Danish Competition and Consumer Authority

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COMPETITIVE MARKETS
AND CONSUMER WELFARE

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DO RANKING BOOSTS HARM CONSUMERS AND COMPETITION?

INDICATIVE EVIDENCE FROM ONLINE TRAVEL AGENCIES

Product ranking on online digital platforms are important to consumers, sellers, and platforms. Complex algorithmic ranking systems enable sellers to improve their placements in the platform's product ranking in exchange for in-creased commissions.

This article presents two studies of the ranking system of an online travel agency: a descriptive analysis of ranking boosts and a behavioral experiment that compares the effectiveness of price reductions to that of ranking boosts in terms of sales.

In combination, the two analyses suggest that ranking boosts on OTAs are more attractive than discounts, and while consumers benefit directly from price reductions, it is unclear how they would benefit from ranking boosts.

As such, encouraging companies to pay for ranking boosts rather discounting prices may be detrimental to consumers.

Read the Article ↓

1. Digital platforms

Digital platforms represent one of the great digital consumer revolutions of the 21st century. Like the rise of the supermarkets in the 1940s, digital platforms offer an unprecedented variety of products, with lower search costs and more intense competition between sellers. This is demonstrated by the growth and prominent position of these platforms in specific markets. In 2020, online travel agencies (OTAs) captured 27 pct. of all online hotel bookings (or 38 pct. of all online hotel bookings in Europe), with Booking Holdings and Expedia Group responsible for more than half of these OTA sales.[1]

Online platforms rely on complex, algorithmic recommender systems to quickly identify and present relevant products to its users [2]. An important part of this process is how products are ranked by the algorithm, since ranking is believed to strongly influence consumer choices on the platform[3].

This article presents two analyses of OTA ranking and ranking boosts. The first, a scraping analysis, investigates the algorithmic rank, and the effect of commission-based boosts on the ranking of sellers. The second uses a randomized online choice experiment to test whether ranking boosts or price reductions attracts more customers.

Main results

- Ranking boosts are common and strongly influence the default OTA ranking
- Hotels that are larger, more expensive or part of an international chain are more likely to use ranking boosts
- In an online choice experiment designed by the DCCA, ranking boosts significantly outperform discounts as a means to attract customers

The article first introduces product ranking and the concept of ranking boosts, then presents the scraping analysis and finally the choice experiment.

2. Product ranking on digital platforms

This article, as well as the Danish Competition and Consumer Authority's (DCCA) recent article about Google advertisements, are both examples of research by the DCCA that shines a light on recommender systems used by digital platforms and how they influence product ranking.[4]
The article was presented to the relevant OTA for comment before publication.

Product ranking is a natural and unavoidable part of an online platform's choice architecture since products must be presented to consumers in some order.

If the order of a specific range of products do not help consumers find what they want they incur increased search costs and ultimately may end up with less relevant products[5]. Meanwhile, sellers have a vested interest in making their products appear as close to the top of a list as possible, since this increase their chance of catching the consumer's interest and ultimately making a sale.

Product ranking falls into two broad categories, i.e. static- and algorithmic ranking models:

1. Static ranking models rank products by an explicit attribute such as price or customer reviews. The advantage of this format is that the ranking criteria are transparent for both consumers and sellers. The disadvantage is that static models cannot capture complex preferences, that are not fully accommodated by a single product attribute.

2. Algorithmic ranking models can take in any number of product and user traits and rank the products in a way that matches complex consumer preferences. Platforms typically label these algorithmic rankings as "recommended", "favorite" or "featured", and they are often the default ranking mechanism used by platforms. While algorithmic ranking allows for more flexible ranking criteria they also come with reduced transparency, since neither consumers nor sellers on the platform can know with any certainty why a product obtains exactly the rank it does on a specific list.

By going beyond the simple order of static ranking models, algorithmic ranking models also allow the platform to boost the rank of a seller in exchange for an increased commission. Because the algorithmic ranking uses a range of inputs, the use of boosts avoids directly violating the logic of the ranking order (which would happen if platforms changed the ranking order of a static list).

Box 1:

In 2021, the DCCA published an analysis of digital platforms targeting Danish consumers. The report investigated the prevalence of the marketing design practices targeting Danish consumers on 107 digital platforms. Product ranking was found to be the third-most prevalent method and was present in 83 pct. of the reviewed sites.[6]

1 HOTREC: Hotel distribution study 2022

2 Fletcher, A, Ormosi, PL., and Savani R. "Recommender systems and supplier competition on platforms." Available at SSRN (2022).

3 Competition and Markets Authority (2022): Evidence Review of Online Choice Architecture and consumer and competition harm: Ranking

4 (in Danish) KFST (2023): Betydningen af annoncer for forbrugernes adfærd på onlinesøgemaskiner

5 Ursu, R. M. (2018), 'The power of rankings: Quantifying the effect of rankings on online consumer search and purchase decisions', Marketing Science 37(4), 530–552

6 (in Danish) KFST (2021) Markedsføring på digitale platforme – vejledende eller vildledende?

3. Ranking boosts

Ranking boosts are any increase in a product's rank that occur, not because the product is superior in terms of price or quality as judged by the algorithm, but because a seller pays the platform to boost its rank[7].

Digital platforms can use several different types of ranking boosts.

1. Pay per click: Top spots are auctioned off to the sellers who then pay some amount for each click on their product.
2. Permanent: Sellers pay a higher commission to be in a partnership program, which increases their rank by some factor. These programs are typically long term or permanent.
3. Temporary: Sellers pay a higher commission in exchange for a temporarily increased rank on the platform. These boosts can be switched off and on by the seller.

The pay-per-click model deviates from the temporary and permanent ranking boosts in significant ways. While temporary and permanent ranking boosts increase a seller's "organic" rank, the pay-per-click model allows any seller to take top spots, regardless of their organic rank. This means that the model provides sellers with an absolute improvement to their rank independent of their algorithmic rank.

This difference makes the pay-per-click more like a traditional ad, in the sense that the seller occupies a reserved spot, and that spot needs to be clearly demarcated as such.

The other two models rely on direct manipulation of the algorithmic rank. This means that these two models provide sellers with a relative improvement to their rank that takes their organic rank as a starting point and boosts it by some factor or level.

Since ranking is an integral part of how platforms present products to consumers, and since boosts are an important part of most platforms' business model, it is increasingly important to understand the role that ranking boosts play in the business-to-platform economy.

This includes how prevalent they are, who buys them, how they interact with other ranking criteria and how they affect consumers' purchases on the platforms.

4. Analysis of an online travel agency's ranking model

Online travel agencies (OTA) are good candidates for analyzing and testing platform ranking. While ranking models exist across most platforms, the uniformity of product offerings on OTAs allows for better comparison between ranks of sellers. This is because products on OTAs have very similar characteristics and because the number of sellers is large. This is contrary to many retail-sites where sellers belong to smaller, distinct, categories, which are not necessarily comparable.

Therefore, the DCCA conducted an analysis of data scraped from a large online travel agency in the fall of 2020. The data analysis aims to better understand three aspects of product ranking and the role of boosts:

- How common are ranking boosts?
- Who buys ranking boosts?
- What factors or characteristics drive the algorithmic ranking, and how does it relate to the static ranking-options such as user reviews and price?
- How do price reductions affect the algorithmic ranking of sellers?
- How do boosts affect the algorithmic ranking of sellers?

The DCCA developed a web crawler for the purpose of the analysis - a program that automatically browses webpages, according to a set of instructions. The actual retrieval of information is referred to as scraping.[8]

> Box 2:
>
> The web crawler was set up with a cookie-less browser from a Danish IP-address, which accessed the online travel agency and filled out the necessary forms. This means that the web crawler probably never saw a personalized site, but simply the default for an unknown consumer from Denmark. The web crawler then browsed through each page of hotel listings. Information from the hotel listings were saved to a database.
>
> The consequence of using a blank browser is that modifications to the search results that would result from personalization strategies are not covered by this analysis.

785 individual searches were conducted by the web crawler, across 68 cities. The data collected included 443,232 listing results with 66,386 unique rooms from 47,673 hotels[9].

5. OTAs ranking of hotels

The algorithmic rank is likely affected by several factors. Some of these would not be possible to scrape, e.g. consumer click behavior, while other would be available but impossible to model with only publicly available data, e.g. picture aesthetics.

7 Bourreau, M., and Gaudin, G. "Streaming platform and strategic recommendation bias." Journal of Economics & Management Strategy 31.1 (2022): 25-47.

8 The web crawler was built in Python 3.7, using the Selenium web driver, while BeautifulSoup was used to scrape information off the site.

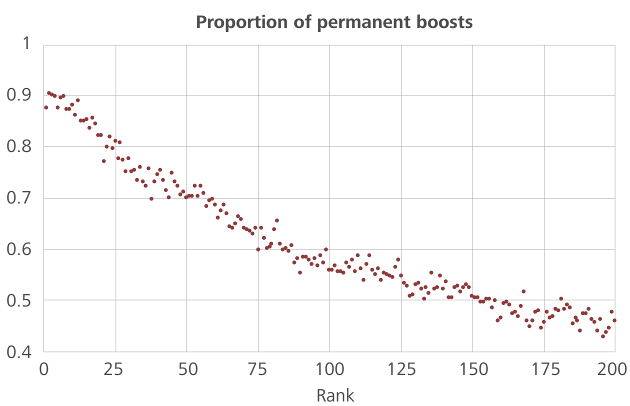
9 The original dataset had 450,755 listing results, but 7523 results were removed for being duplicates, with the highest ranked listing being retained.

However, by looking at the characteristics of the hotels that appear high or low in the ranking, it is possible to assess which factors predict better ranks. The next sections first outline the prevalence of ranking boosts and the relationship between different hotel attributes and the OTA's algorithmic ranking.

5.1. How common are ranking boosts?

37.1 pct. of the 47,683 hotels in the scraped dataset had permanent ranking boosts, which in this case means that they are part of specific partner program that the platform offers to sellers against an increased commission. Figure 1 shows the percentage of listings with permanent ranking boosts, as a function of the rank, with lower ranks meaning closer to the top spot on the product listing.

Figure 1: **Share of listings with permanent ranking boosts per rank level**



Note: Each dot represents the proportion of listings with permanent ranking boosts (y-axis), for a particular position in the ranking (x-axis). A higher number on the x-axis equals further distance from position 1 on the list.

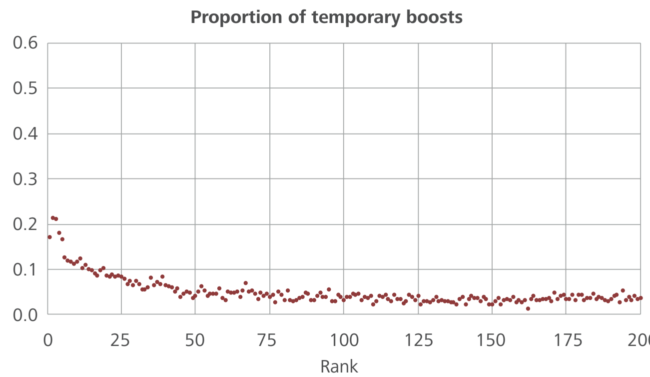
Each page on the OTA presents 25 search results to the user. As can be seen in figure 1 the share of listings with permanent ranking boosts grows rapidly when approaching the first few pages, reaching 85.5 pct. on the first page (rank 1-25) and 74.2 pct. on the second (rank 26-50).

4.3 pct. of hotels purchased temporary ranking boosts at some point within the scraping period. Temporary ranking boosts display a similar, though less pronounced, increase in frequency when approaching the first pages. It is worth noting that a hotel can employ both temporary and permanent ranking boosts.

The percentage of temporary ranking boosts on the first page is 11.8 pct., and 6.1 pct. on the second page (see figure 2). For the top-five spots on the OTA, temporary ranking boosts were observed in 18.9 pct. of listings.

Both these results follow naturally from the fact that the purpose of boosts is to bring the listed items closer to the front page.

Figure 2: **Share of listings with temporary ranking boosts per rank-level**

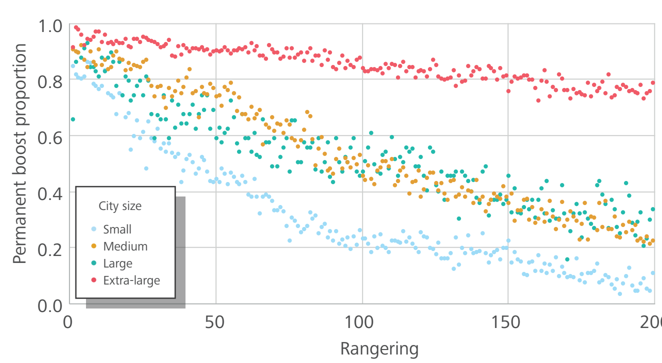


It is important to note that temporary ranking boosts are targetable, i.e. the sellers can increase their rank exclusively towards a specific customer group.

Because the data was collected with a static setup, see box 2, the true percentage of temporary ranking boosts may be both higher or lower for an individual user of the platform.

City size and number of competitors seems to play an important role for the prevalence of ranking boosts. Grouping cities into four segments of equal range based on the number of sellers, demonstrates that there are systematic differences in the proportion ranking boosts (see figure 3).

Figure 3: **Share of listings with permanent ranking boosts per rank-level – differentiated by number of sellers**



Note: City size (number of sellers) are grouped into four categories and plotted as different colors (blue = small, green = medium, yellow = large and red = extra-large).

In cities with the most sellers, 94.6 pct. of results on the first page have permanent ranking boosts, while in the cities with fewest sellers this is only the case for 74.2 pct. of results. For the largest cities, the percentage of sellers with permanent ranking boosts decreases by 2.7 pct. on each page over the first five pages, while for the smallest cities it decreases by 13.1 pct.

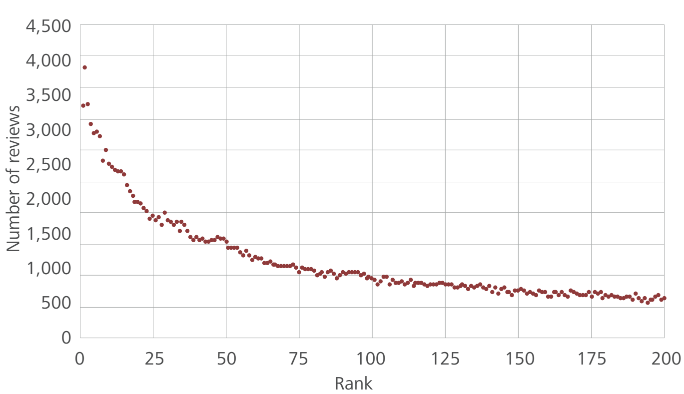
5.2. Algorithmic ranking and demand

The OTA lists expected demand for a hotel as one of the parameters for the algorithmic ranking. This makes sense because the platform derives its profit from commissions. The higher the demand for a hotel, the more likely it is that new customers will like it too and so the platform has an incentive to show it prominently. While demand was not possible to scrape directly, the site did contain data on hotels' total number of reviews.

The number of reviews a hotel has is largely a result of how many customers they have had in the past. It is not an unbiased variable since this number accumulates over the lifetime of the seller on the platform. It is likely to be insensitive to short term changes in demand, and biased against new entrants. However, it is still a valuable marker for long-term demand.

There is a pronounced relationship between a hotel's number of reviews and their rank, with a correlation of -0.47. Thus, hotels with more demand have a better position, on average, in the platform's algorithmic ranking[10].

Figure 4: **Average number of user reviews**

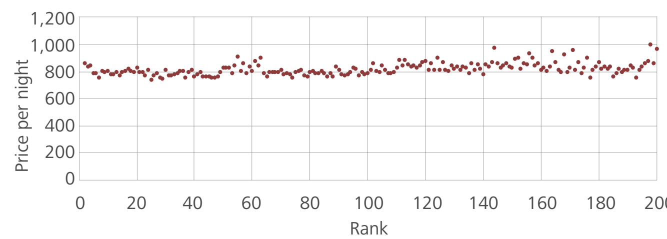


5.3. Algorithmic ranking and price and customer reviews (static factors)

One interesting aspect of the algorithmic ranking is how it relates to static factors such as price and review scores[11], that are typically offered by platforms as alternative (static) ranking models.

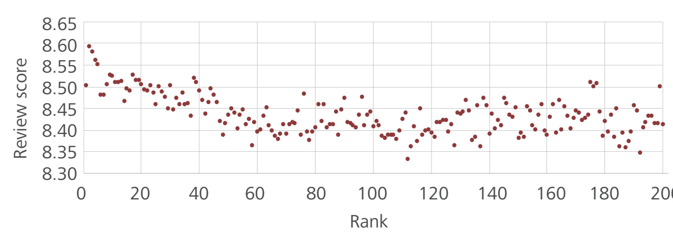
As can be seen from figure 5a, algorithmic ranking does not seem to correlate with price[12]. This suggests that the rank only depends on the price to a limited extent[13]. The review score in figure 5b similarly does not appear to have a relation to the rank either, with a correlation of .06.

Figure 5a: **Average price per night for the top 200 hotels**



Note: Each observation in this figure is an average of prices for a number of hotels on each specific rank

Figure 5b: **Average user review score for the top 200 hotels**



Note: Review score goes from 1-10.

As such, it appears that the static ranking options do not systematically correspond to or predict the algorithmic ranking. Prices may be uncorrelated because demand is evenly distributed for differently priced hotels, and user ratings may be uncorrelated because hotels with lower ratings can compensate by offering cheaper rooms.

While prices in general appear unrelated to the algorithmic ranking, price discounts could still play a role. Like ranking boosts, price discounts are a way for sellers to increase the shortterm visibility and attractiveness of their product. If discounts make rooms more attractive, we would expect the algorithmic ranking to favor discounted rooms and this appears to be the case to some extent, with an average of 19.1 pct. of sellers carrying price discounts on the first page, decreasing to 15.6 pct. on the fifth page (see figure 6).

10 An alternative explanation could be that popular hotels more often invest in ranking boosts or that investing in ranking boosts increases review count over time due to higher demand. Figure 7 and 8 demonstrates that more popular hotels are more likely to buy permanent boosts but not temporary.

11 Other static ranking options could be the number of stars, distance from certain landmarks and similar options.

12 The measure used for price, is the nightly price, i.e. the price divided by the number of nights.

13 Note that this outcome in and of itself does not preclude that price influences hotel ranks. Strong competition on prices could lead to a similar pattern. However, similar results are obtained in the regression analyses presented in section 5.4.

Figure 6: **Proportion of price discounts**

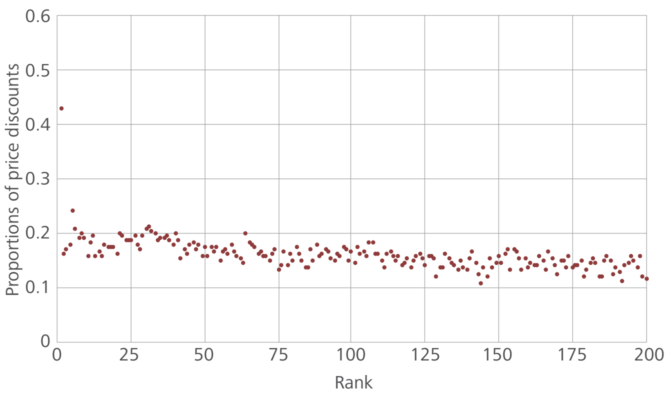
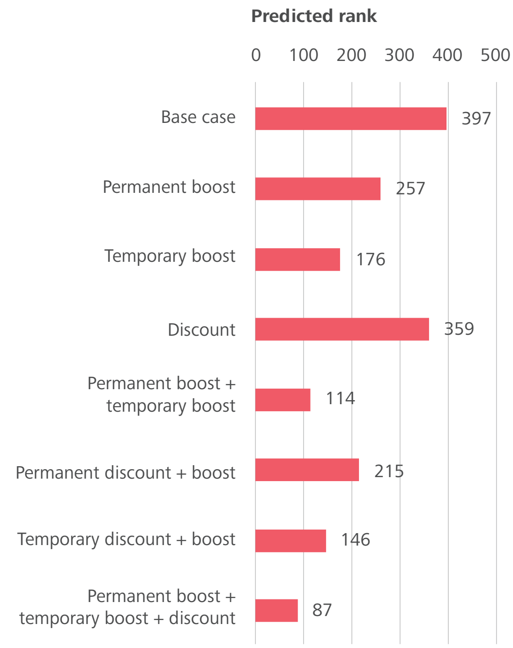


Figure 7: **predicted changes in rank for a base case hotel**



Note: Different bars represent the rank of the base case hotel, with different combinations of discounts, temporary ranking boosts and permanent ranking boosts. The base case hotel is a hotel with mean values across background variables, with no boosts and no discount.

5.4. Estimating the effect of ranking boosts

To better understand how hotels are ranked, and the role that ranking boosts play in ranking, an estimation of the ranking was performed.

The target for estimation was the log of the rank instead of the actual rank. To control for characteristics of the hotel, a number of control variables were included into the model, such as the price and the review score and count. The appendix contains full description of the model.[14]

Note that some control variables have missing values, namely the number of reviews a hotel has and the corresponding review score. This is likely due to the OTA not displaying a review score, when a hotel has few reviews. These listings (n=66,206) are not included in the model sample, reducing the sample size to 377,026.

For illustrative purposes, the models are presented through figures illustrating the effects of changes to different hotel variables. The full models can be found in the appendix. Using a base case of a hotel with mean values across background variables, figure 7 illustrates the estimated effect of acquiring temporary and permanent ranking boosts, as well as the effect of having temporary price discounts.

In this estimation the base case hotel is from a city with a high number of sellers. The appendix contains examples using base cases from smaller cities. These show largely similar results.

Since the estimations rely only on publicly available data there is a risk of bias from omitted variables, e.g. from not including actual data on demand for different hotels, user click stream data or data on hotel complaints or refund demands. While omitted variable bias cannot be ruled out, appropriate controls have been implemented where possible, for instance by using review numbers as proxy for long term demand.

Note that while hotel prices are accounted for in the model, the "discount" does not refer to the price reduction itself, instead it represents a binary indicator of whether there is a temporary discount on the hotel.[15]

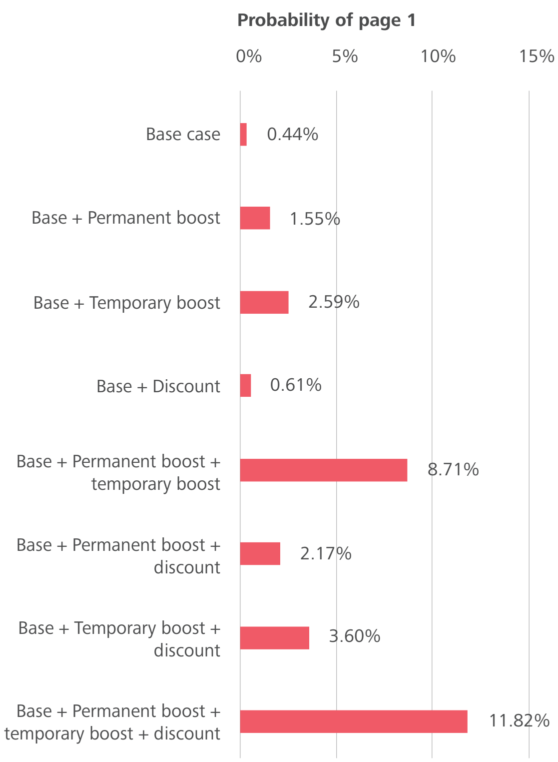
As can be seen from figure 7, the estimated effect of boosts on the hotel rank are large. The base case hotel has a rank of 397, while the same hotel with both temporary and permanent ranking boosts has an estimated rank of 114 – a difference of 283 ranking positions.

A different way of looking at the effects of boosts is the probability of appearing on page 1 (top 25 spots). This was modelled using a logistic regression with the same control variables as the log-linear estimation. The results are illustrated in figure 8.

14 The model is specified using all two-way interactions with permanent and temporary ranking boosts, and then simplifying the model through iterative elimination of terms insignificant at the 0.001 level.

15 This is marked on the OTA by a crossed-out reference price

Figure 8: **Predicted probability of a base case hotel having purchased a temporary ranking boost**



Note: Different bars represent the probability of the base case hotel appearing on page 1, with different combinations of discounts, temporary ranking boosts and permanent ranking boosts. The base case hotel is a hotel with mean values across background variables, with no boosts and no discount..

The logistic model shows the same patterns as the estimation of rank. The base case hotel with no promotions has a 0.4% chance of being on the first page. Having a permanent ranking boost, increases this to a 1.6% chance, while a temporary ranking boost increases the probability to appear on first page to 2.6%. Purchasing both boosts increases this further to an 8.7% chance, and including the price discount has the best chance of 11.8%.

5.5 Who buys ranking boosts?

If boosts are used mainly by entrants, it can help them overcome the disadvantage of not having the necessary historical demand for a prominent rank in the algorithmic model.

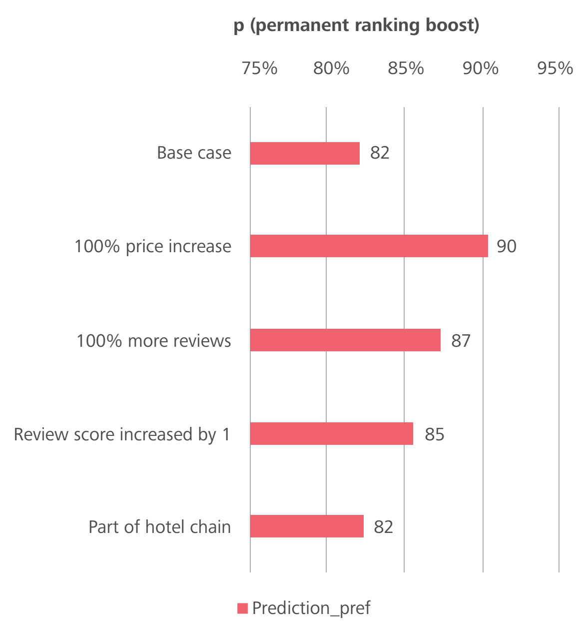
However, if boosts are used mainly by incumbents, it could increase their existing market power and make it even harder for entrants to enter the market and grow.

Thus, ranking boosts matters for the competitive pressure in a market but the direction of this effect depends on which types of hotels are buying the boosts.

To answer this question, the DCCA built two models to explain who buys 1) temporary and 2) permanent ranking boosts.

Note, that the estimates for the permanent ranking boost deviate from the descriptive values reported earlier. There are two reasons for this:
Firstly, the base case in the model uses cities with 1,000 or more hotels, where the estimate for preferred partner are higher (56%). Secondly, the estimate is based on hotels who could qualify for the boost[16].

Figure 9: **Predicted probability of a base case hotel having purchased a permanent ranking boost**

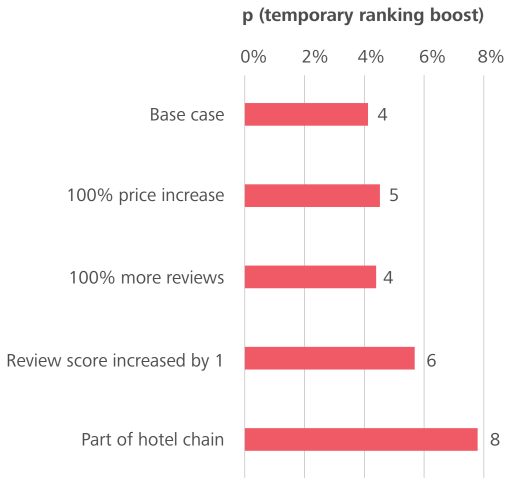


Note: Different bars represent the probability of the base case hotel having a permanent ranking boost, modified by variations in price, amount of reviews, review score (scale of 1-10) and membership of a hotel chain.

As can be seen in figure 9 and 10, the number of reviews on the platform, which is related to long-term demand of the hotel, increases the probability of having either a permanent or temporary ranking boost. Being part of a hotel chain, also increases the probability of having purchased a temporary ranking boost. Lastly, more expensive hotels are also more likely to purchase boosts.

16 Having a certain review score is a prerequisite for having the permanent ranking boost. The number of hotels screened out by this criterion is 20,149 or around 6 pct.

Figure 10: **Predicted probability of a base case hotel having purchased a temporary ranking boost**



Note: Different bars represent the probability of the base case hotel having a temporary ranking boost, modified by variations in price, amount of reviews, review score (scale of 1-10) and membership of a hotel chain.

Thus, ranking boosts do not appear to be predominantly purchased by less established hotels, but rather by those that are more established – and expensive.

5.6 Scraping summary

The algorithmic ranking seems to have little in common with the static ranking (price and review-score), and the algorithmic rank is more correlated with other factors, such as the number of reviews a seller has, a proxy for the long-term demand for a hotel.

Purchases of permanent ranking boosts are much more frequent than price discounts or temporary ranking boosts, especially in cities with many hotels, where 95% of hotels on the first page had permanent ranking boosts.

Estimations of the ranking model suggest that ranking boosts play a large role in determining the ranking of a seller in the algorithmic ranking model. Considering the prevalence of ranking boosts, as well as their estimated effect, ranking boosts can be considered to be a major part OTA ranking.

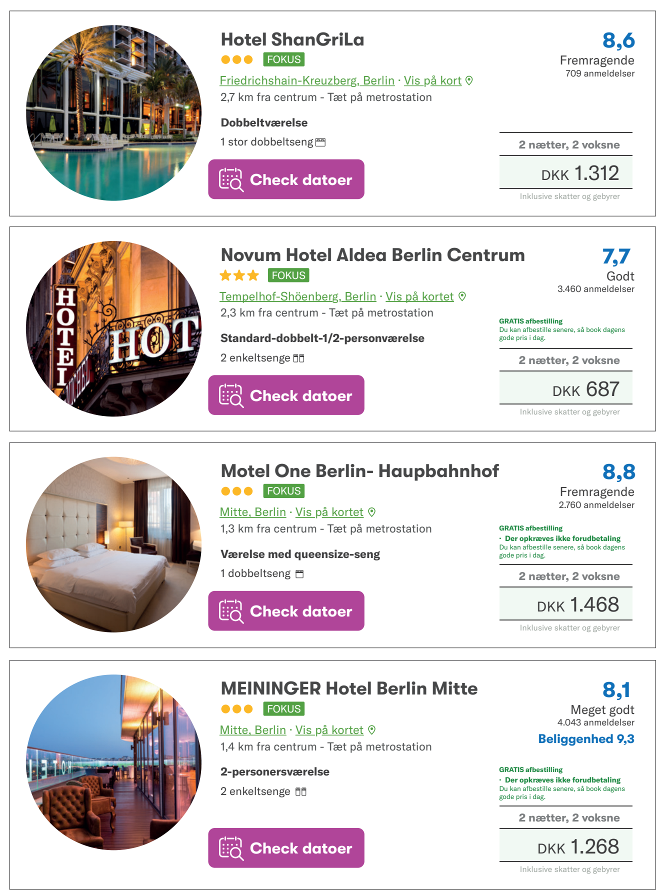
Finally, both permanent and temporary ranking boosts appear to be used more by established hotels, hotels that are more expensive and hotels that are part of international chains.

6. Do boosts or price reduction attract more customers? – an experimental test.

If a seller on a platform wants to increase sales it can choose to boost its rank, offer customers a discount or both. But which is the better strategy? This is an important question since both strategies can be seen as an investment by the hotel to increase future profits or market shares but only one of them directly benefits the consumer. While investing in ranking-boosts can be expected to increase prices on hotel rooms, a price-reduction obviously has the opposite effect.

The scraping data cannot answer this question as it does not contain data on the reasons why the hotels chose different strategies, or how well they worked. Therefore, an experiment was set up to test how the different strategies of hotels directly affect consumer choice.

Figure 11: **Example image of the experiment**



6.1 Experiment design and external validity

An experiment makes it possible to test causal hypotheses, such as whether a boost or a discount more effectively attracts consumers, but any result must be considered alongside the experiment's external validity. This corresponds to how well the experiment captures the nature of the choice consumers face in the real world[17].

To ensure high external validity it is important to consider a range of elements, including the design of the experiment, the recruitment and instruction of participants and the nature of the task that participants have to carry out.

In this experiment participants were asked to choose a hotel in Berlin from a list of 50 ranked options. The interface was designed to closely mimic the design of an existing OTA (see figure 11) and all ranks, prices and pictures were sourced using scraped data.

This ensures that the nature of the choice task was simple and similar to how consumers choose hotels on real OTAs. The use of scraped data ensured that all the features in the experiment (pictures, names etc.) and variables (prices, ranks etc.) corresponded to what consumers would see in a real market.

Participants were recruited through a survey and entered into the experiment if they expressed interest in staying at a hotel in Berlin over the course of the next 6 months. This ensured that participants in the experiment had an explicit interest in travel and in the hotels they could choose from. Finally, participants were offered the chance to win a voucher of 500 DKK (~67 EUR) to the hotel they picked. This incentive meant that participants had a real stake in the choice task and had to balance price and quality, since the voucher would apply to only the hotel they chose and they would have to pay any remaining difference in price themselves.

6.2. Simulation of hotel strategies

A central challenge in testing the effect of ranking boosts on consumer choice is how to modify the ranking in the experiment. For this analysis, the DCCA did not have access to the ranking algorithm of the OTA and any modification to the rank had to depend on an estimate of the ranking-boosts magnitude.

It is unlikely that any available estimate of ranking boosts would be entirely correct. Further, it is reasonable to assume that the platform regularly modifies the weight of the ranking boosts, as well the ranking model itself This means that even a perfect estimate might not be perfect for long. Therefore, the experiment is not an attempt to achieve a perfect representation of ranking boosts in the OTA's ranking model but rather a test of the attractiveness of ranking boosts vs. price reductions in an OTA context using real data (hotels and ranks).

To test the attractiveness of ranking boosts vs. discounts each hotel in the experiment was randomly assigned to one of four strategies:

- Neutral – No ranking boosts or price reductions
- Price discount – hotel price was discounted by 10 pct. with the previous price visible and crossed out
- Ranking boost – The hotel was given a ranking boost of 10 or 20 positions, as well as a marker indicating that it had been (temporarily) boosted.
- Price discount + ranking boost – a combination of the two interventions

Prior to the experiment, hotels were stripped of pre-existing price reductions and booster markers. [18]

Strategies were then assigned randomly but with a fixed distribution of 50 pct. neutral hotels, 20 pct. using price discount, 20 pct. using ranking boost, and 10 pct. using price discount and ranking boost. The distribution was inspired by the level of temporary ranking boosts in the scraping analysis (11.8 pct. on the first page), and price reductions (19.1 pct. on the first page), but adjusted upwards to 20 pct. to broaden the representation of boosted hotels, and match the group size.

It is worth noting that a permanent ranking boost at the time of the experiment, was marketed at the cost of a 3-percentage points increase in commissions. Meanwhile the effect of a permanent ranking boost on the base case hotel, was estimated to represent an increase of 140 rank positions. On that basis, the ranking increase that a hotel would receive from a 10-percentage point increase in commissions, is likely to be underestimated in the experiment.

Temporary ranking boosts were chosen as the ranking boost in the experiment, because of their relative infrequency, compared to permanent ranking boosts. Ranking boosts are a relative merit in the sense that if all sellers buy the same boost, their rank remains the same[19]. This is nearly the case for permanent ranking boosts– with a prevalence of 85 pct. on the first page. The temporary ranking boosts, on the other hand, were present in only 11.8 pct. of cases, on the first page.

17 Competition and Markets Authority (2023): Experiments at the CMA: How and when the CMA uses field and online experiments.

18 3 out of 50 hotels, had preexisting temporary ranking boosts. These hotels were moved down 9 ranking positions on the list, before assignment of strategies, based on conservative estimates of the effect of ranking boosts. Hotels with permanent ranking boosts did not receive a penalty. While discounted prices might affect the ranking to some extent as well (see figure 5), ranks were not changed with price reductions in the experiment, in order to make a clean comparison between ranking boosts vs price reductions.

19 Note that this does not remove the incentive to buy a ranking boost for an individual seller. If a seller purchases a ranking boost, they enjoy an increased rank, relative to the sellers who do not have one. Likewise, if a seller refuses to buy a ranking boost, their rank will decrease as other sellers buy ranking boosts. Also note that this excludes the presence of potential interaction effects between ranking boosts and price that might change the weight of other hotel parameters in their algorithmic ranking score.

To reduce incidental overlap between attractive hotels and attractive strategies, assignment was done thirty times, creating thirty scenarios, with random assignment of strategies in each scenario.

To estimate the effect of larger vs. smaller ranking boosts, a ranking boost boosted a hotel by 10 positions in half the scenarios and by 20 in the other half.

6.3 Analysis design

The analysis used a multinomial logit model, which is the typical method used for discrete choice experiments. It is useful when attempting to explain individuals' choice of an option among a set of alternatives.

The model estimates the probability of picking one of multiple options as a function of its features. Hence, the model is well suited to estimate how the strategy of a hotel, affects the probability of that hotel being chosen.

The model was specified to include the four strategies (neutral, price-reduction, ranking boost, price-reduction + ranking boost), with the neutral group acting as a reference group. To control for the possibility that some hotels are more attractive than others, dummies were created for each hotel.

A second model was constructed which included the differential size of the ranking boost (10 or 20 ranking positions) in the ranking boost, and price-reduction + ranking boost groups, to estimate the effect of larger and smaller boosts.

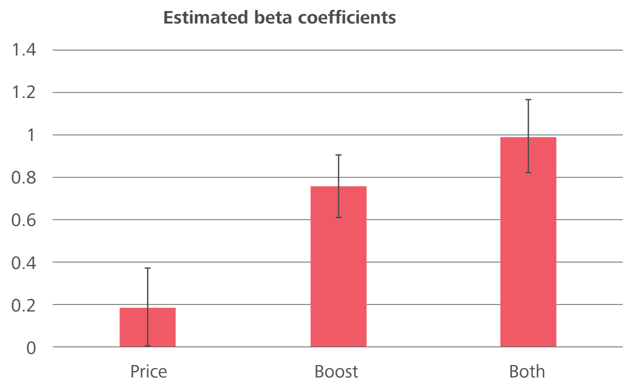
6.4. Results

1,114 consumers completed the experiment. Consumers were evenly split between sexes, and the average age was 50.4 (sd=18.5).

All strategy groups outperformed the neutral group with statistically significantly effects. However, there were large differences in the magnitude of these effects.

As seen in figure 12 the impact from the temporary ranking boost was 4.1 times larger than the price reduction, while the ranking boost + price reduction was 5.4 times larger. The difference between ranking boost and price reduction + ranking boosts was statistically significant as well.

Figure 12: **Effects on likelihood of choosing a particular hotel in the choice set, depending on the strategy employed**

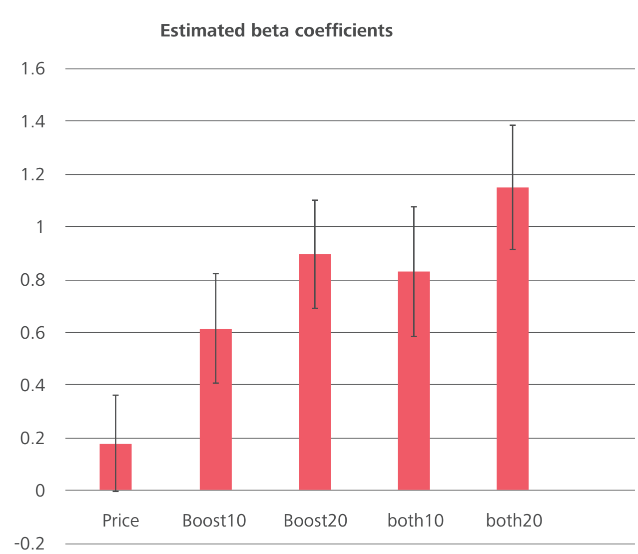


Including the size of the ranking boost in the model (for both the "Ranking boost" strategy, and the "Price reduction + ranking boost strategy"), shows that the effect size depends on the magnitude of the boost.

As seen in figure 13, the difference between the price reduction + ranking boost and the ranking boost only, was insignificant with a boost of 10, but significant with a boost of 20. The effect of a 10 spot boost was 3.5 times larger than the price reduction, while the 20 spot boost was 5 times larger.

With the more complex model, the effect of price reductions is reduced to marginal significance (p=0.056), while all other strategies remain significant.

Figure 13: **Changes in likelihood of choosing a particular hotel in the choice set, depending on the strategy employed and accounting for size of the boost**



7. Conclusion

The experiment demonstrates that in the simulated OTA environment ranking boosts significantly out-perform 10 pct. price reductions. While the true size of ranking boosts on the OTA is unknown, the experiment found that even the smaller boost of 10 ranking positions had significantly more impact on consumer choice in a simulated OTA environment than the price reduction. The experiment also demonstrated that larger boosts had larger effects on consumer choice.

These results highlight the large effects that product ranking and ranking boosts can play in digital consumer choice. This is congruent with the results of the scraping analysis, which showed large uptakes of temporary ranking boosts and close to complete uptake of permanent ranking boosts on the first pages of the search results.

In combination, the two analyses suggest that ranking boosts on OTAs outperform price reductions as a means to generate sales. While consumers benefit from price reductions, it is unclear how they would benefit from ranking boosts

Thus, when platforms encourage sellers to boost their ranks rather than lowering their prices it may be detrimental to consumers.

Appendix – Modelling ranking

Explanation of variables:
The same set of data was used for all models presented in the analysis. Data is briefly described below, after which the models are presented.

- Rank: This variable measures the rank from the top, such that rank 1 is the top result, and rank 33 is the 33rd result.
- Permanent ranking boost: Dummy variable describing whether a listing had a permanent ranking boost.
- Temporary ranking boost: Dummy variable describing whether a listing had a temporary ranking boost.
- Nightly price: The price per night (price divided by the length of stay). In case of a discount, the discounted price was used as the current price.
- Discount: Dummy variable indicating whether the hotel carried a rebate.
- Number of reviews: The amount of reviews that a hotel had at the time of scraping.
- Average review: Average value of hotel reviews defined by the OTA.
- Number of hotels: Binning of number of hotels in the city at the time of scraping. The bins are created to be of equal numerical size, starting with the lowest amount of sellers. The interval values are:
  - Small: 0-320
  - Medium: 320-573
  - Large: 573-825
  - Extra-large: 825-1078

Note: that a hotel can have a larger amount of sellers than 1078, which appears to leave sellers undisplayed, unless the users filters. In fact, the site often cut off at 40 pages of 25 results each (1000), although higher values are found in the dataset (max value 1078).

Chain hotel: Dummy variable indicating whether a hotel was part of a chain. The dummy is based on the value scraped from listing data of the OTA defining the chain that a hotel belongs to.

First model-set: Estimating ranking
To estimate the ranking of listings, variations are made of the following equation:

$$\log(Y_i+1)=X_i\beta+\epsilon_i$$

Where X_i is the rank of a hotel in a search on the OTA, and X_i is a vector of explanatory variables.

The relation between the explanatory variables and the rank cannot be linear by the definition of rank. A rank is censored, in the sense that a listing cannot increase their rank beyond the first spot in the ranking (rank=1). As such, a hotel listing in the 10th spot can at maximum increase their ranking by 9 spots. Therefore, a linear model is not appropriate for this case.

The rank was log-transformed, thus changing the relationship between the ranking and explanatory variables to semi-elastic, ie. the estimates of β can be interpreted as the percentage change in Y, that results from a 1-point increase in X. In the cases where explanatory variables are themselves transformed, the relationship becomes elastic, ie. β represents the percentage change in Y that arises from a percentage change in X.

A number of background variables are included in the model (see explanation of variables), but the models put special emphasis on the permanent and temporary ranking boosts. While the first model only includes the background variables, the second model includes main effects for promotional activities (ranking boosts and price reductions). The third model puts special focus on the ranking boosts, and is built by first including all two-way interactions that include a ranking boost, and then removing effects with significance of less than 0.01. This is the model which is reported in the article.

	Model 1	Model 2	Model 3
Constant	7.564*** (0.021)	6.442*** (0.021)	5.722*** (0.024)
Number of reviews (log)	-0.329*** (0.001)	-0.250*** (0.001)	-0.163*** (0.001)
Nightly price (log)	-0.078*** (0.002)	0.023*** (0.002)	0.009*** (0.002)
Nr. of hotels :M	0.700*** (0.006)	0.708*** (0.006)	0.763** (0.007)
Nr. of hotels :L	0.818*** (0.007)	0.837*** (0.007)	0.962*** (0.008)
Nr. of hotels :XL	1.706*** (0.005)	1.763*** (0.005)	1.713*** (0.006)
Avg. Review	-0.136*** (0.002)	-0.102*** (0.002)	-0.054*** (0.002)
Permanent ranking boost		-0.309*** (0.003)	1.863*** (0.033)
Temporary ranking boost		-0.508*** (0.007)	0.843*** (0.093)
Discount		-0.165*** (0.004)	-0.100*** (0.006)
Hotel chain		-0.506*** (0.004)	-0.469*** (0.004)
Number of reviews (log) x Permanent ranking boost			-0.179*** (0.002)
Nr. of hotels M x Permanent ranking boost			-0.119*** (0.011)
Nr. of hotels L x Permanent ranking boost			-0.304 (0.014)
Nr. of hotels XL x Permanent ranking boost			0.106*** (0.009)
Avg. Review x Permanent ranking boost			-0.147*** (0.003)
Permanent ranking boost x Discount			0.077*** (0.008)
Nr. of reviews (log) x Temporary ranking boost			-0.256*** (0.004)
Nr. of hotels: M x Temporary ranking boost			-0.145*** (0.036)
Nr. of hotels: L x Temporary ranking boost			-0.700** (0.051)
Nr. of hotels: XL x Temporary ranking boost			-0.375*** (0.031)
Avg. Review x Temporary ranking boost			0.046*** (0.010)
Temporary ranking boost x Discount			-0.082*** (0.016)
Temporary ranking boost x Hotel chain			0.351*** (0.018)
R-squared	0.485	0.529	0.554
N	377026	377026	377026

Significance: ***=p<0.001;**=p<0.01;*=p<0.05

Second model-set: Probability of listing on page 1
To estimate the probability of being on page 1, variations are made of the following equation:

$$P(S_i=1) = \frac{e\{X_i\beta\}}{1+e\{X_i\beta\}}$$

Where S_i is the result page that the listing appears on, and X_i is a vector of explanatory variables. Model 2 is a different way of looking at the ranking. Instead of having the model fit a consistent trend through the ranks, it focuses on the first page of the search results.

The model is specified using the same methodology as model 1.

	Model 1	Model 2	Model 3
Constant	-22.106*** (0.199)	-19.892*** (0.212)	-19.275*** (0.260)
Number of reviews (log)	1.525*** (0.010)	1.350*** (0.011)	1.206*** (0.022)
Nightly price (log)	0.458*** (0.018)	0.282*** (0.020)	0.324*** (0.021)
Nr. of hotels :M	-1.225*** (0.026)	-1.391*** (0.027)	-1.769** (0.055)
Nr. of hotels :L	0.234*** (0.040)	0.140*** (0.041)	-0.089*** (0.083)
Nr. of hotels :XL	-2.213*** (0.023)	-2.523*** (0.024)	-3.044*** (0.061)
Avg. Review	0.886*** (0.017)	0.792*** (0.018)	0.814*** (0.019)
Permanent ranking boost		0.914*** (0.025)	-0.130*** (0.178)
Temporary ranking boost		1.571*** (0.032)	2.095*** (0.745)
Discount		0.368*** (0.024)	0.340*** (0.024)
Hotel chain		0.743*** (0.019)	1.160*** (0.047)
Number of reviews (log) x Permanent ranking boost			0.129*** (0.025)
Nr. of hotels M x Permanent ranking boost			0.536*** (0.064)
Nr. of hotels L x Permanent ranking boost			0.289 (0.093)
Nr. of hotels XL x Permanent ranking boost			0.569*** (0.067)
Permanent ranking boost xHotel chain			-0.390*** (0.052)
Number of reviews (log) x Temporary ranking boost			0.437*** (0.044)
Nightly price (log) x Temporary ranking boost			-0.275*** (0.067)
Nr. of hotels: M x Temporary ranking boost			0.391*** (0.141)
Nr. of hotels: L x Temporary ranking boost			1.196** (0.276)
Nr. of hotels: XL x Temporary ranking boost			1.229*** (0.125)
Avg. Review x Temporary ranking boost			-0.296*** (0.061)
Temporary ranking boost x Hotel chain			-0.649*** (0.072)
Nagelkerke R-sq	0.429	0.470	0.475
N	377026	377026	377026

Significance: ***=p<0.001;**=p<0.01;*=p<0.05

Third model-set - Who buys boosts

The third set of models estimates the probability of buying the ranking boosts, and are variations of the following equation:

$$P(R_i=1) = \frac{e\{X_i\beta\}}{1+e\{X_i\beta\}}$$

Where R_i is a dummy variable for whether listing i has a boost. Separate models are made for temporary and permanent ranking boosts. The sample for permanent boosts was limited to hotels deemed eligible (review score > 7).

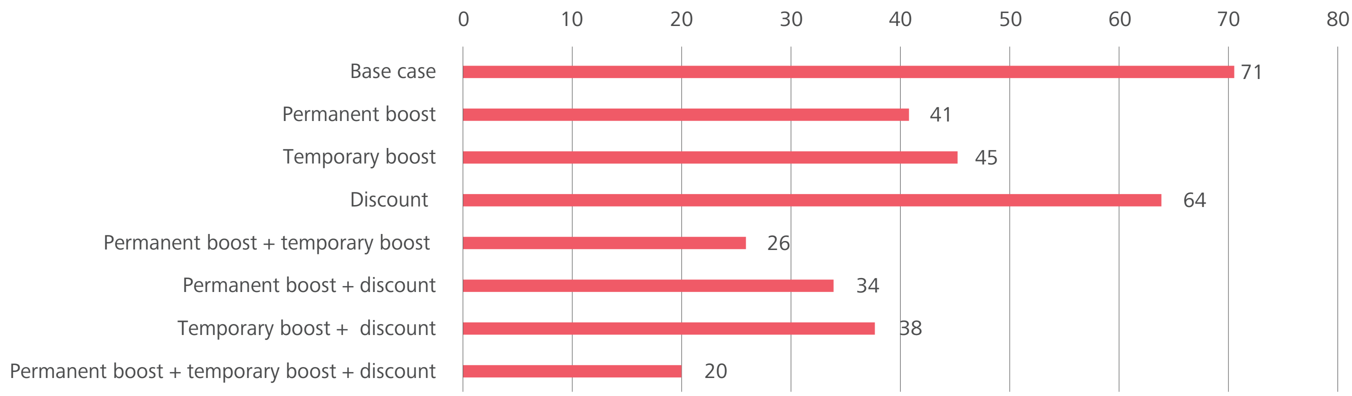
	Permanent ranking boost	Temporary ranking boost
Constant	-12.767*** (0.079)	-8.157*** (0.153)
Number of reviews (log)	0.594*** (0.003)	0.086*** (0.006)
Nightly price (log)	0.003*** (1.045)	0.006*** (0.132)
Nr. of hotels :M	0.166*** (0.017)	0.332** (0.045)
Nr. of hotels :L	0.928*** (0.021)	-0.255*** (0.066)
Nr. of hotels :XL	1.270*** (0.014)	0.764*** (0.039)
Avg. Review	0.252*** (0.006)	0.332*** (0.013)
Hotel chain	0.016 (0.013)	0.674*** (0.024)
Nagelkerke R-sq	0.320	0.035
N	353061	377026

Significance: ***=p<0.001;**=p<0.01;*=p<0.05

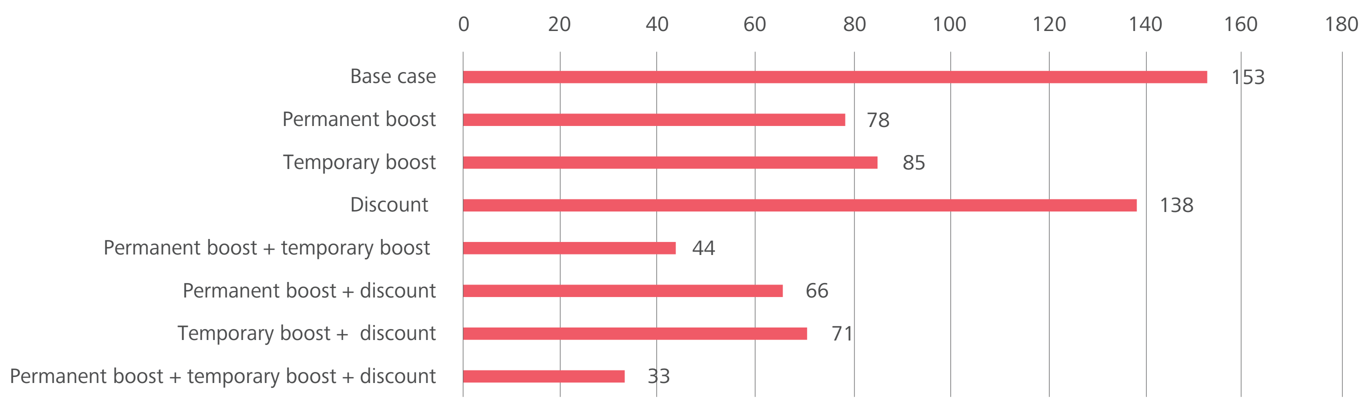
Base cases in small/medium/large cities

In order to show how the prediction changes with the number of sellers in a city, model predictions for the base case hotel in other cities are shown on the next pages. Note that only the value of “number of sellers” changes, the other control variables are constant across cities. The main consequence of this, is seen in the “large” category, where the probability of being on page 1 is higher than in medium or small cities. At a glance this is counterintuitive, as more sellers should reduce the probability of a seller being on page 1. The reason for this is that the number of reviews is generally lower in the “large” category, such that the base case hotel has a relatively good score in this category of cities.

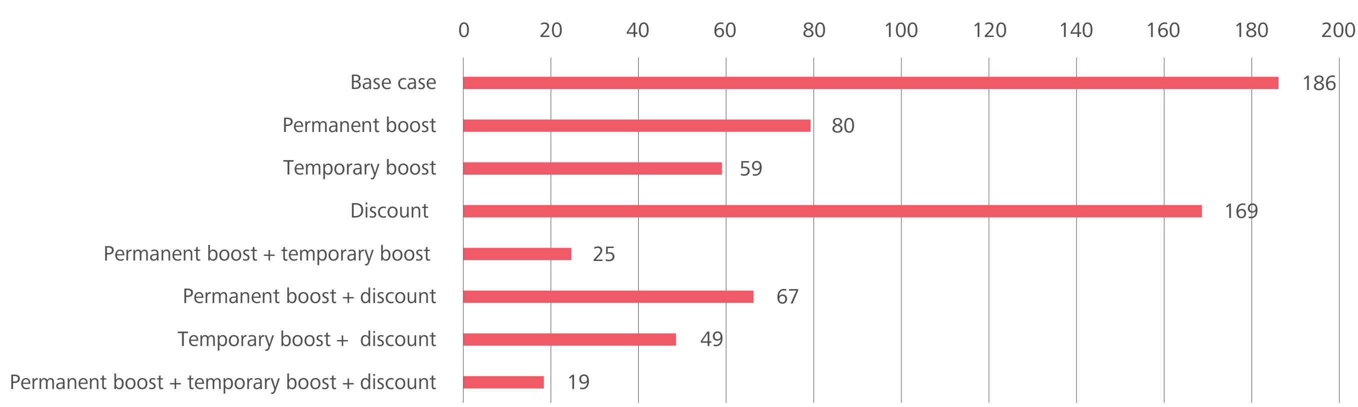
Predicted rank (Small city)

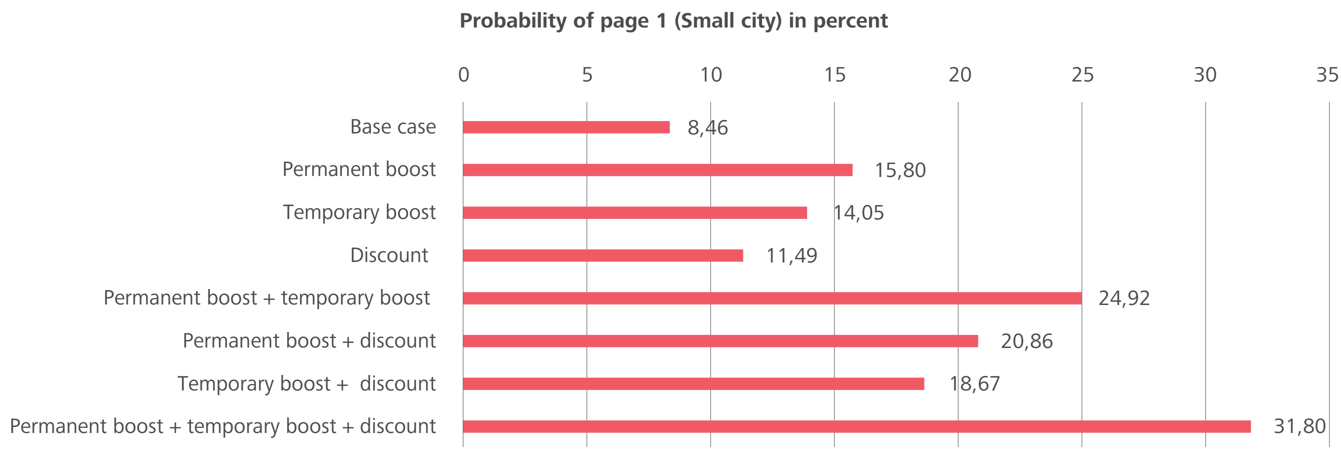


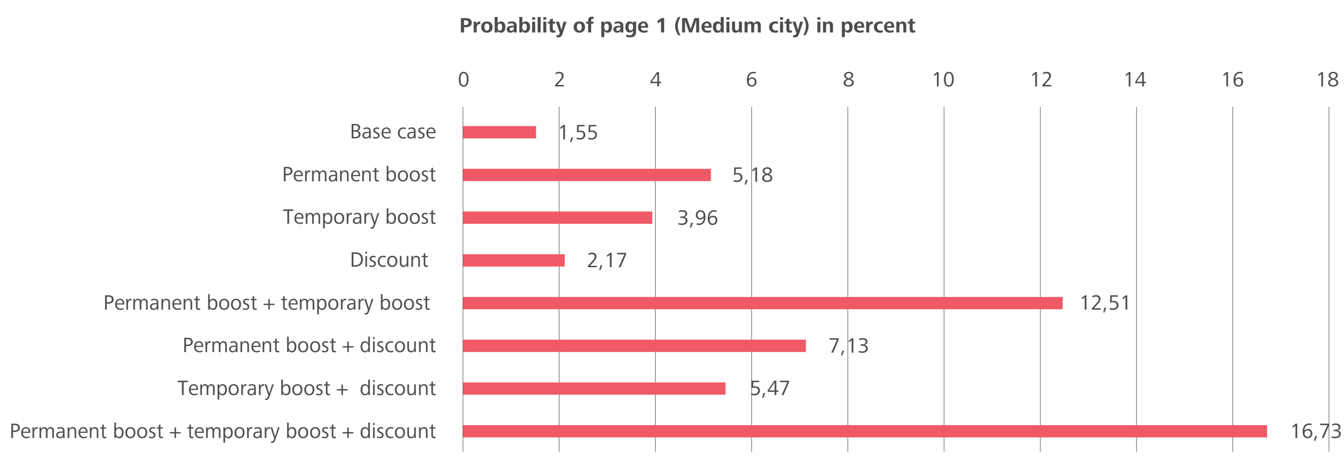
Predicted rank (Medium city)

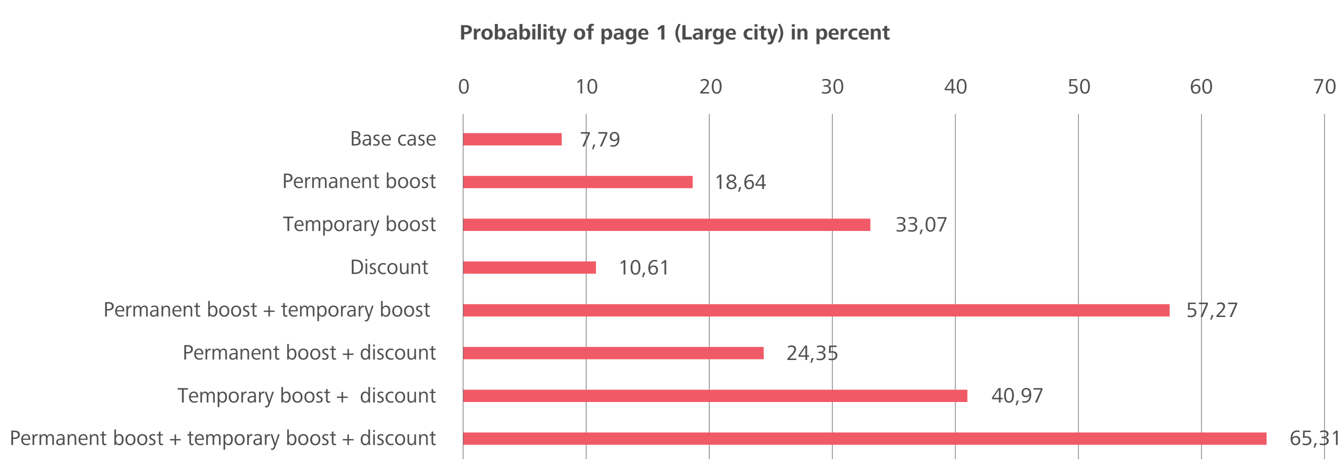


Predicted rank (Large city)




Probability of page 1 (Small city) in percent
0
5
10
15
20
25
30
35
Base case
8,46
Permanent boost
15,80
Temporary boost
14,05
Discount
11,49
Permanent boost + temporary boost
24,92
Permanent boost + discount
20,86
Temporary boost + discount
18,67
Permanent boost + temporary boost + discount
31,80


Probability of page 1 (Medium city) in percent
0
2
4
6
8
10
12
14
16
18
Base case
1,55
Permanent boost
5,18
Temporary boost
3,96
Discount
2,17
Permanent boost + temporary boost
12,51
Permanent boost + discount
7,13
Temporary boost + discount
5,47
Permanent boost + temporary boost + discount
16,73


Probability of page 1 (Large city) in percent
0
10
20
30
40
50
60
70
Base case
7,79
Permanent boost
18,64
Temporary boost
33,07
Discount
10,61
Permanent boost + temporary boost
57,27
Permanent boost + discount
24,35
Temporary boost + discount
40,97
Permanent boost + temporary boost + discount
65,31