotiate different CPCs for specific types of hotels. To deal with these potential problems, our approach is twofold.

First, we conduct a comparable analysis using data for the same city and observation period of another MSP, namely Google Hotels. This platform is, at the time of our study, an independent MSP that is not integrated with an OTA. Google Hotels is likely to be affected by similar heterogeneity in the promotional behavior of hotels over time, like Kayak. If we only find that Booking Holdings offers are only given more prominence on Kayak but not on Google Hotels, this is consistent with our hypothesis of joint profit-maximization in the Booking Holdings.

Second, we conduct complementary analyses using the Kayak data. We expect that CPCs for independent hotels, at least, are relatively constant over time at Kayak, as independent hotels have to make use of an intermediary to list their rooms on the MSP. As the CPC conditions for chain hotels could be more flexible, we run the analyses separately for independent and chain hotels. This also provides insight into potentially different CPCs paid by OTAs depending on the hotel type.

Moreover, it is noteworthy that what should matter in theory for the incentives of an integrated entity with an OTA and an MSP is the overall profitability – consisting of both CPC at the MSP and booking commissions net of CPCs at the OTA. Hence, the level of CPC that the integrated OTA pays the integrated MSP is anyway of limited informational value for studying the effects of vertical integration.

5 Data

In this section, we present the data set and its main characteristics along with a classification of sales channels and a conceptualization for the display of prices and offers.

5.1 Collection and features

Data collection. For our analysis, we mainly rely on data comprising hotel and channel rankings on Kayak, plus prices that hotels post on different channels. As control variables, we need data on the characteristics of hotels and channels which can explain their attractiveness for consumers as well as data on their determinants of the profitability of an hotel offer for Kayak. The data was collected as described in Larrieu (2019) from October 2014 to September 2017 on Kayak.com.[29] In particular, 2,375 search requests were made for 410

[29] Search results were collected every day from 6am–8am using a web-scraping program from a Windows desktop. IP addresses were randomized in each iteration using a list of French IPs located in the region of Paris. For each iteration, the cache of the browser was cleared of all cookies and historical searches

distinct reservation dates for one night for two people with different time horizons (mainly 4, 14, 30, and 180 days before arrival).[30] We also collected TripAdvisor information on hotels' characteristics and reviews over time. Moreover, we retrieved time series data from Google Trends for our observation period to approximate the sales channel popularity (see Appendix A for a description).

We now describe the hotels in the data set as well as characteristics of the data set used for the analyses.

Table 1: Descriptive statistics

Variable	# Obs.	Min	p50	Mean	Max	SD
	Hotel characteristics					
Stars	1,784	0	3	3.2	5	0.9
Chain	1,784	0	0	0.3	1	-
# Rooms	1,784	1	45	76	1,093	98
# Reviews	1,716	1	142	173	4,659	225
Score	1,716	2.6	4.3	4.3	4.7	0.2
	Time-varying variables					
Hotels per request	2,375	27	1,111	933	1,222	319
# Offers per hotel	2,174,571	1	7	8	22	4
Price	17,002,174	3	155	183	10,000	124

Hotels in the data set. Our data set contains 1,784 distinct hotels which are in the greater Paris area. In the upper panel of Table 1, we provide various hotel characteristics. Hotels in our data set have, on average, 76 rooms and three stars. Overall, 30% of the hotels are affiliated with a chain, the most prominent ones being Ibis Hotels, Best Western, and Mercure (see Table 11 in Appendix B). As shown in Table 12 in Appendix B, hotels with one to three stars have, on average, 62 rooms, while four- and five-star hotels have an average of 104 rooms.[31] For the time-varying hotel characteristics, we report the number of reviews and the average consumer rating on TripAdvisor at the moment of the reservation as a measure for hotel popularity. For the reservation date, hotels in our data set received, on average, 173 reviews with an average rating of 4.3 out of 5.

Ranked hotel and channel offers. In the lower panel of Table 1, we show descriptive statistics on the hotel offer level. The number of hotels in the search results ranges between 27 and more than 1,222 with an average of 933 hotels which have between one and 22 different

to appear as a new user without any personalization that may affect the Kayak ranking algorithm.

30 The data set is not balanced since not all existing reservation dates were queried with all possible time horizons. However, 80% of reservation dates were queried with at least five distinct time horizons. Other time horizons were collected in order to account for intertemporal price discrimination following revenue management and are kept in the analysis.

31 This is consistent with French statistics on the hotel industry by INSEE, see INSEE website.

online sales channels. On average, for each hotel, eight sales channels display an offer. In total, our data set contains more than 17 million observations. The average price for one night is 183 euros[32] and is negatively correlated with the time horizon.[33]

Sales channels in the data set and ownership. We observe 828 distinct sales channels, most of which comprise direct channels by hotels. We distinguish between hotels' direct channels and online travel agencies. For the OTAs, most of them are linked to two different groups. On the one hand, the Expedia Group owns different OTAs (Expedia.com, Classic Vacations, Hotels.com, Hotwire.com, Venere.com, and Egencia), is affiliated with some travel companies (voyage-sncf.com, Abritel HomeAway, Travelocity, and Orbitz – including ebookers, HotelClub and CheapTickets), and has Liberty Media as its parent company, which is the main shareholder of TripAdvisor. On the other hand, Booking Holdings Inc. owns and operates several travel meta-search platforms, OTAs and other travel websites, including Booking.com, Priceline.com, Agoda.com, Kayak.com, Cheapflights, Rentalcars.com, Momondo, and OpenTable. The remaining sales channels are either competing OTAs such as HRS.com and smaller ones (Presitiga, Melia, Hotelopia.com, HotelsClick, Amoma.com (bankrupt since 2019), Weekendesk, Lastminute group, etc.) or linked to French national companies in the travel sector (Tablet as part of the Michelin guide, Splendia owned by the online platform Voyage-Privé.com). In addition, there is a large national player, AccorHotels.com, hosting the majority of the big brands (Ibis, Mercure, Novotel, etc.) in France. It offers hotels the chance to appear on its own platform in exchange for a commission. Therefore, AccorHotels.com has a strategy of offering both its own brand hotels but also independent ones on its platform. We do not consider some particular offers (8%) for which Kayak is mentioned as a sales channel because we do not observe the identity of the sales channel really mediating the transaction. We finally classify sales channels depending on their group affiliation (Booking Holdings and Expedia Group), thereby distinguishing independent sales channels between online travel agencies ('Other OTAs') and the hotel direct channel (Table 2).

[32] We observe some extreme prices of up to 965,832€ in the data set. To remove outliers, we restrict the sample to prices lower than 10,000€, which is large enough for the price of an hotel room for one night in Paris even in a Palace category. This leads to a drop of 28 observations.

[33] The average price is strictly decreasing as the arrival date approaches, from 189€ at 6 months before the arrival to 182€, 180€ and 178€ respectively for one month, 14, and 4 days before the arrival date.

Table 2: Sales channels' availability and classification

Group	# obs	% in obs	Sales channel	# obs	% in obs
Booking Holdings	4,804,339	28%	Booking.com	1,899,278	40%
			Agoda.com	1,487,904	31%
			Others	1,417,157	29%
Expedia Group	6,747,875	40%	Hotels.com	1,713,173	25%
			Expedia.fr	1,397,825	21%
			Venere.com	1,315,041	19%
			Voyages-sncf.com	995,594	15%
			Ebookers.com	708,853	11%
			Others	617,389	9%
Other OTAs	4,856,541	29%	Amoma.com	737,503	15%
			Hotelopia.com	691,228	14%
			Logitravel.fr	561,550	12%
			HotelTravel.com	479,809	10%
			Rumbo.fr	448,225	9%
			HRS.com	316,822	7%
			Others	1,621,404	33%
Direct channel (e.g. hotel website)	593,419	3%	...		
Total	17,002,174	100%			

5.2 Descriptive statistics

In this subsection, we first describe the concentration of offers among specific sales channels. We then investigate price dispersion and price leadership and compare their respective occurrence by group and sales channels.

Distribution of offers across sales channels. The market is concentrated with seven large OTAs covering 60% of the offers, while 800 small sales channels only account for 5% of price offers (2). The top seven OTAs include Booking.com, Expedia, Hotels.com, the national player voyages-sncf as well as the smaller platforms Agoda and Venere. The direct channel (hotel websites) only accounts for 3% of the sales channel observations. Behind the apparent diversity of sales channels in the market, the two big groups account for 70% of price offers displayed by Kayak. Other OTAs account for 29% of the offers, translating in total to the same weight as Booking Holdings alone. We also note that the direct channel of the hotel is rarely available.

Price leader(s). For a given hotel, we define the price leader(s) as the sales channel(s) offering the lowest price (see Figure 3 in green). In 62% of the hotel offers, the price leader is unique, meaning that there is a strictly lower price than others. In the remaining 38%, several sales channels (up to 15) offer the same cheapest price. Different price leaders can be affiliated with the same group. At this level, there is a unique group price leader in 72% of the cases (Table 3).

Table 3: Number of price leader(s) at the sales channel and group levels

# Sales channel(s)	Freq.	Percent
1	1,303,460	62%
2	166,252	8%
3	182,218	9%
≥ 4	441,475	21%
Total	2,093,405	100%

# Group(s)	Freq.	Percent
1	1,505,549	72%
2	403,855	19%
3	151,146	7%
4	32,855	2%
Total	2,093,405	100%

Even though the hotel's direct channel is not often among the sales channels, when available it is actually one of the cheapest providers in 53% of cases, more than the main online travel agencies Booking.com (37%) and Hotels.com (37%). This also holds at the group-level (Table 4). When only considering cases in which there is a unique price leader among the sales channels, the direct channel of hotels is most often (54%) the cheapest channel compared to any other OTA. In comparison, when two sales channels both have the lowest price, Booking Holdings has a higher probability (44%) of being among them compared to other groups.

Table 4: Price leadership given availability by number of price leader(s)

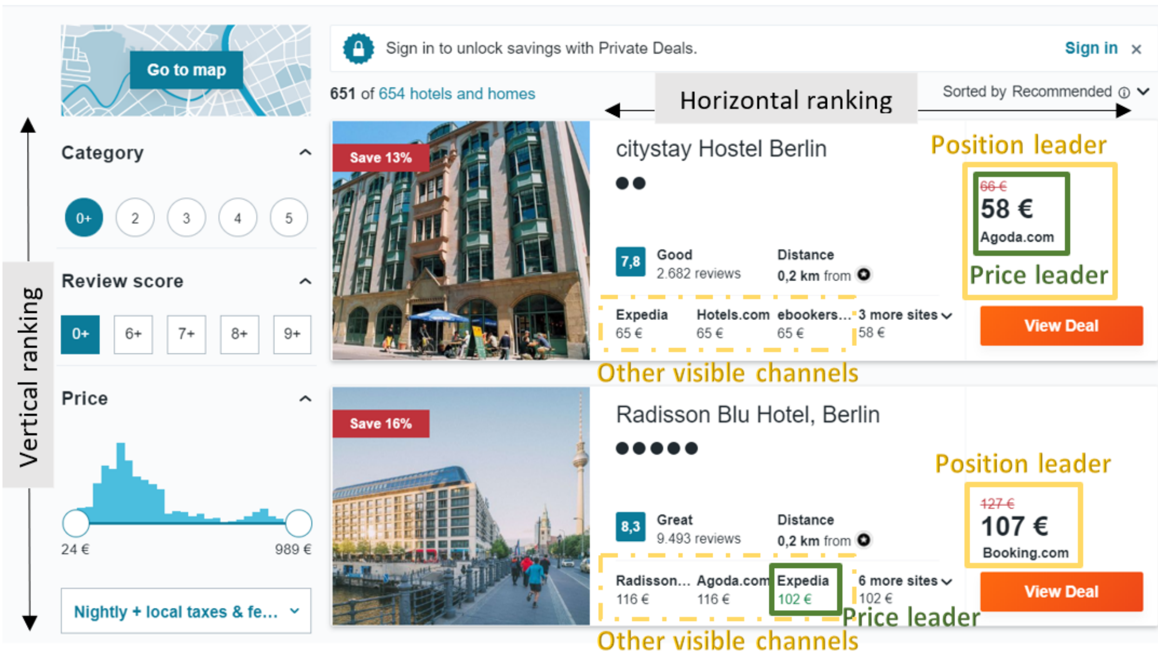
# Sales channel(s) price leader(s)	All	1	2	3	≥ 4
Direct channel	53%	54%	18%	38%	68%
Booking Holdings	37%	10%	44%	61%	87%
Expedia Group	32%	7%	13%	67%	89%
Other OTAs	23%	14%	16%	18%	26%

As Kayak is a price comparison website, we expect the sales channels with the lowest prices to be more visible than others. In particular, we expect a unique price leader to typically be most prominent (the position leader). To investigate this, we now relate the price leader frequencies to visibility and position leader frequencies.

5.3 Ranking decisions

Horizontal ranking. For each request, Kayak as a meta-search website lists the offers of different hotels (vertically). For a given hotel, Kayak displays the offered price of different sales channels (horizontally). One sales channel is highlighted and three others are visible but less prominent (see Figure 3 in yellow), while the remaining sales channels are hidden in a submenu which consumers have to click on if they want to see them. We define the

Figure 3: Rankings and classifications



highlighted sales channel as the position leader.[34]

While several channels can simultaneously be price leaders, there is always a unique position leader. Overall, in 96% of the hotel offers, the position leader is among the (possibly multiple) price leaders and this proportion increases with the number of price leaders. In more than 30% of the cases, there are multiple price leaders. When the position leader is not the unique price leader, the channel belongs to either the Booking Holdings or Expedia Group in 81% of the cases, with Booking Holdings comprising 43%. Table 5 shows that the OTAs of Booking Holdings are more often (12%) the position leader than the price leader – the difference being six times greater for Booking Holdings compared to the Expedia Group. In contrast, compared to Booking Holdings, the direct channel of the hotel appears less often in the first position although it is five times more often cheaper.

Table 5: Price vs Position leadership given availability

Group	Position leader	Unique Price leader	Difference
Booking Holdings	22%	10%	12%
Expedia Group	9%	7%	2%
Other OTAs	11%	14%	-3%
Direct channel	38%	54%	-16%

[34] It is also called the sales channel in the *buy box*, especially in the retail industry.

As the entire group does not necessarily reflect the case of each single OTA, we compare the share of price and position leaders at the sales channel-level in Table 13 of Appendix C. The results are even more pronounced as Booking.com is five times more the position leader than the price leader. For other OTAs, the results are less conclusive. Hotels.com and Expedia.fr are more often the position leader than the price leader, but still to a lesser degree than Booking.com while other OTAs are always less often the position leader than the price leader.

Kayak claims that it bases the ranking on customer popularity or ratings (see Section 3). Thus, an explanation of the discrepancy between price and position leader could be that the channels with an outstanding prominence at Kayak are particularly popular in France. If Kayak values the popularity in the horizontal ranking algorithm, it would make them visible more often compared to a ranking based on the cheapest price. Table 10 in Appendix A shows that Booking.com and Expedia.fr are indeed relatively more popular than others. However, this does not hold for Hotels.com. Another explanation for the particular prominence may be that specific sales channels (OTAs as well as hotels) pay more to be placed more prominently (we will come back to this point).

Vertical ranking. Besides choosing how to rank the offers of different sales channels by one hotel horizontally, Kayak also decides how to rank the hotels vertically in the search results. Table 6 describes how the position of a hotel varies with price leadership across sales channels. We report the average position of the first hotel appearing in the search results for which the respective sales channel (or group) is the *unique price leader*. For instance, the first hotel with the channel Booking.com being the unique price leader is shown on Kayak at the 26^{th} position on average, which is much more prominent than for hotels for which Expedia.fr is the unique price leader, where such a hotel offer is shown first only at the 375^{th} position on average. We observe a similar pattern when aggregating the offers to the group-level. For instance, while the first hotel offer, where an OTA of Booking Holdings has the lowest price appears on average on the 18^{th} position, the first offer where an OTA of the Expedia Group is the cheapest appears, on average, only at the 38^{th} position. These statistics indicate that offers of OTAs by the Expedia Group are less likely to be shown, as hotels with the strictly lowest price on such OTAs are less prominent. However, these patterns do not take into account that some channels may be less visible than others, and that channel availability could be correlated with hotel popularity, which we will address in our regression analyses.

Table 6: First hotel position with unique price leader by channel

Group	Position	SD	Seller	Position	SD
Booking Holdings	18	56	Booking.com	26	63
			Agoda.com	47	61
Direct	15	55	Direct	15	55
Expedia Group	38	87	Expedia.fr	375	330
			Hotels.com	260	309
			Voyages-sncf	286	329
			Venere.com	392	338
			(...)		
Other OTAs	6	23	Amoma.com	41	109
			Hotelopia.com	185	218
			Logitravel.fr	36	82
			(...)		

6 Estimation results

6.1 Horizontal ranking

In Table 7, we report the estimation results for the model described in equation 1. The dependent variable is in column (1) the probability of being visible (among the four first sales channels) and in column (2) the probability of being a position leader.

A higher price reduces the probability for a sales channel to be visible. For a hotel, a sales channel has a higher probability of being visible if it offers the cheapest price together with other sales channels (multiple price leaders) and this effect is twice as large if the sales channel is the only one to offer the cheapest price. Turning to the position leadership of sales channels (column (2)), the results on visibility and position leadership are similar. While the price level is particularly important for the visibility of a sales channel, being the unique price leader appears to be particularly relevant for becoming the position leader.

With respect to the ownership of sales channels, we find that, other things equal, sales channels not affiliated with Booking Holdings are less likely to be visible. Furthermore, we find that OTAs not belonging to Booking Holdings have a lower probability of being the position leader. The finding that the direct channel has a higher probability of being visible than OTAs of Booking Holdings emerges once controlling for the popularity of sales channels is an average result. This may be the result of hotels possibly having to pay relatively high CPCs for their direct channel which may lead to financial incentives of the MSP to make them more prominent.[35]

[35] If we exclude cases from the sample where an OTA of Booking Holdings is the price leader, the direct channel is the position leader in 53% of the cases compared to 32% and 13% for the Expedia Group and

Table 7: Visibility and Position Leadership at the group-level

	Linear Probability Model	
	Visible	Position Leader
	(1)	(2)
ln(price)	-0.86***	-0.02***
	(0.00)	(0.00)
Price leadership		
(ref: Not price leader)		
Among price leaders	0.37***	0.21***
	(0.00)	(0.00)
Unique price leader	0.36***	0.81***
	(0.00)	(0.00)
Group		
(ref: Booking Holdings)		
Direct channel	-0.01***	0.02***
	(0.00)	(0.00)
Expedia Group	-0.11***	-0.07***
	(0.00)	(0.00)
Other OTAs	-0.05***	-0.03***
	(0.00)	(0.00)
Constant	4.78***	0.11***
	(0.01)	(0.00)
Hotel × Request Fixed Effects	yes	yes
Channel Popularity	yes	yes
N	15,495,039	15,495,039

Notes: Dependent variable: indicator sales channel visible (column 1) or position leader (column 2). Unit of observation: search request – hotel – channel. Linear regressions include hotel – request fixed effects. Standard errors (in parentheses) are robust to heteroscedasticity and adjusted for serial correlation inside clusters. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Chain affiliation. 30% of hotels in the data are affiliated with chains (see Table 1), and chain affiliation may play a role on meta-search platforms as well as at OTAs: Chains may have better bargaining power and generally benefit from an increased visibility thanks to chain-level websites. We therefore estimate the same models including a chain indicator and compare the results. We report the results in Table 16 in Appendix E.1. We find that the results are comparable to the baseline findings, with the exception of the effect related to the direct channel of hotels. Interestingly, other things equal, this sales channel has a lower probability of being visible than one of Booking Holdings, which is mainly due to hotels affiliated with a chain.

Sales channel-level. We also conducted the analyses at the sales channel-level, which

other OTAs, respectively.

could disguise different signs within a given group. For instance, the Expedia Group contains highly popular platforms in France, such as Voyages-sncf or Expedia, but also others that are not as popular, such as Venere.com. Similarly, Booking.com and Agoda.com are of different popularity as well. Despite controlling for channel popularity, the estimated effects may be different as popular platforms may drive the overall effect at the group-level. Table 17 in Appendix E.1 contains estimation results regarding the horizontal ranking from Table 7 at the sales channel-level. The reference category for the sales channel affiliation is Booking.com. One can see that the effect is driven by Booking.com being more visible, while Agoda.com as the other sales channel of Booking Holdings has a lower probability of being visible with a similar magnitude to other OTAs. Therefore, it seems that Kayak gives Booking.com particularly more prominent placing and not necessarily other sales channels of the group. Results on visibility and position leadership are very similar.

Robustness. We report in Appendix E.2 the results of using different estimation techniques. The results of using a probit and logit model (without hotel fixed effects but with time-constant hotel characteristics) in Table 18 do not qualitatively change. We have estimated in addition a conditional logit model and find that results differ slightly in that the direct channel is *less* likely to be the position leader than Booking Group OTAs (Table 19), and accordingly sales channels of chain-affiliated hotels generally seem to have a lower probability of being visible (Table 20). Results from the analysis at the sales channel-level (Table 21) are as before.

Finding 1 (Horizontal ranking)**.** *Other things equal, sales channels belonging to the Expedia Group or independent OTAs have, on average, a lower probability of being visible or of being the position leader than sales channels belonging to Booking Holdings.*

6.2 Vertical ranking

We report estimation results for Equation 2 in Table 8. The dependent variable is the ranking position of a hotel in the search results, multiplied by -1. A positive coefficient implies a *better* ranking position in the Kayak search results.

We find that Kayak assigns hotels a better ranking position the more sales channels there are available. More sales channels make it more likely that consumers will find a channel that they prefer, which increases the likelihood of a click. We do not observe that the price of the cheapest offer affects the ranking position significantly. The number of sales channels which have the lowest price does not play a significant role in most specifications either.

Kayak assigns hotels a worse ranking position when an OTA of the Expedia Group is among the channels showing an offer with the lowest price. As there can be multiple price leaders, in column (b) we restrict the sample to hotels that have only one group with the

Table 8: Hotel ranking at the group-level (vertical ranking)

	Ordinary Least Square		
	Rank in search result		
# Group Price leaders(s)	All	Unique	Multiple
	(a)	(b)	(c)
min ln(price)	3.85	5.69	9.53
	(4.90)	(4.96)	(7.84)
# Sales Channels	2.98***	2.47***	5.90***
	(0.83)	(0.78)	(1.27)
# Sales Channels Price leader(s)	-0.43	0.19	-3.22***
	(0.77)	(1.38)	(1.15)
Group Price leader indicators			
Booking Holdings	0.45	(Ref.)	12.31**
	(2.50)	(Ref.)	(5.75)
Expedia Group	-7.98***	-7.71***	-0.35
	(2.77)	(2.79)	(7.25)
Direct channel	-1.18	11.05**	-30.77***
	(3.75)	(4.65)	(7.04)
Other OTAs	-0.06	1.78	6.03
	(2.46)	(2.82)	(3.92)
Constant	-582.65***	-620.43***	-585.83***
	(69.28)	(71.57)	(92.42)
Request FE	yes	yes	yes
Hotel FE	yes	yes	yes
Group availability	yes	yes	yes
Hotel Popularity	no	yes	yes
Channel Popularity	yes	yes	yes
N	2,022,992	1,457,823	565,104

Notes: Dependent variable: ranking of hotel in search results (multiplied by -1). Unit of observation: search request – hotel. Linear regressions include hotel and request fixed effects. Standard errors (in parentheses) are robust to heteroscedasticity and adjusted for serial correlation inside clusters.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

price leader among the sales channels, and in column (c) to multiple ones. We observe that when there is a unique price leader, hotels with the strictly lowest price on an Expedia OTA receive a worse ranking position. However, in the case of unique price leadership, the hotels' direct channels receive a better ranking position than Booking Holdings' channels (though, as we will see later, still worse than the OTA Booking.com). Finally, we observe in column (c) that when there are multiple price leaders, Kayak tends to favor Booking Holdings' OTAs, while the hotels' direct channel tends to get a significantly worse position.

Chain affiliation. We conducted the same analysis distinguishing hotels with and without a chain affiliation in Table 22 in Appendix F.1. Our results indicate that when the direct channel is among the cheapest channels, independent hotels are ranked better, while chain hotels are ranked worse. It might be that independent hotels pay a particularly high CPC, possibly because they lack bargaining power vis-a-vis MSPs and/or because MSPs are a particularly important means of promotion for those hotels active there.

Sales channel-level. We also conducted the analysis of the vertical ranking distinguishing the sales channels in Table 23 in Appendix F.1. We find that results obtained in the group analysis are driven by certain sales channels. First, the effect of the Expedia Group stems from the OTAs Expedia and Venere.com. Second, the results reveal that the effect on the hotel ranking when independent OTAs are available is mainly driven by certain platforms, such as Hotelopia.com. However, this is not a general result for all independent OTAs. In addition, the more detailed analysis suggests that hotels are ranked better if Voyages-sncf – one of the most popular OTAs in France – is among the available sales channels, irrespective of its price leadership. This suggests that Kayak takes into account the popularity of platforms.

Sequential ranking decisions. From our outside perspective as researchers, the optimization of the horizontal and vertical ranking occurs *simultaneously.* Therefore, we do not control in our estimation in Table 8 for the possibility that not only the *price* but also the *position leadership* may have an impact on the vertical ranking. However, allowing for the possibility that these are *sequential* decisions, we also report in Table 24 in Appendix F.1 the results of a specification where we add controls for a) position leadership and b) joint price and position leadership. We still observe that being a hotel which has the lowest price at an Expedia OTA worsens the vertical ranking of the hotel, though this effect is then only weakly significant. As a complementary metric, we perform a test of joint significance for the Expedia Group coefficients indicating price and position leadership as well as the combination of the two. We find that the hypothesis of joint significance can only be rejected with a probability of $p = 0.2562$. We interpret this as a weak indication that hotels with price leadership on an Expedia OTA are ranked worse, even when assuming that the ranking decisions are sequential.

Robustness. We also estimate comparable specifications to the ones of Table 8 using the rank-ordered logit model. In the rank-ordered logit, every hotel has a latent score and the estimator accounts for the condition that the first ranked hotel should have a higher score than the second one, and the second ranked hotel has a higher score than the third one, and so on. We estimated this model accounting for rankings of the first 10 and the first 20 listed hotels (Tables 25 and 26 in Appendix F.2) and find qualitatively similar results.

Finding 2 (Vertical ranking)**.** *Other things equal, hotels where an OTA of the Expedia Group has the lowest price have, on average, a worse ranking position in the Kayak search results.*

6.3 Comparison with a non-integrated meta-search site

In subsection 6.2, we show that the position of a hotel in the vertical ranking on Kayak appears to be worse if this hotel has lower prices on an OTA of the Expedia Group, which is the competitor of Booking Holdings (Table 8). Specifically, hotel offers with the lowest price on one of the OTAs of the Expedia Group have, on average, a less favorable position in the hotel search results, even when controlling for measures of OTA popularity.

One could be concerned that this result is driven by unobserved heterogeneity in channel and hotel-specific cost-per-click fees. We therefore analyze whether we see the same pattern for a meta-search platform which is not integrated with an OTA.

Due to data (un)availability, we focus specifically on Google Hotels as one of the most popular MSPs for which we have also obtained data for a period of about six months.[36] Appendix D contains details on data collection and compares the data with that used in the main analysis in terms of the observation period and the set of available hotels. It shows that our main results remain for the restricted Kayak sample, which is used for the comparison with Google Hotels.

Table 9 contains regression results for the vertical ranking of a hotel as in column 3 of Table 8, but with the sample being restricted to the observations we also have available for Google Hotels. In the first column, we report the regression results for the hotel rank on Kayak. One can see that restricting the sample does not change the result qualitatively as compared to the full sample (see also Appendix D for a full discussion). Specifically, we see that a hotel receives a worse position on Kayak if it also offers he lowest price on one of the Expedia Group OTAs. In the second column, we perform the same exercise for the ranking of hotels in search results for Google Hotels. Conversely to the results obtained with the Kayak search results, we do not see the pattern of hotels with lower prices on an OTA of Expedia being ranked worse. Finally, in column 3, we explain the difference of the ranking position that each hotel has on the two platforms. Here we see that hotels are not ranked differently if a Booking Holdings OTA is the price leader. However, the difference in the ranking for hotels with low prices on Expedia is significant and large.

Finding 3 (MSP without integration)**.** *We do not see the pattern that hotels with lower prices on OTAs of the Expedia Group get a worse ranking when the MSP is not integrated with OTAs.*

[36] See HOTREC - European Hotel Distribution Study 2020 as cited in Fn. 7.

Table 9: Vertical ranking on Kayak versus Google Hotels

	Kayak (1)	Rank Kayak (2)	Google (3)	Rank Difference Kayak-Google (4)
min ln(price)$_{\text{Kayak}}$	3.85	-5.16		105.19***
	(4.90)	(8.12)		(36.39)
min ln(price)$_{\text{Google}}$			-322.05***	238.97***
			(16.05)	(39.73)
# Sales Channels Price leader(s)	-0.43	0.09	0.74	-0.86
	(0.77)	(1.81)	(0.51)	(1.89)
# Sales Channels	2.98***	1.63	1.28***	0.51
	(0.83)	(1.89)	(0.36)	(1.91)
Price Leader indicators				
Booking Holdings	0.45	1.48	-0.97	-3.16
	(2.50)	(4.79)	(1.47)	(5.14)
Expedia Group	-7.98***	-10.62*	-1.05	-13.12**
	(2.77)	(5.67)	(1.61)	(5.92)
Direct channel	-1.18	-10.69	-2.57	-8.26
	(3.75)	(8.17)	(2.80)	(8.41)
Other OTAs	-0.06	-6.88	-8.45***	2.91
	(2.46)	(5.13)	(2.26)	(5.84)
Constant	-582.65***	-563.12***	1216.50***	-1924.49***
	(69.28)	(181.33)	(131.21)	(180.61)
Request FE	yes	yes	yes	yes
Hotel FE	yes	yes	yes	yes
Group Availability	yes	yes	yes	yes
Hotel Popularity	yes	yes	yes	yes
Channel Popularity	yes	yes	yes	yes
N	2,022,992	127,964	127,964	127,964

Notes: Dependent variable: ranking of hotel in search results (multiplied by -1) in columns 1-3 and the difference of the rank of a hotel on Kayak and Google in column 4. We use the whole sample of Kayak data in column (1), and in columns (2) and (4) only the data which overlaps with the sample of Google hotels. Unit of observation: search request – hotel. Linear regressions include hotel and request fixed effects. Standard errors (in parentheses) are robust to heteroscedasticity and adjusted for serial correlation inside clusters. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

7 Conclusion

We study the impact of the vertical integration between online travel agents (OTAs) and meta-search platforms (MSP) on the ranking algorithm used for the positioning of hotels and their sales channels on the MSP. We distinguish between the horizontal ranking of sales channels for a given hotel and the vertical ranking of hotels for a search request.

Our empirical analyses focus on the search results of the meta-search platform Kayak that belongs to Booking Holdings. The analyses of the horizontal ranking indicate that sales channels of OTAs by Booking Holdings are more often position leaders (i.e., highlighted sales channel on hotel offers) than price leaders (i.e., among the cheapest sales channels).

Using linear hotel and request fixed effects regressions that also account for prices and popularity measures, we additionally show that OTAs of Booking Holdings have a higher probability than any other OTA of being among the visible providers and of being the highlighted sales channel. For the vertical ranking, our results suggest that hotels are ranked worse in the Kayak search results when an OTA of the Expedia Group is the cheapest sales channel.

We provide various robustness checks. We contrast the order of search results on Kayak to those of Google Hotels, which is a non-integrated MSP. For the vertical ranking, we do not observe that hotels are ranked worse on Google Hotels when an OTA of the Expedia Group is the cheapest sales channel. We also distinguish sales channels within groups and show that the two major OTAs Booking.com and Expedia drive the main results. Moreover, we distinguish hotels affiliated with chains from independent ones and show that for the horizontal ranking, the direct channel of independent hotels is positioned more prominently compared to Booking Holdings, while for the vertical ranking independent hotels present on Kayak with a direct website are favored too. We also run non-linear regressions and obtain qualitatively similar results.

Overall, our results are consistent with the hypothesis that the ranking decision of an MSP is affected by concerns beyond hotel and sales channel popularity. While this finding is not surprising for a profit-maximizing firm, it raises the question of whether the MSP optimizes its ranking only with respect to its own revenues (as it claims), or whether it takes the joint revenues of the integrated firm into account.

If the cost per click revenues for all sales channels and hotels were equal and constant across time, one could interpret our results such that – even controlling for differences in hotel and sales channel popularity – the MSP favors its affiliated sales channels in its ranking decisions. Based on this assumption, the observation that non-affiliated sales channels are becoming less visible (and hotels with lower prices on competing sales channels) would indicate that the MSP uses its ranking to favor its own subsidiaries.

In practice, cost per click revenues might vary substantially across channels and time. This is also reflected in our findings that hotels which are affiliated with a chain (and are therefore less likely to pay a high CPC) are, on average, ranked differently than independent hotels.

However, even if our results are solely driven by higher payments of the sales channels affiliated with the MSP, one has to bear in mind that these payments occur within an organization under the same ownership. As integrated companies should have the means to compensate these payments, our results could still be consistent with the MSP favoring its own subsidiary. Furthermore, we do not observe these patterns in the hotel rankings of Google Hotels, which are similarly affected by commission payments.

A limitation is that our empirical analysis focuses on Booking Holdings' case. A scope for improvement would be to enrich the analysis by studying other independent MSPs or an MSP affiliated with other groups. In particular, Expedia Group, the second biggest player in the industry, is also vertically integrated with several OTAs (like Expedia, Hotels.com, etc.) and the MSP Trivago. A similar analysis of this group would provide insights on whether our results are Booking Holdings-specific or apply more generally to the industry.

Our analysis cannot provide a definite conclusion on what sort of ranking of hotels and channels is socially optimal. However, we would like to point out two potential risks of a meta-search site's ranking optimization. First, the empirical analysis indicates that the ranking optimization of an MSP may lead to a worse positioning of hotels with lower prices on competing sales channels. This may in turn have effects similar to a price parity clause (see also Hunold et al. (2020) in this regard). PPCs have been prohibited in many countries as they can lead to high commission rates and final prices. Second, deviations from a ranking that produces the highest match values for consumers may reduce not only consumer surplus but also allocational efficiency, as it may become more likely that consumers will not find the offer that best fits their needs. It is unfortunately beyond the scope of the present article to assess whether these risks actually materialize.

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Appendices

A Google Trends data

In the Kayak data, we identify 22 OTAs. For each OTA, we download the associated relative search volume on Google (Google Trends) for the ”search term” in France per month between 2014 and 2018.

On Google Trends, it is possible to look at searches of these keywords related to the ”search term” in general, the respective website, or any other category deemed relevant by Google. As we do not observe the category ”website” for all OTAs, we use the more general query ”search term” and adapt the request when necessary (for instance, ”Tablet hotels” instead of Tablet).

Besides these 22 OTAs, we distinguish between the hotel's direct channel and large hotel chains and websites of independent hotels. We collect data from Google Trends for the nine biggest hotel chains and normalize the value to zero for websites of small independent hotels. For each reservation date, we compute a popularity index (up to 100) by sales channel defined as the current Google Trends value divided by the maximum Google Trends value among the available sales channels for the request. The average popularity is higher for online travel agents than for hotel chains (Table 10), which is mostly driven by some very popular websites like Booking.com and voyages-sncf.fr, the French national railroad ticket booking website.

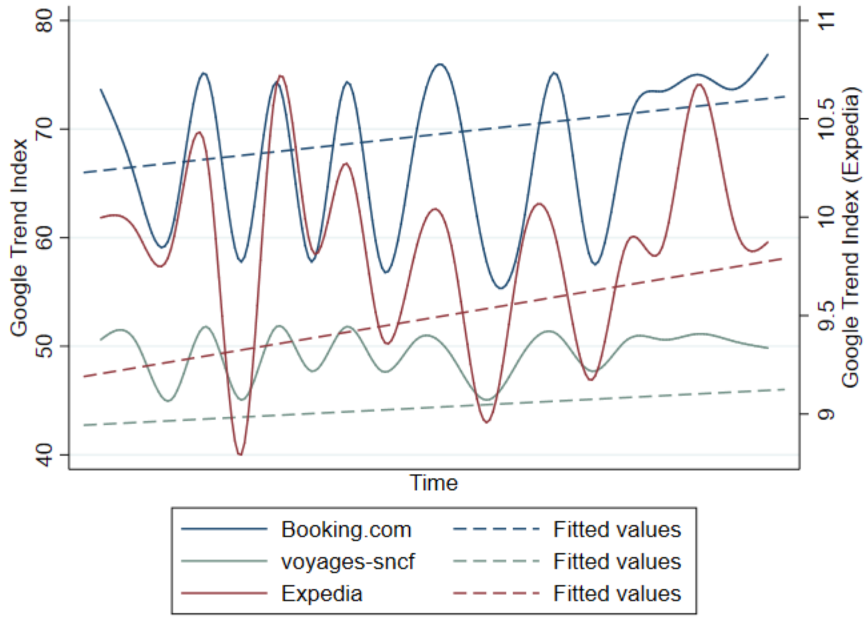
Table 10: Sales channels' popularity index

OTAs	Index
Booking.com	99
voyage-sncf.fr	75
TripAdvisor	66
Expedia.fr	15
Others	≤ 5
All	22

Hotel chain	Index
Ibis	29
Novotel	16
Best Western	11
Mercure	9
Kyriad	9
Others	≤ 6
All	9

The Google Trends index is subject to considerable variation during the observation period. Figure 4 displays the Google Trends Index for the three main OTAs. Besides seasonal patterns, there is a general upward trend suggesting main OTAs are becoming increasingly popular. This is consistent with previous work by Hunold et al. (2018) showing that Booking.com gained in popularity in Europe from 2014 to 2017.

Figure 4: Variation of Google Trends index for main OTAs



B Hotel characteristics

Table 11: Hotel chain affiliation

Affiliation	Freq.	Percent	Chain name	Percent
No chain	1,206	68%	-	-
			Ibis	18%
			Best Western	11%
			Mercure	10%
			Campanile	6%
Chain	578	32%	Novotel	6%
			Adagio	5%
			Kyriad	4%
			Première Classe	4%
			Others	37%
Total	1,784	100%	Total in chain	100%

Table 12: Average number of rooms by category of stars

Stars	Freq.	Percent	# Rooms
Not rated	11	1%	22
1	49	3%	63
2	249	14%	62
3	876	49%	62
4	514	29%	103
5	85	5%	105
Total	1,784	100%	76

C Price vs Position leader by sales channel

Table 13: Price vs Position leader by sales channel

Sales channel	Position leader	Unique Price leader	Difference
Hotels.com	11%	1%	10%
Expedia.fr	8%	1%	7%
Venere.om	2%	1%	1%
voyages-sncf	3%	1%	3%
Ebookers.com	17%	25%	-8%
HotelClub	20%	25%	-5%
TripAdvisor	2%	17%	-15%
CheapTickets	2%	2%	0%
Booking.com	30%	6%	24%
Agoda.com	12%	15%	-3%
Amoma.com	25%	34%	-9%
Hotelopia.com	2%	3%	0%
Logitravel.fr	18%	24%	-6%
HotelTravel.com	9%	12%	-3%
Rumbo.fr	8%	11%	-3%
HRS.com	6%	6%	0%
Direct	38%	54%	-16%

D Additional analysis of Google Hotels data

For the robustness check conducted in Subsection 6.3, we obtained additional data from Google Hotels. It covers a period from April, 15, 2015, to September, 22, 2015 (while the data set of Kayak goes from October 2014 to September 2017). In the following paragraphs, we describe the preparation of this data set and how we combined it with the data from Kayak, and we also discuss potential discrepancies.

Data collection The data from Google Hotels was obtained by a similar procedure as the Kayak data in Larrieu (2019). Search results were collected every day from 6 to 8am using a web scraping program from a Windows desktop. IP addresses were randomized in each iteration using a list of French IPs located in the Paris region. For each iteration, our browser cache was cleared of all cookies and historical searches so as to appear as a new user without any personalization that may affect the Google Hotels ranking algorithm. This lead to 961 search results for 156 distinct reservation dates for one night for two people with different time horizons (mainly 4, 14, 30, and 180 days before arrival).[37] In total, data for 2,260 different hotel names was collected, which decreased to about 1,100 unique hotels due to different naming across time.

Data merge Hotels across the two platforms Kayak and Google Hotels were matched by their name similarity and manually. As a result, 1,093 distinct hotels could be matched. Thereby, we cover 61% of the initial sample (1,784 hotels). However, taking into account that we only consider the period from April, 15, 2015, to September, 22, 2015, the coverage increases. Out of the 1,215 hotels present on Kayak for the relevant observation period, we identify 850 hotels also on Google Hotels, yielding a coverage of 69%. This overlap is comparable to the overlap of about 70% of hotels on Booking.com and Expedia in Europe as found in Hunold et al. (2020). The data was then further amended with data from TripAdvisor as before.

Matched vs. non-matched hotels One might wonder whether the subsample of hotels for our robustness analysis differs from the overall Kayak sample used in the main body of the article. In the following, we provide comparison tables discussing these points. First, we report the statistics of the whole Kayak sample (Panel A) versus the subset of hotels present on Kayak during the observation period of our robustness check (Panel B) in Table 14. Here, we note that while the average number of stars is slightly higher in the 'shorter' period, the hotels appear to be smaller in terms of rooms and belong less often to a chain. Second, within the 'shorter' time period, we can compare hotels on Kayak which we observe on Google Hotels as well (847, Panel C) and those we do not (365+3, Panel D).[38] It appears that hotels which are present only on Kayak and not on Google Hotels have slightly less stars (3.22 vs. 3.25), a lower number of rooms (49 vs. 62) and are less often part of a hotel chain (21 vs. 24%).

[37] Like the Kayak data, the Google data set is not balanced since not all existing reservation dates were queried with all possible time horizons.

[38] Three additional hotels were identified on both platforms, but there was overlap regarding the dates and time horizons when the data was collected.

Table 14: Characteristics of hotels in the Kayak data set

Variable	# Obs	Mean	Std. Dev.	Min	Max
Panel A: Whole time period					
Stars	1,715	3,19	0,86	0	5
# Rooms	1,715	76	97	1	1,093
Chain	1,715	33%	0,5	0	1
Panel B: Only short time period					
Stars	1,215	3,24	0,83	0	5
# Rooms	1,215	58	81	1	1,025
Chain	1,215	23%	0,4	0	1
Panel C: Short time period, hotels also on Google Hotels					
Stars	847	3,25	0,85	0	5
# Rooms	847	62	90	5	1,025
Chain	847	23%	0,4	0	1
Panel D: Short time period, hotels only on Kayak					
Stars	368	3,21	0,79	0	5
# Rooms	368	49	52	1	464
Chain	368	21%	0,4	0	1

These 847 distinct hotels correspond in the matched data to 300 requests, i.e., search results of hotels on both MSPs, reflected in 262,811 hotel positions. The majority of requests (73%) were made for a lead time of 4, 14, 30, or 180 days. In the analyses, we will restrict the sample to the i) hotels which are also available on Kayak, ii) the same dates, iii) the same booking horizon, and iv) the period when all forms of price parity clauses were still allowed, that is, until July 1, 2015.

Effects of data filtering Finally, we verify that we get qualitatively the same results with the data from Kayak even when restricting the sample in the same dimensions as the Google data set. Table 15 shows the result of the baseline model for the Kayak data until July 1, 2015, using all available hotels, travel dates, and booking horizons. Subsequently, we restrict the sample to the same observation period (column 2), the same set of hotels in both data sets (column 3), and apply both restrictions in column (4). Finally, in column (5) we restrict the Kayak sample further to hotel-travel date observations with the same booking horizon as available in the Google data. One can see that even when imposing these restrictions, results remain qualitatively the same.

Table 15: Kayak hotel ranking - different filters

	Ordinary Least Square Rank in search results				
	1	2	3	4	5
Restriction	-	Time	Hotels	Time & Hotels	T., H.& time lag
min ln(price)$_{\text{Kayak}}$	4.62	27.29***	3.15	27.01***	-5.16
	(5.96)	(7.78)	(7.12)	(9.12)	(8.12)
# Sales Channels Price leader(s)	-0.32	0.44	-0.76	-0.20	0.09
	(0.87)	(1.30)	(0.99)	(1.44)	(1.81)
# Sales Channels	6.61***	1.84	6.73***	1.89	1.63
	(0.90)	(1.46)	(0.96)	(1.54)	(1.89)
Group Availability indicators					
Booking Holdings	-3.17	10.37	-3.65	10.84	25.81***
	(5.34)	(6.70)	(5.84)	(7.00)	(6.94)
Expedia Group	-9.68**	8.60*	-3.26	14.95***	14.27**
	(4.69)	(4.66)	(5.44)	(5.30)	(6.05)
Direct website	-8.31	-22.15***	-10.34	-20.94**	0.04
	(6.24)	(8.53)	(6.88)	(9.17)	(10.57)
Other OTAs	3.75	4.06	1.74	4.00	0.85
	(3.34)	(3.65)	(3.91)	(4.04)	(5.02)
Price Leader indicators					
Booking Holdings	3.43	-3.29	4.37	-1.61	1.48
	(2.99)	(3.96)	(3.52)	(4.57)	(4.79)
Expedia Group	-7.29**	-7.12*	-8.62**	-8.47*	-10.62*
	(3.25)	(4.29)	(3.73)	(4.91)	(5.67)
Direct website	-3.79	-12.24	-4.30	-12.19	-10.69
	(4.28)	(7.52)	(4.98)	(8.81)	(8.17)
Other OTAs	0.03	-1.50	0.14	-1.57	-6.88
	(2.87)	(4.14)	(3.34)	(4.75)	(5.13)
Constant	-597.36***	-903.91***	-586.06***	-621.49***	-563.12***
	(97.89)	(122.11)	(119.83)	(174.68)	(181.33)
Request FE	yes	yes	yes	yes	yes
Hotel FE	yes	yes	yes	yes	yes
Hotel Popularity	yes	yes	yes	yes	yes
Channel Popularity	yes	yes	yes	yes	yes
N	1,386,537	494,869	992,858	354,003	127,964

Notes: Dependent variable: ranking of hotel in search results (multiplied by -1). Unit of observation: search request – hotel. Linear regressions include hotel and request fixed effects. Standard errors (in parentheses) are robust to heteroscedasticity and adjusted for serial correlation inside clusters. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

E Robustness checks: Horizontal ranking

E.1 Further results

Table 16: Visibility and Position Leadership by chain affiliation

	Linear Probability Model	
	Visible ($\# \leq 4$)	Position Leader ($\# = 1$)
ln(price)	-0.86***	-0.02***
	(0.00)	(0.00)
Price leadership (ref: Not price leader)		
Among price leaders	0.37***	0.21***
	(0.00)	(0.00)
Unique price leader	0.35***	0.81***
	(0.00)	(0.00)
Group (ref: Booking Holdings)		
Expedia Group	-0.09***	-0.06***
	(0.00)	(0.00)
Direct channel	0.03***	0.05***
	(0.00)	(0.00)
Other OTAs	-0.04***	-0.02***
	(0.00)	(0.00)
Chain × Group		
Expedia Group	-0.06***	-0.03***
	(0.00)	(0.00)
Direct channel	-0.11***	-0.07***
	(0.00)	(0.00)
Other OTAs	-0.04***	-0.03***
	(0.00)	(0.00)
Constant	4.78***	0.11***
	(0.01)	(0.00)
Hotel × Request Fixed Effects	yes	yes
Channel Popularity	yes	yes
N	15,495,039	15,495,039

Notes: Dependent variable: indicator sales channel visible (column 1) or position leader (column 2). Unit of observation: search request – hotel – channel. Linear regressions include hotel – request fixed effects. Standard errors (in parentheses) are robust to heteroscedasticity and adjusted for serial correlation inside clusters. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Visibility and Position Leadership at the sales channel-level

		Linear Probability Model			
		Visible ($\# \leq 4$)		Position Leader ($\# = 1$)	
ln(price)		-0.84***	-0.84***	-0.01***	-0.01***
		(0.00)	(0.00)	(0.00)	(0.00)
Price leadership (ref: Not price leader)					
Among price leaders		0.43***	0.43***	0.26***	0.26***
		(0.00)	(0.00)	(0.00)	(0.00)
Unique price leader		0.29***	0.28***	0.90***	0.90***
		(0.00)	(0.00)	(0.00)	(0.00)
Sales Channel (ref: Booking.com)					
Booking Holdings	Agoda.com	-0.14***	-0.46***	-0.15***	-0.22***
		(0.00)	(0.00)	(0.00)	(0.00)
Expedia Group	Expedia	-0.22***	-0.50***	-0.14***	-0.21***
		(0.00)	(0.00)	(0.00)	(0.00)
	Hotels.com	-0.06***	-0.38***	-0.11***	-0.19***
		(0.00)	(0.00)	(0.00)	(0.00)
	Venere.com	-0.31***	-0.63***	-0.19***	-0.27***
		(0.00)	(0.00)	(0.00)	(0.00)
	Voyages-sncf	-0.27***	-0.37***	-0.16***	-0.19***
		(0.00)	(0.00)	(0.00)	(0.00)
	(...)				
Direct		-0.06***	-0.37***	-0.12***	-0.19***
		(0.00)	(0.00)	(0.00)	(0.00)
Other OTAs	Amoma.com	-0.03***	-0.35***	-0.13***	-0.20***
		(0.00)	(0.00)	(0.00)	(0.00)
	Hotelopia.com	-0.20***	-0.52***	-0.13***	-0.21***
		(0.00)	(0.00)	(0.00)	(0.00)
	Logitravel.fr	-0.04***	-0.36***	-0.11***	-0.18***
		(0.00)	(0.00)	(0.00)	(0.00)
	(...)				
Constant		4.75***	5.08***	0.17***	0.25***
		(0.01)	(0.01)	(0.00)	(0.00)
Hotel × Request Fixed Effects		yes	yes	yes	yes
Channel Popularity		no	yes	no	yes
N		15,495,039	15,495,039	15,495,039	15,495,039

Notes: Dependent variable: indicator sales channel visible (column 1) or position leader (column 2). Unit of observation: search request – hotel – channel. Linear regressions include hotel -request fixed effects. Standard errors (in parentheses) are robust to heteroscedasticity and adjusted for serial correlation inside clusters. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

E.2 Non-linear models

Table 18: Probit and Logit (coefficients)

	Visible ($\# \leq 4$)		Position Leader ($\# = 1$)	
	Probit	Logit	Probit	Logit
ln(price)	-0.07***	-0.12***	-0.08***	-0.13***
	(0.00)	(0.00)	(0.00)	(0.00)
Price leadership				
(ref: Not price leader)				
Among price leader	0.84***	1.36***	1.65***	3.58***
	(0.00)	(0.00)	(0.00)	(0.00)
Unique price leader	2.11***	3.73***	3.23***	6.28***
	(0.00)	(0.00)	(0.00)	(0.00)
Group				
(ref: Booking Holdings)				
Expedia Group	-0.47***	-0.77***	-0.61***	-1.22***
	(0.00)	(0.00)	(0.00)	(0.00)
Direct channel	-0.12***	-0.16***	0.23***	0.32***
	(0.00)	(0.00)	(0.00)	(0.01)
Other OTAs	-0.53***	-0.87***	-0.18***	-0.35***
	(0.00)	(0.00)	(0.00)	(0.00)
Hotel characteristics	yes	yes	yes	yes
Hotel Popularity	yes	yes	yes	yes
Channel Popularity	yes	yes	yes	yes
N	15,089,110	15,089,110	15,089,110	15,089,110

Notes: Dependent variable: indicator sales channel visible (columns 1 and 2) or position leader (columns 3 and 4). Unit of observation: search request – hotel – channel. Regressions are estimated with probit (columns 1 and 3) or logit (columns 2 and 4). Standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 19: Visibility and Position Leadership at the group-level

	Conditional Logit			
	Visible ($\# \leq 4$)		Position Leader ($\# = 1$)	
	(1)	(2)	(3)	(4)
ln(price)	-31.76***	-31.91***	-3.70***	-3.66***
	(0.13)	(0.13)	(0.06)	(0.06)
Price leadership				
(ref: Not price leader)				
Among price leaders	1.58***	1.57***	3.14***	3.14***
	(0.01)	(0.01)	(0.01)	(0.01)
Unique price leader	1.51***	1.51***	4.70***	4.76***
	(0.01)	(0.01)	(0.01)	(0.01)
Group				
(ref: Booking Holdings)				
Direct channel	-0.34***	-0.22***	-1.08***	-0.53***
	(0.00)	(0.00)	(0.01)	(0.01)
Expedia Group	-0.84***	-0.75***	-1.25***	-0.77***
	(0.00)	(0.00)	(0.00)	(0.00)
Other OTAs	-0.63***	-0.51***	-1.63***	-1.09***
	(0.00)	(0.00)	(0.00)	(0.01)
Channel Popularity	no	yes	no	yes
N	13,017,822	13,017,822	15,108,629	15,108,629

Notes: Dependent variable: indicator sales channel visible (columns 1 and 2) or position leader (columns 3 and 4). Unit of observation: search request – hotel – channel. Regressions are estimated with conditional logit. Standard errors (in parentheses) are robust to heteroscedasticity and adjusted for serial correlation inside clusters. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 20: Visibility and Position Leadership by chain affiliation

	Conditional Logit	
	Visible	Position Leader
	($\# \leq 4$)	($\# = 1$)
	(1)	(2)
ln(price)	-31.83***	-3.65***
	(0.13)	(0.06)
Price leadership		
(ref: Not price leader)		
Among price leaders	1.57***	3.14***
	(0.01)	(0.01)
Unique price leader	1.51***	4.75***
	(0.01)	(0.01)
Group		
(ref: Booking Holdings)		
Direct channel	0.16***	-0.39***
	(0.01)	(0.01)
Expedia Group	-0.70***	-0.67***
	(0.00)	(0.00)
Other OTAs	-0.45***	-1.04***
	(0.00)	(0.01)
Chain × Group		
Direct channel	-0.72***	-0.31***
	(0.01)	(0.02)
Expedia Group	-0.23***	-0.36***
	(0.00)	(0.01)
Other OTAs	-0.24***	-0.17***
	(0.01)	(0.01)
Channel Popularity	yes	yes
N	13,017,822	1,5108,629

Notes: Dependent variable: indicator sales channel visible (column 1) or position leader (column 2). Unit of observation: search request – hotel – channel. Regressions are estimated with conditional logit. Standard errors (in parentheses) are robust to heteroscedasticity and adjusted for serial correlation inside clusters. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 21: Visibility and Position Leadership at the sales channel-level

		Conditional Logit			
		Visible (# $\leq$ 4)		Position Leader (# = 1)	
ln(price)		-31.32***	-31.42***	-3.18***	-3.16***
		(0.13)	(0.13)	(0.06)	(0.06)
Price leadership (ref: Not price leader)					
Among price leaders		1.92***	1.91***	3.38***	3.42***
		(0.01)	(0.01)	(0.01)	(0.01)
Unique price leader		1.23***	1.21***	5.07***	5.05***
		(0.01)	(0.01)	(0.01)	(0.01)
Sales Channel (ref: Booking.com)					
Booking Holdings	Agoda.com	-1.01***	-2.55***	-1.62***	-3.16***
		(0.00)	(0.01)	(0.00)	(0.01)
Expedia Group	Expedia	-1.49***	-2.81***	-1.48***	-2.79***
		(0.00)	(0.01)	(0.00)	(0.01)
	Hotels.com	-0.51***	-2.03***	-1.14***	-2.67***
		(0.00)	(0.01)	(0.00)	(0.01)
	Venere.com	-2.24***	-3.79***	-2.92***	-4.45***
		(0.00)	(0.01)	(0.01)	(0.01)
	voyages-sncf	-1.70***	-2.16***	-2.10***	-2.68***
		(0.00)	(0.00)	(0.01)	(0.01)
	(...)				
Direct		-0.75***	-2.23***	-1.62***	-3.04***
		(0.01)	(0.01)	(0.01)	(0.01)
Other OTAs	Amoma.com	-0.52***	-2.06***	-2.15***	-3.59***
		(0.01)	(0.01)	(0.01)	(0.01)
	Hotelopia.com	-1.47***	-3.02***	-2.60***	-4.08***
		(0.01)	(0.01)	(0.02)	(0.02)
	Logitravel.fr	-0.57***	-2.11***	-1.40***	-2.84***
		(0.00)	(0.01)	(0.01)	(0.01)
	(...)				
Channel Popularity		yes	yes	yes	yes
N		13,017,822	12,610,524	151,08,629	15,108,629

Notes: Dependent variable: indicator sales channel visible (columns 1 and 2) or position leader (columns 3 and 4). Unit of observation: search request – hotel – channel. Regressions are estimated with conditional logit. Standard errors (in parentheses) are robust to heteroscedasticity and adjusted for serial correlation inside clusters.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

F Robustness checks: Vertical ranking

F.1 Further results

Table 22: Hotel ranking by chain affiliation

	Ordinary Least Square Rank in search results		
# Price leaders	All	Multiple	Unique
min ln(price)	5.35	11.12	5.74
	(4.87)	(7.81)	(4.93)
# Sales Channels	3.04***	6.26***	2.47***
	(0.82)	(1.24)	(0.78)
# Sales Channel(s) Price Leader(s)	0.04	-2.37**	0.10
	(0.76)	(1.14)	(1.37)
Group Price leader indicators			
Booking Holdings	2.87	22.69***	(Ref.)
	(2.69)	(5.94)	(Ref.)
Expedia Group	-6.63**	1.52	-8.41***
	(2.83)	(7.02)	(3.11)
Direct channel	11.48**	-4.98	13.03**
	(5.10)	(9.03)	(5.95)
Other OTAs	4.89*	13.80***	2.02
	(2.68)	(4.47)	(3.19)
Chain $\times$ Group Price leader			
Booking Holdings	-4.79	-19.11*	(Ref.)
	(3.95)	(10.57)	(Ref.)
Expedia Group	-2.10	6.18	3.17
	(3.80)	(13.25)	(6.03)
Direct channel	-26.84***	-25.30**	-12.39
	(6.69)	(12.45)	(9.17)
Other OTAs	-11.32***	-20.62***	-2.68
	(4.13)	(7.61)	(6.36)
Constant	-587.20***	-595.69***	-613.37***
	(69.66)	(92.85)	(71.56)
Availability FE	yes	yes	yes
Group X Availability FE	yes	yes	yes
Request FE	yes	yes	yes
Hotel FE	yes	yes	yes
Hotel Popularity	yes	yes	yes
Channel Popularity	yes	yes	yes
N	2,022,992	565,104	1,457,823

Notes: Dependent variable: ranking of hotel in search results (multiplied by -1). Unit of observation: search request – hotel. Linear regressions include hotel and request fixed effects. Standard errors (in parentheses) are robust to heteroscedasticity and adjusted for serial correlation inside clusters.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 23: Hotel ranking at the sales channel level

		Ordinary Least Square		
		Rank in search results		
#Price leader(s)		All	Unique	Multiple
min ln(price)		4.07	6.02	9.18
		(4.80)	(5.17)	(6.18)
Channel Availability indicators				
Direct		-4.22	7.19	-21.26***
		(5.03)	(4.95)	(6.65)
Booking Holdings	Booking.com	30.04***	19.62**	18.11
		(8.82)	(9.04)	(13.57)
	Agoda.com	-3.73	-6.22*	-3.38
		(3.20)	(3.21)	(4.47)
Expedia Group	Expedia	-3.54	-4.49	6.72
		(3.11)	(2.92)	(5.52)
	Hotels.com	-0.58	-3.84	3.12
		(2.95)	(2.81)	(5.77)
	(...)			
Other OTAs	Amoma.com	1.40	3.04	-2.42
		(2.91)	(3.03)	(3.89)
	Hotelopia.com	-14.61***	-14.16***	-12.26***
		(2.87)	(3.00)	(3.98)
	Logitravel.fr	-3.64	-1.19	-8.59**
		(2.43)	(2.33)	(3.78)
	(...)			
Channel Price leader indicators				
Direct		-1.95	9.42*	-35.93***
		(3.35)	(4.90)	(5.53)
Booking Holdings	Booking.com	0.32	(Ref.)	3.05
		(1.92)	(Ref.)	(2.64)
	Agoda.com	2.63	-0.92	7.91**
		(2.34)	(4.23)	(3.13)
Expedia Group	Expedia	0.92	-26.38***	-9.90**
		(2.79)	(6.76)	(4.08)
	Hotels.com	-2.00	1.79	-1.07
		(2.74)	(5.12)	(4.13)
	(...)			
Other OTAs	(...)			
Constant		-571.85***	-599.29***	-628.04***
		(67.81)	(71.47)	(83.76)
Request FE		yes	yes	yes
Hotel FE		yes	yes	yes
Hotel Popularity		yes	yes	yes
Channel Popularity		yes	yes	yes
N		2,022,992	1,264,515	758,405

Notes: Dependent variable: ranking of hotel in search results (multiplied by -1). Unit of observation: search request – hotel. Linear regressions include hotel and request fixed effects. Standard errors (in parentheses) are robust to heteroscedasticity and adjusted for serial correlation inside clusters.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 24: Hotel ranking at the group-level (vertical ranking)

	Ordinary Least Square		
	Rank in search result		
# Group Price leaders(s)	All	Unique	Multiple
min ln(price)	4.53	5.95	9.46
	(4.90)	(4.96)	(7.82)
# Sales Channels	3.05***	2.49***	5.83***
	(0.83)	(0.78)	(1.26)
# Sales Channels Price leader(s)	-0.78	-0.08	-3.04***
	(0.76)	(1.39)	(1.15)
Group Price leader indicators			
Booking Holdings	4.08	(Ref.)	13.37**
	(3.07)	(Ref.)	(5.71)
Expedia Group	1.84	-21.88*	2.44
	(3.32)	(11.49)	(7.33)
Direct channel	-28.79***	-34.57**	-38.64***
	(4.57)	(14.45)	(7.22)
Other OTAs	2.57	-12.90	7.54*
	(2.88)	(11.24)	(3.90)
Group Position Leader (ref: Booking Holdings)			
Expedia Group	-9.87	-11.75*	-32.23
	(7.11)	(7.13)	(23.88)
Direct channel	-34.09***	-34.23***	-40.48**
	(9.30)	(10.09)	(18.60)
Other OTAs	-2.71	-12.42	18.66
	(8.88)	(9.33)	(19.63)
Group Price & Position Leaders			
Booking Holdings	-6.57	-17.83	-21.29*
	(5.74)	(11.15)	(12.88)
Expedia Group	-3.60	8.56	6.13
	(6.52)	(8.57)	(20.94)
Direct channel	70.48***	64.06***	48.72***
	(10.41)	(15.53)	(16.02)
Other OTAs	-1.11	9.66	-44.69***
	(8.25)	(10.29)	(15.67)
Constant	-588.06***	-604.66***	-564.82***
	(69.53)	(72.16)	(94.05)
Request FE	yes	yes	yes
Hotel FE	yes	yes	yes
Group availability	yes	yes	yes
Hotel Popularity	yes	yes	yes
Channel Popularity	yes	yes	yes
N	2,022,992	1,457,823	565,104

Notes: Dependent variable: ranking of hotel in search results (multiplied by -1). Unit of observation: search request – hotel. Linear regressions include hotel and request fixed effects. Standard errors (in parentheses) are robust to heteroscedasticity and adjusted for serial correlation inside clusters. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

F.2 Non-linear models

Table 25: Hotel ranking at the group-level (vertical ranking)

	Rank-Ordered Logit (10)		
	Rank in search result		
# Group Price leaders(s)	All	Unique	Multiple
min ln(price)	-0.18***	-0.22***	0.16**
	(0.03)	(0.04)	(0.07)
# Sales Channel(s)	-0.01	-0.01**	0.03**
	(0.00)	(0.01)	(0.01)
# Sales Channel(s) Price Leader(s)	0.01	0.02	-0.02
	(0.01)	(0.02)	(0.02)
Group Price leader indicators			
Booking Holdings	0.10***	(Ref.)	-0.00
	(0.03)	(Ref.)	(0.11)
Expedia Group	0.01	-0.13***	-0.04
	(0.04)	(0.04)	(0.11)
Direct channel	-0.10***	-0.30***	0.08
	(0.04)	(0.04)	(0.08)
Other OTAs	-0.11***	-0.27***	0.02
	(0.03)	(0.03)	(0.07)
Request FE	yes	yes	yes
Hotel characteristics	yes	yes	yes
Group availability	yes	yes	yes
Hotel Popularity	yes	yes	yes
Channel Popularity	yes	yes	yes
N	2,023,051	1,457,882	565,169

Notes: Dependent variable: ranking of hotel in search results (multiplied by -1). Unit of observation: search request – hotel. Regressions are estimated with rank ordered logit and include request fixed effects. Standard errors (in parentheses) are robust to heteroscedasticity and adjusted for serial correlation inside clusters.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 26: Hotel ranking at the group-level (vertical ranking)

	Rank-Ordered Logit (20)		
	Rank in search result		
# Group Price leaders(s)	All	Unique	Multiple
min ln(price)	-0.24***	-0.27***	-0.06
	(0.02)	(0.02)	(0.04)
# Sales Channel(s)	-0.01*	-0.01	0.01
	(0.00)	(0.00)	(0.01)
# Sales Channel(s) Price Leader(s)	0.01*	0.06***	-0.01
	(0.01)	(0.01)	(0.01)
Group Price leader indicators			
Booking Holdings	-0.02	(Ref.)	-0.13*
	(0.02)	(Ref.)	(0.06)
Expedia Group	-0.05**	-0.08***	-0.08
	(0.02)	(0.02)	(0.07)
Direct channel	-0.06**	-0.03	-0.11**
	(0.02)	(0.03)	(0.05)
Other OTAs	-0.12***	-0.11***	-0.10***
	(0.02)	(0.02)	(0.04)
Request FE	yes	yes	yes
Hotel characteristics	yes	yes	yes
Group availability	yes	yes	yes
Hotel Popularity	yes	yes	yes
Channel Popularity	yes	yes	yes
N	2,023,051	1,457,882	565,169

Notes: Dependent variable: ranking of hotel in search results (multiplied by -1). Unit of observation: search request – hotel. Regressions are estimated with rank ordered logit and include request fixed effects. Standard errors (in parentheses) are robust to heteroscedasticity and adjusted for serial correlation inside clusters.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$