Trade-Offs Between Ranking Objectives: Reduced-Form Evidence and Structural Estimation

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Abstract

Online retailers and platforms typically present alternatives using ranked product lists. By adjusting the ranking, these platforms influence consumers’ choices and, in turn, conversions, platform revenues, and consumer welfare. In this paper, I study the trade-offs between ranking algorithms that target these different objectives. First, I highlight and provide reduced-form evidence for a key factor shaping these trade-offs: cross-product heterogeneity in position effects. To quantify the effects of different rankings, I then develop an empirical framework based on the search and discovery model of Greminger (2022). For this framework, I show that the ranking that maximizes conversions also maximizes consumer welfare, implying no trade-off between these two objectives. Moreover, I develop and test a heuristic ranking algorithm to maximize revenues. Finally, I estimate the model and compare the effects of the rankings developed for the different objectives. The results highlight the effectiveness of the different rankings and reveal that the proposed heuristic to maximize revenues also increases consumer welfare, suggesting that the trade-off between revenue maximization and consumer welfare also is limited.

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1 Introduction

Many consumers purchase products from online retailers or search platforms. These online platforms typically present alternatives on product lists, where items in higher positions have been shown to receive more clicks and purchases (e.g., De Los Santos and Koulayev, 2017; Ursu, 2018). These so-called position effects allow online platforms to increase conversions or revenues by implementing ranking algorithms that target these objectives (e.g., Ghose et al., 2014). At the same time, rankings also affect consumers, and platforms concerned about competition may also use them to improve consumer welfare (e.g., Ursu, 2018). However, a ranking algorithm pursuing one objective may come at a cost to the others, creating trade-offs between different objectives and raising concerns about potentially adverse effects. For example, platforms in competitive markets and regulators are concerned that the revenue-maximizing ranking might harm consumers.1 Similarly, whether and to what degree the conversion-maximizing ranking reduces revenues should still concern even the most growth-centered online retailer.

This paper studies the trade-offs between ranking objectives and pursues three main goals. First, it uses exogenous ranking variation to document how position effects vary across products and shows how this heterogeneity shapes these trade-offs. Second, it develops a novel empirical framework that better reflects how consumers interact with ranked product lists and enables researchers, practitioners, and regulators to predict the effects of different rankings. Finally, it develops and compares ranking algorithms that platforms can implement to maximize revenues, conversions, or consumer welfare.

I begin by documenting a key factor determining the trade-offs between ranking objectives: cross-product heterogeneity in position effects. When some products have larger position effects than others, promoting them will increase the conversion rate and, consequently, impact the platform’s revenues when it takes a price-based sales commission or markup. As a result, the relative size of a product’s position effect will determine how algorithms targeting conversions or revenues will rank it and how these algorithms will affect consumers.

Whereas product heterogeneity naturally leads to variation in position effects, how they vary across different products is a priori unclear. If consumers can easily find and choose their preferred alternatives, even when ranked at the bottom, these alternatives will have smaller position effects and benefit little from being promoted. In contrast, if consumers struggle to find their preferred alternatives unless they appear at the top of the list, these alternatives will have larger position effects. In this case, promoting them will increase conversions and revenues, while also helping consumers find better options.

To quantify differences in position effects across alternatives, I use data from Expedia with a randomized ranking of hotels. Having such exogenous ranking variation allows identifying

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1 For example, in a recent report, the UK’s Competition and Markets Authority defines an “unfair” ranking as one that influences “what a consumer sees to gain commercial advantage” (CMA, 2021). Moreover, Donnelly et al. (2023) find that a large online platform also considers consumer welfare effects when personalizing rankings.
position effects without the convoluting effects resulting from the platform promoting popular alternatives (Ursu, 2018). I find that, after controlling for other attributes, lower-priced alternatives have larger position effects. More broadly, I also find that desirable alternatives—alternatives that are more frequently searched and purchased—tend to have larger position effects.

These reduced-form results provide two insights into the trade-offs between ranking objectives. First, because desirable alternatives have larger position effects, promoting them increases conversions and helps consumers find better-matching alternatives. Hence, the trade-off between maximizing conversions and consumer welfare is limited. Second, as lower-priced options have larger position effects, maximizing the platform’s revenues entails a trade-off between increasing conversions and maintaining the average purchase price. Specifically, promoting lower-priced options increases the conversion rate because they have larger position effects. However, it also shifts demand toward these lower-priced options and, as a result, reduces the average price consumers pay. The relative sizes of these two effects then determine how well the objective of revenue maximization is aligned with the other two.

While these reduced-form results are informative for the trade-offs between ranking objectives, fully quantifying these trade-offs requires an empirical framework that can predict the revenue and consumer welfare effects of different rankings. To this end, I develop a novel structural search model that builds on the search and discovery framework of Greminger (2022). The model offers a clear mechanism for how rankings influence consumers’ choices and better explains the data than the Weitzman (1979) model—an established approach to quantifying the effects of rankings (Ursu et al., 2024).

In the search and discovery model, upon arriving on the platform, consumers observe the first few alternatives on the list. They then sequentially decide between scrolling down the list to discover more products and viewing the detail pages of previously discovered products to learn more about them. The model explains the observed position effects through consumers not discovering all products on the list. Hence, rankings in the search and discovery model influence consumers’ choices by determining which alternatives they discover.

This mechanism differs from how rankings influence consumer behavior in the Weitzman model. In the Weitzman model, rankings do not affect what consumers see or discover. Instead, consumers already see the entire list at the start of their search, and rankings only affect the costs of searching the different alternatives. As I show in a model comparison, this difference is not only conceptual; it also enables the search and discovery model to better fit position effects—the key factor determining the effects of different rankings.

Similar to the Weitzman model, estimating the search and discovery model via maximum likelihood is challenging because it admits a complicated likelihood function. To address this, I derive a characterization of consumers’ choices that simplifies the likelihood function and develop a computationally efficient simulation procedure to calculate it. Moreover, I show

2The code will be made available as a ready-to-use Julia package with a Python wrapper, enabling researchers and
how the model parameters are identified in data with and without information on how many alternatives consumers discovered. As a special case, my estimation approach also proves useful in estimating the Weitzman model.

Next, I develop ranking algorithms for each of the following three objectives: maximizing revenues (or profits), conversions, and consumer welfare. In principle, the optimal ranking can be found by comparing all possible rankings. However, the number of possible rankings is typically too large for an exhaustive comparison. To address this, I develop algorithms that do not iterate over all possible rankings, making it feasible for researchers and platforms to obtain the (near-)optimal ranking for each objective.

To develop these ranking algorithms, I follow prior work and focus on the case where the platform does not announce the ranking change (e.g., Ursu, 2018; Chu et al., 2020; Derakhshan et al., 2022; Compiani et al., 2024). However, unlike prior work, I leverage my empirical framework to also quantify how different rankings affect consumers when they learn about the change. This additional analysis consistently shows that when consumers become aware of the ranking change, each ranking’s intended effects are further amplified. Hence, the proposed rankings remain effective for their respective objectives when consumers are aware of ranking changes.

For the objectives of maximizing consumer welfare or conversions, I prove that a simple “Utility-Based Ranking” maximizes both. In line with the reduced-form evidence, this result implies that there is no trade-off between these two objectives: promoting high-utility options helps consumers find better-matching products, which also maximizes the chance they discover an alternative they are willing to buy.

For the objective of maximizing platform revenues, I propose a heuristic ranking algorithm that constructs the “Bottom-Up Ranking.” Maximizing revenues is challenging because the demand for an alternative in a given position depends on the ordering of alternatives in other positions. Hence, ranking algorithms that assign alternatives sequentially may perform poorly because they do not account for this influence. However, when consumers scroll down the list to discover products, an alternative’s demand is unaffected by the ordering of alternatives above it. In contrast, the ordering of alternatives below does influence demand, as some consumers will not discover all of them. As a result, ranking alternatives sequentially from the bottom up, rather than from the top down, reduces the influence of the ordering of other alternatives and makes the proposed heuristic more effective in maximizing revenues.

I compare the Bottom-Up Ranking with a “Rank-1 Ranking” and a “Price-Decreasing Ranking.” The former ranks alternatives based on the revenues they generate in the first position. It entails fewer steps than the Bottom-Up Ranking and emulates a simple ranking algorithm that uses alternatives’ past revenues—an approach that is easy to implement and likely used in practice. The Price-Decreasing Ranking instead displays the most expensive alternatives first, making it trivial to implement. As I show, it would also maximize revenues if position practitioners to easily estimate the model in either of the two programming languages.
effects were homogeneous, rendering it an effective benchmark for assessing the importance of the position effect heterogeneity the reduced-form evidence revealed.

Finally, I estimate the model on the Expedia data and quantify the effects of the different rankings in a counterfactual analysis. The results suggest that the average consumer welfare effects are small: consumers would only be willing to pay 7¢ to see the consumer-welfare-maximizing ranking over a neutral randomized ranking. However, consumers who eventually book a hotel have much larger welfare gains of up to $10.3. Only a small portion of this gain stems from reduced discovery costs, suggesting that rankings primarily affect consumers by helping them discover different alternatives. The proposed Bottom-Up Ranking does similarly well for consumers. It promotes high-utility alternatives to increase conversions, leading to consumer welfare gains of 6¢ and $8.6 respectively.

On the platform side, I find that the consumer-welfare-maximizing ranking also increases revenues by 11.1%. This follows from the ranking also maximizing conversions, which, in turn, generates more revenues for the platform. However, by shifting some demand toward more expensive alternatives, the Bottom-Up Ranking achieves an even larger revenue increase of almost 18.0%. In contrast, the Rank-1 Ranking and the Price-Decreasing Ranking perform worse, increasing revenues only by 15.4% and 3.8%, respectively. Both also yield worse outcomes for consumers, suggesting that the proposed Bottom-Up Ranking offers an effective way for platforms not only to increase revenues but also to improve consumer welfare over these simpler rankings. It also performs remarkably well compared to the revenue-maximizing ranking, further confirming its effectiveness in increasing revenues.

Combined, my results suggest that the trade-offs between maximizing revenues, conversions, and consumer welfare are more limited than one might expect. Moreover, they show that the proposed Bottom-Up Ranking can help platforms increase revenues while also enabling consumers to find better-matching products.

1.1 Related Literature

This paper makes several contributions to the marketing literature. First, I provide reduced-form evidence on how position effects vary with product attributes, and highlight the implications for the trade-offs between ranking objectives. These results add to the literature that has highlighted the importance of position effects on ranked product lists, while mostly abstracting away from their heterogeneity (e.g., Ghose et al., 2012, 2014; De Los Santos and Koulayev, 2017; Ursu, 2018).

\footnote{Ghose et al. (2014) consider how position effects vary with product attributes in one of their analyses and found mixed results. The difference in results may be attributed to potential endogeneity in the ranking, which I address by following Ursu (2018) and using data with a randomized ranking. Derakhshan et al. (2022) analyze heterogeneity across an undisclosed popularity index in a reduced two-product analysis. In contrast, heterogeneity in position effects has received considerable attention in the literature studying position effects in the context of search advertising (e.g., Narayanan and Kalyanam, 2015; Jeziorski and Moorty, 2018).}
Second, I contribute to the literature documenting possible trade-offs between ranking objectives (Zhang et al., 2021; Donnelly et al., 2023; Compiani et al., 2024; Kaye, 2024). Closest to this paper is Compiani et al. (2024), who extend the Weitzman model to develop near-optimal ranking algorithms and quantify their effects when alternatives differ in their pre-search potential. I instead develop an empirical implementation of the search and discovery model of Greminger (2022).

Unlike the popular Weitzman model, the search and discovery model does not assume that consumers observe the entire list page without effort. Moreover, it rationalizes position effects through a different mechanism: product discovery. In a comparison, I show how these conceptual differences enable the search and discovery model to better explain the data. These results complement Greminger (2022), who used simulations to show how assuming that consumers observe the entire list when they initially only reveal the first few products—as is the case on any platform offering more than just a few alternatives—bias estimates and meaningfully affect counterfactual results.

More broadly, my empirical framework contributes to the empirical search literature that has proposed various other approaches to quantify ranking effects. By allowing consumers to go back up on the list, my approach relaxes a limitation of the “top-down” search models (Chan and Park, 2015; Choi and Mela, 2019). Moreover, my approach integrates the clicking and scrolling decisions in a sequential framework. Unlike models that separate these decisions into two stages (Derakhshan et al., 2022; Chung, 2024), this allows it to fit data where consumers continue scrolling after a first click. Gibbard (2023) estimates the two-stage model of Gibbard (2022) that features “browsing” of products on the list. That model differs from my approach in that it assumes consumers decide on the order in which to browse products on the list, rather than scrolling down and discovering products along a ranked product list.

Finally, my paper also contributes to the operations literature by providing ranking algorithms for different objectives (e.g., Ryzin and Mahajan, 1999; Derakhshan et al., 2022). My approach differs from prior work in this literature in that I derive these algorithms for a search model that can rationalize the data and use the model to quantify their effects.

4Compiani et al. (2024) and Kaye (2024) use the same data as this paper to estimate their respective models and quantify the effects of different rankings.

5By studying the effects of rankings, this paper also differs from recent work by Zhang et al. (2023), who use the search and discovery model to study how different search routes affect consumers’ search behavior.

6Early work in this stream of literature did not consider search (e.g., Ryzin and Mahajan, 1999; Talluri and Van Ryzin, 2004). Ursu and Dzyabura (2020) focus on a retailer deciding how to place independent categories within a store. Chu et al. (2020) and Derakhshan et al. (2022) develop ranking algorithms for different search models. However, the proposed models contradict the data and, as a result, would not be suitable for an empirical analysis. The former implies that there are no position effects for consumers who choose the outside option, which is not the case in my data (see Appendix G.1). The latter implies that consumers inspect all alternatives on the product list up to some rank, which contradicts any data where consumers do not click on the first alternative on the list.
2 Data and Reduced-Form Evidence

I use click-stream data from Expedia. The data can be obtained from Kaggle.com and contains information on clicks and purchases for 166,039 search sessions between November 2012 and June 2013. A search session starts at the point where a consumer has submitted a query for a hotel stay on Expedia. Following this query, Expedia presents a list of the available options. On this list, consumers observe various hotel characteristics, such as the price per night and the review score. They then can scroll down to reveal more hotels on the list, or click on one of the presented items. Clicking on an item leads to the hotel’s detail page that reveals further information and allows booking the hotel. Ursu (2018) provides a comprehensive discussion of the dataset, and I apply similar criteria to prepare the final sample (see Appendix H).

2.1 Data Summary

The main feature of the data is that for about 30% of search sessions, Expedia randomly assigned hotels that fit the query to positions on the list. As Ursu (2018) highlights, this exogenous variation is essential to identify position effects without convoluting the effect of more desirable hotels being ranked higher. Suppose hotels instead are positioned on top of the list based on unobservable characteristics that also lead to more clicks and purchases. In that case, it is challenging to disentangle correlations with such unobservables, potentially leading to an overestimation of position effects. For the remaining 70% of consumers in the sample, Expedia used its ranking algorithm to assign hotels to positions.

Table 1 summarizes the dataset on a hotel and session level for consumers who observed the randomized ranking. In total, there are 51,510 sessions in this sample. On average, there are 1.14 clicks per session, and about 8% of sessions ended with a hotel booking. The number of alternatives on the product list of a session varies between 5 and 38. This variation does not result from consumers not browsing further, but from these queries being for hotels in destinations or on dates where only a few hotels had available rooms. Some destinations may also offer more alternatives, but the data contain only the results displayed on the first page. As Ursu (2018) notes, this imposes little restriction as position effects are identified from differences across positions.

2.2 Reduced-Form Evidence of Position Effect Heterogeneity

I now use these data to provide empirical evidence of how position effects differ between alternatives. This heterogeneity is important for the trade-offs between ranking objectives because

The data is available under the following link: https://www.kaggle.com/c/expedia-personalized-sort/data.

Appendix H provides a detailed description of each variable. The “no reviews” variable is a dummy indicating whether a hotel has no reviews. This is coded as a “review score” of zero in the raw data. However, given that it differs from a “review score” of zero and a missing “review score,” I treat this dummy separately.
|                        | N     | Mean | Median | Std. Dev | Min. | Max. |
|------------------------|-------|------|--------|----------|------|------|
| **Hotel-level**        |       |      |        |          |      |      |
| Price (in $)           | 1,357,106 | 171.70 | 141.04 | 114.03 | 10.00 | 1000.00 |
| Star rating            | 1,333,734 | 3.34  | 3      | 0.89    | 1    | 5    |
| Review score           | 1,354,996 | 3.81  | 4.00   | 0.97    | 0.00 | 5.00 |
| No reviews             | 1,354,996 | 0.04  | 0      | 0.19    | 0    | 1    |
| Chain                  | 1,357,106 | 0.62  | 1.00   | 0.48    | 0.00 | 1.00 |
| Location score         | 1,357,106 | 3.26  | 3      | 1.53    | 0    | 7    |
| On promotion           | 1,357,106 | 0.24  | 0      | 0.43    | 0    | 1    |
| **Session-level**      |       |      |        |          |      |      |
| Number of items        | 51,510 | 26.35 | 31     | 8.46    | 5    | 38   |
| Number of clicks       | 51,510 | 1.14  | 1      | 0.66    | 1    | 25   |
| Made booking           | 51,510 | 0.08  | 0      | 0.27    | 0    | 1    |
| Trip length (in days)  | 51,510 | 3.07  | 2      | 2.42    | 1    | 40   |
| Booking window (in days)| 51,510 | 53.67 | 31     | 62.49   | 0    | 498  |
| Number of adults       | 51,510 | 2.08  | 2      | 0.94    | 1    | 9    |
| Number of children     | 51,510 | 0.43  | 0      | 0.82    | 0    | 9    |
| Number of rooms        | 51,510 | 1.14  | 1      | 0.46    | 1    | 8    |

Notes: Summary statistics for sessions under the randomized ranking.

It determines how different rankings impact conversions. For example, suppose some alternative A has a larger position effect than another alternative B. In this case, promoting A over B will increase conversions because its demand gain from being promoted exceeds the demand loss for the demoted alternative B. Because conversions also affect revenues, this rationale directly implies that position effect heterogeneity determines which alternatives different ranking algorithms promote and, hence, how they affect the other objectives.

To capture this heterogeneity, I estimate the following linear probability model (LPM):

\[
P(Y_{ij} = 1|z_{ij}, pos_{ij}) = x_j'\beta_1 + w_i'\beta_2 - pos_{ij}\gamma - pos_{ij}x_j'\theta + \tau_d.
\] (1)

Each observation is a hotel j in destination d displayed on position pos_{ij} = 1, 2, \ldots in a consumer session i. Hotel attributes (e.g., price) are gathered in column vector x_j, whereas query characteristics (e.g., trip length) are gathered in column vector w_i. Depending on the specification, y_{ij} is a dummy indicating whether j was clicked on or booked in session i. I include pos_{ij} with a negative sign to simplify the interpretation of the estimated position effects. Finally, \tau_d is a fixed effect on the destination level, and z_{ij} gathers x_j, w_i and \tau_d.

I define the position effect as the effect of moving a hotel up by one position, conditional on its attributes. Given the specification in (1), this position effect is given by

\[
\text{Position effect}_{ij} = P(Y_{ij} = 1|z_{ij}, pos_{ij} = h) - P(Y_{ij} = 1|z_{ij}, pos_{ij} = h + 1) = \gamma + x_j'\theta,
\] (2)

where h is the current position of hotel j. With this definition, having a larger position effect
means that the hotel will gain more clicks or bookings when being moved higher up on the list. Moreover, note that the position effect measures absolute changes in the click-through rate and booking probability. These are the relevant metrics because heterogeneity in absolute changes, rather than proportional changes, determines differences in the list’s overall conversion rate and platform revenues.

The full results of the reduced-form analysis are available in Appendix B. Here, I only discuss the main results that characterize the heterogeneity in the position effects. To simplify the interpretation of the effects, the estimates are scaled to represent percentage changes in either the click-through rate or booking probability.

Figure 1 shows the distribution of the estimated position effects across the hotels in the data. It reveals that there is substantial heterogeneity in these position effects. For clicks, the upper end of the distribution is close to 0.3, meaning that the click-through rate for some hotels can increase up to 0.3 percentage points when they move one position higher up on the list. For other hotels, the position effect is closer to zero, implying that these hotels would not gain many clicks when being promoted. Similarly, the estimated position effects reveal substantial heterogeneity. Whereas some hotels can gain up to 0.015 percentage points in their booking probability when moving a position higher up on the list, others may not gain any bookings. Though the position effects are estimated to be negative for some hotels in the data, I attribute these rare cases to some coefficients not being estimated precisely, as indicated by the large standard errors for some coefficients reported in Table 5 in Appendix B.

This heterogeneity results from differences in the attributes across hotels in the data. Figure 2 shows the estimated average position effect at different prices, keeping other attributes at their respective average. The results reveal that, conditional on other attributes, lower-priced hotels have larger position effects on average. For clicks, the position effect decreases from more than 0.25 to below 0.1 as the price increases from the 10th to the 90th percentile. For bookings, the position effect decreases from about 0.015 to about 0.007 percentage points.

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9 Only the overall position effect depends on the value of these other attributes, whereas differences in the effects between price levels are independent of other hotel attributes (see equation (2)).
Figure 2 – Estimated Position Effects for Different Prices

Notes: Estimated position effects at different price percentiles, with other attributes kept at their respective average. The bars indicate 95% confidence intervals calculated from standard errors clustered on the session level.

Figure 3 – Estimated Position Effects for Different Direct Effects

Notes: Boxplots for the estimated position effects for hotels in the data, grouped into percentiles of their direct effect $x'_j \beta$. Values outside the 1.5 interquartile-range are omitted.

Figure 3 generalizes the analysis to attributes other than price. It shows the estimated position effects for the hotels in the data, grouped by their respective direct effects $x'_j \beta$. This direct effect determines the average number of clicks or bookings of a hotel independent of its positions. Hence, it is a data-driven measure of how desirable a hotel is on average. The figure reveals a clear pattern: hotels with a larger direct effect tend to have larger position effects. For example, the median position effect for clicks is only about 0.14 among hotels with a direct effect in the lowest percentile, whereas it almost 0.25 for hotels in the highest percentile. Hence, hotels that are more likely to be clicked on or booked on any position are also more likely to gain from being moved higher up on the list.

This pattern is further confirmed by the coefficient estimates reported in Table 5 in Appendix B. The sign of the interaction term in $\gamma$ opposes the sign of $\beta_1$ in the direct effect for all characteristics, although the effects are not always statistically significant. Hence, I conclude that desirable alternatives—alternatives that on average are more likely to be searched and chosen—have larger position effects on average.
2.3 Implications

These results imply that maximizing revenues through a ranking entails a trade-off similar to the one underlying a monopolist pricing problem. For the case where alternatives differ only in their price, my results suggest that moving higher-priced alternatives higher up on the list decreases conversions, but shifts demand to these alternatives. This parallels a price increase in a monopolist pricing problem: it reduces the quantity sold (“demand effect”), while increasing the average price paid by consumers (“price effect”). As in the monopolist pricing problem, maximizing revenues requires balancing these two effects when designing rankings.

The descriptive evidence further reveals that other attributes also entail demand effects. A ranking can also use these demand effects by moving products with desirable attributes higher up on the list. For example, suppose there are two hotels with the same price, but one has a higher review score, a desirable attribute that amplifies position effects. My results suggest that, in this case, placing the higher-rated hotel at the top increases conversions and revenues because of these demand effects.

Combined, these results suggest that a ranking that maximizes the platform’s revenues could potentially benefit both the platform and consumers. The heterogeneity in position effects I document implies that rankings can increase the conversion rate and, hence, the platform’s revenues by promoting desirable products. This, in turn, could also benefit consumers by helping them find these desirable alternatives and possibly save them effort and time to go down the list.

Determining whether such win-win situations can indeed occur requires deriving rankings for the different objectives and quantifying differences between them. To this end, I now develop a structural search model for how consumers interact with product lists. I defer a detailed comparison with the Weitzman (1979) model until after presenting the results from my model.

2.4 Robustness of Results

The randomized ranking ensures that a hotel’s position is exogenous so that the position effects can be estimated consistently (Ursu, 2018). However, a hotel’s price may not be exogenous if it is correlated with unobservable hotel attributes. Table 5 in Appendix B addresses this endogeneity concern by additionally reporting estimates for a specification that adds hotel fixed effects, effectively controlling for such unobservable hotel attributes. Overall, the estimates, including the price coefficient, are close to the baseline and confirm the results.10

Appendix B further shows that the results are also robust to using a Probit model or alternative specifications that treat position more flexibly.

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10 Ursu (2018) argues that with frequent pricing experiments on online travel agencies, there is little concern for price endogeneity. This is also in line with previous studies that used data from online travel agencies. Specifically, Chen and Yao (2017) and De Los Santos and Koulayev (2017) use control function approaches to account for price endogeneity and find that it makes little difference.
3 Model and Estimation Approach

To model how consumers interact with a ranked product list, I adapt the search and discovery (SD) model of Greminger (2022). In this model, consumers sequentially decide between discovering products, searching among already-discovered alternatives, and ending their search by taking the best option found so far or the outside option. The resulting decision process closely matches how consumers interact with ranked product lists: they discover alternatives by scrolling down the list, reveal more information on an alternative by going to its detail page, and end their search by choosing an alternative or leaving the page.

3.1 The Empirical Search and Discovery Model

Each consumer faces a ranked product list displaying a finite number of hotels \( j \in J \) in positions \( h_j \in \{1, \ldots, |J|\} \). To simplify notation, I suppress consumer subscripts throughout.

When booking a hotel, a consumer receives utility

\[
    u_j = u^I_j + \nu_j = x_j'\beta + \nu_j + \epsilon_j,
\]

where \( u^I_j \) is the part of utility already revealed on the product list. \( x_j \) is a vector of hotel attributes observed in the data (e.g., price) and \( \beta \) are the corresponding preference weights. \( \nu_j \) and \( \epsilon_j \) are idiosyncratic taste shocks.

The utility of the outside option of not booking any hotel is given by \( u_0 = \beta_0 + \eta \). \( \eta \) is another idiosyncratic taste shock, whereas \( \beta_0 \) captures the mean willingness to pay for a hotel.

The taste shocks \( \nu_j \) and \( \epsilon_j \) are i.i.d. normal with respective means \( \mu_\nu \) and \( \mu_\epsilon \), and variances \( \sigma^2_\nu \) and \( \sigma^2_\epsilon \). The shock for the outside option \( \eta \) follows a standard uniform distribution. In estimation, I set \( \mu_\nu = \mu_\epsilon = 0 \) and \( \sigma^2_\nu = \sigma^2_\epsilon = 1 \), as I discuss in more detail in Section 3.5.

Initially, consumers know their preference weights \( \beta \) and the value of the outside option, but not the attributes and the taste shocks of hotels on the list. Instead, consumers reveal these values by sequentially deciding between scrolling down the list (discovering) and clicking on hotels to view their detail pages (searching). By scrolling down the product list, a consumer reveals \( u^I_j \) for the next hotel on the list. By searching \( j \), the consumer reveals the idiosyncratic taste shock \( \epsilon_j \).

11I do not include preference and search cost heterogeneity because it would be difficult to separately identify the two without observing the search order (see Yavorsky et al., 2021; Morozov et al., 2021).

12Whereas this distributional assumption facilitates taking draws from truncated distributions as required for likelihood simulation procedure, the same estimation approach also works for alternative assumptions for the distribution of \( \eta \). Appendix E provides additional results for a specification with a different upper bound. The results are qualitatively similar, albeit with somewhat smaller welfare effects due to fewer consumers being predicted to search. If the number of consumers who visit the website but do not search any alternative were observed, the upper bound of this distribution could also be estimated.

13Expedia’s website currently reveals one alternative at a time and also did so during the sample period (see online appendix C of Ursu, 2018). Moreover, Appendix E provides results of a specification where consumers discover three alternatives with each discovery, highlighting that such a specification fits the data worse.
I further impose two precedence constraints: consumers cannot search a hotel before discovering it, and they cannot book a hotel before searching it. These constraints are necessary for the optimal policy to remain tractable (Greminger, 2022). They also naturally apply in the present setting because Expedia does not allow booking hotels from the list, and it is not possible to click on a hotel listing that is not yet on the screen.

Both clicking and scrolling are costly actions. When scrolling to discover additional hotels, consumers incur discovery costs \( c_d \). As I do not observe consumers not visiting Expedia and only observe consumers who discover at least the first hotel on the list, I assume that the first discovery is free.\(^{14}\) When clicking on a listing to search it, consumers incur search costs \( c_s \). I further assume that there is free recall: going back and searching a previously discovered listing or booking a previously searched hotel does not add extra costs.

Consumers do not know the specific alternatives available in the market. However, they have beliefs about the alternatives they will discover. To model these beliefs, I assume that consumers believe that the alternatives are independent draws from the joint distribution of hotel attributes and taste shocks. More formally, I assume that consumers believe that the attributes \( x_j \) are realizations of independent vector random variables \( X_j \) that are independent of the shocks, and that consumers know the distributions of these random variables and of the taste shocks.

To capture beliefs about the ranking of the list, I further assume that consumers believe that the expected value of the list utility that will be revealed in position \( h \), \( U_j^j(h) \), is a function \( \mu(h) \) that depends on \( h \). Substantively, this assumption means that consumers have some uncertainty about the ranking and that they do not know how exactly the available alternatives are ordered. For example, when \( \mu(2) > \mu(3) \), consumers expect that the alternative they will reveal in the third position has a smaller utility on average, while also knowing that the utilities they will reveal can deviate from this expectation.

This approach has the advantage that the function \( \mu(h) \) fully characterizes consumers’ beliefs about the ranking algorithm. Parametrizing and estimating \( \mu(h) \) then allows to relax the rational expectations assumption where consumers would know how Expedia ranks alternatives. Note, however, that the assumption that consumers know the overall distribution of \( X_j \) still constrains these beliefs. Consumers know the overall shape of the distribution of attributes such that they are correct about the mean across all positions. Hence, this approach only relaxes the rational expectations assumption about the ranking of alternatives, not the distribution of attributes in the market.

Finally, I impose the substantive assumption that \( \mu(h) \) weakly decreases in \( h \). This assumption implies that consumers expect alternatives further down the list to offer a lower utility on average. This assumption is required for the optimal policy to remain tractable (Greminger, 2022). However, it does not restrict the model in the present case. Appendix G.1 shows that

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\(^{14}\)Expedia initially reveals up to three alternatives, depending on the screen size. However, assuming that consumers discover the first three alternatives for free leads to a worse model fit (see Appendix E).
even if the model were estimated without this restriction, it would necessarily produce estimates that imply that the assumption holds.

3.2 Optimal Policy

Consumers maximize their expected utility by sequentially choosing one of the available actions in periods \( t = 1, 2, \ldots \). To track the available actions formally, let \( h(t) \) denote the position that will be discovered next, and \( A(t) \) the set of alternatives the consumer has already discovered. Moreover, I define the consideration set \( S(t) \) as the set of alternatives the consumer has searched up to period \( t \). Given these definitions, the consumer chooses in period \( t \) between discovering the next alternative from position \( h(t) \), searching an already-discovered alternative from \( A(t) \), and ending the search by choosing an already-searched alternative in \( S \).

Greminger (2022) proves that the optimal policy for this dynamic decision process is fully characterized by three types of reservation values, one for each type of action available to the consumer. These reservation values are defined as the value of a hypothetical outside option that makes a myopic consumer indifferent between immediately taking it and choosing the respective action. Crucially, the myopic net benefit of an action does not depend on any other available alternatives or the availability of future discoveries. Hence, the reservation value for an action can be obtained in isolation from other actions and without having to consider myriad future periods. In my empirical model, the reservation values for the three different actions are given by:

- **Purchase value**: \( z^p_j = u_j = x'_j \beta + \nu_j + \varepsilon_j \).
- **Search value**: \( z^s_j = x'_j \beta + \nu_j + \xi \), where \( \xi \) solves
  \[
  \int_{\xi}^{\infty} [1 - F(\varepsilon)]d\varepsilon = c_s
  \]  
  and \( F \) is the CDF of \( \varepsilon_j \).
- **Discovery value**: \( z^d(h) = \mu(h) + \Xi \), where \( \Xi \) solves
  \[
  \int_{\Xi}^{\infty} [1 - G(u)]du = c_d
  \]  
  and \( G \) is the CDF of \( (U^j_l(h) - \mu(h)) + \min\{\xi, \varepsilon_j\} \). This distribution is determined by the consumers’ beliefs and does not change with position \( h \).

Given these reservation values, the optimal policy is simple: always choose the available action with the largest reservation value. For example, when the purchase value of an already-searched alternative is the largest reservation value available, the consumer ends her search by choosing that alternative. If instead the search value of an already-discovered alternative is

\[15\] Appendix G.3 and online appendix EC.2 of Greminger (2022) provide further details.
largest, the consumer searches that alternative. Finally, if the discovery value is the largest, the consumer scrolls down to reveal the alternative in the next position.

Defining the maximum utility and search values from the respective sets as \( \hat{u}(t) = \max_{j \in S(t)} u_j \) and \( \hat{z}^s(t) = \max_{j \in S(t)} z_j^s \), the optimal policy can be summarized by the following three rules:

**Stopping:** Choose \( j \in S(t) \) and end search whenever \( u_j = \hat{u}(t) \geq \max\{\hat{z}^s(t), z^d(h(t))\} \).

**Search:** Search \( j \in A(t) \) whenever \( z^s_j = \hat{z}^s(t) \geq \max\{\hat{u}(t), z^d(h(t))\} \).

**Discovery:** Discover the next position \( h(t) \) whenever \( z^d(h(t)) \geq \max\{\hat{u}(t), \hat{z}^s(t)\} \).

### 3.3 Position Effect Mechanism in the SD Model

By modeling the action of scrolling down the list page, the discovery model provides a clear mechanism for the observed position effects: consumers decide to stop scrolling before discovering all alternatives. As I now show, this mechanism also explains the shape of the position effect heterogeneity revealed by the reduced-form evidence.

Intuitively, an alternative gains clicks and demand from higher positions through two distinct channels in the SD model. First, being promoted makes it more likely that consumers discover the alternative. This increases clicks and demand because it cannot be searched or chosen unless it is discovered. Second, the alternative can preclude consumers from discovering alternatives further down the list. This increases the alternative’s clicks and demand because it can avoid the comparison with alternatives further down the list that consumers might prefer.

Both these effects are amplified by the list utility of the alternative being moved. The larger the list utility of an alternative, the more likely it will be clicked and chosen when discovered, and the more likely it precludes consumers from continuing to the next position. Hence, an alternative’s position effect increases in its list utility. Given that a higher list utility also leads to more clicks and bookings in the SD model, this means that the SD model also predicts heterogeneity in position effects consistent with the descriptive evidence: desirable hotels have larger position effects.

Proposition 1 formalizes this intuition. The proof in Appendix A extends Greminger (2022) by deriving expressions for position effects in clicks and purchases conditional on an alternative’s list utility. Importantly, the proof does not rely on specific distributional assumptions or values for the parameters. Hence, the result follows from the position effect generating mechanism rather than a specific parametrization.

**Proposition 1.** Position effects in the SD model weakly increase in the list utility \( u^l_j = x_j^l \beta + \nu_j \) for an alternative being moved up.
3.4 Estimation Approach

To operationalize the assumption that the belief function $\mu(h)$ weakly decreases across positions $h$, I assume the following functional form

$$\mu(h) = \mu_1 + \rho \log(h)$$  \hspace{1cm} (6)

and impose the restriction that $\rho \leq 0$.

The shape of this function determines how clicks and bookings decrease across positions. Hence, imposing such a functional form is similar to imposing a functional form on how search costs change with an alternative’s position, as applied in prior work that uses the Weitzman model to capture position effects (e.g., Chen and Yao, 2017; Ursu, 2018; Chung et al., 2024).

With $\log(1) = 0$, the chosen form in (6) implies a non-linear decrease starting from some $\mu_1$. This allows the model to fit the observed non-linear decrease in clicks across positions by estimating only a single parameter, $\rho$ (see Appendix E). $\mu_1$ is not a parameter that needs to be estimated. Instead, it is implied by the assumption that the average $\mu(h)$ across positions is known to consumers and will be recovered from the empirical distribution of hotel attributes (see Appendix G.3).

The goal of the estimation is to estimate the model parameters $\theta = (\beta, \beta_0, c_s, c_d, \rho)$ using data for $N$ consumers visiting the product list. The data for each consumer $i$ contain the chosen alternative $j$; the consideration set $S_i$ tracking the alternatives the consumer clicked on; and the positions $h_{ij}$ and attributes $x_j$ for all alternatives in $J_i$, the set of products on the consumer’s product list.

Given these data, the estimation procedure solves

$$\max_\theta \mathcal{L}(\theta) = \sum_{i=1}^{N} \log P(\text{observed choices of } i|(x_j, h_{ij})\forall j \in J_i; \theta)$$

$$= \sum_{i=1}^{N} \log P(\text{click all } k \in S_i, \text{ choose } j \in S_i|(x_j, h_{ij})\forall j \in J_i; \theta).$$  \hspace{1cm} (7)

The inner probability depends on the parameters gathered in $\theta$ and conditions on the hotel attributes and the ranking observed in the data. In what follows, I omit highlighting this dependence to simplify exposition and again suppress the consumer subscript $i$.

3.4.1 Likelihood Contributions

The individual likelihood contribution of a consumer is given by the probability of her observed choices under the optimal policy. One approach to operationalize this idea would be to use the three rules of the optimal policy to construct inequalities and maximize the likelihood of these inequalities holding. However, as for the Weitzman model, such an approach would lead to
complex likelihood contributions that can be difficult to compute. Moreover, it would require observing the search and the scrolling orders, neither of which are available in the Expedia data.\textsuperscript{16}

I develop a novel approach that circumvent these issues. Specifically, I derive several implications of the optimal policy that characterize the choices of a consumer who eventually chooses some (inside or outside) option $j$. By characterizing all other actions relative to the chosen option, these implications simplify the likelihood contributions and omit the need to observe the search order to compute them.\textsuperscript{17}

Proposition 2 provides the four implications. It builds on effective values—values that combine the different reservation values and fully characterize which alternative a consumer eventually chooses in the SD model (Greminger, 2022).\textsuperscript{18} Formally, the effective values of an option $j$ are defined as $w_j = \min\{z^d(h_j), \bar{w}_j\}$ and $\bar{w}_j = \min\{z^s_j, u_j\}$, where the second value does not depend on the position. For the outside option, the effective values are given by $w_0 = \bar{w}_0 = u_0$.

**Proposition 2.** Given the effective values $w_j$ and $\bar{w}_j$ for some alternative $j$, the optimal policy implies the following for a consumer who chooses this alternative $j$:

**Stopping:** The consumer discovers all alternatives in the awareness set $A(\bar{w}_j)$, which is the set of alternatives up to position $\bar{h}(\bar{w}_j) = \min_{h_k > h_j} \bar{w}_j \geq z^d(h_k)$.

**Search and early discovery:** The consumer searches all alternatives in $S_\neg = \{k : z_k \geq w_j, k \in A(\bar{w}_j), h_k < h_j\}$ and no other alternatives.

**Search and late discovery:** The consumer searches all alternatives in $S_\pos = \{k : z_k \geq \bar{w}_j, k \in A(\bar{w}_j), h_k \geq h_j\}$ and no other alternatives.

**Choice:** The consumer chooses $j \in S_\neg \cup S_\pos \cup \{0\}$ if $u_k < w_j \forall k \in S_\neg$ and $u_k \leq \bar{w}_j \forall k \in S_\pos \cup \{0\}$.

The stopping implication shows that the effective value of the chosen alternative fully determines the alternatives a consumer discovers. It follows from the search and stopping rules. Consumers stop scrolling in some position $\bar{h}$ once they discover an alternative that offers sufficiently high search and purchase values to be searched ($z^s_j > z^d(\bar{h})$) and chosen ($u_j > z^d(\bar{h})$). The effective value $\bar{w}_j$ combines both conditions through the minimum function. By additionally imposing a lower bound on $h_j$, the stopping implication also ensures that the consumer discovered the alternative she eventually chose.

The two search implications provide conditions for the search values of the alternatives that a consumer discovered. Given the set of discovered alternatives, they follow from the search and stopping rules. These rules imply that consumers search all alternatives that offer

\textsuperscript{16} Related work estimating the Weitzman model with the present data assumes that searches occurred in order of the positions (Ursu, 2018; Chung et al., 2024).

\textsuperscript{17} By discarding the search order, the approach can also be used when the search order is observed.

\textsuperscript{18} Effective values were introduced by Armstrong (2017) and Choi et al. (2018) for the Weitzman model. Greminger (2022) generalizes the idea to the SD model to account for discovery.

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a sufficiently large search value to be either searched before discovering \((z_k^s > z_d(h_j))\), after discovering but before searching \((z_k^s > z^s_j)\), or after searching \((z_k^s > u_j)\) the eventually chosen option \(j\).

Finally, the choice implication provides the conditions for the utility of alternatives in the consumer’s consideration set. It immediately follows from the consumer always choosing the alternative with the highest utility.

These four implications fully characterize a consumer’s choice conditional on the chosen alternative’s effective value. With these implications in hand, the individual likelihood contribution \(L^i(\theta)\) now can be calculated by taking expectations over the shocks determining the effective value \(\tilde{w}_j\) of the chosen option \(j\) and computing the probability of the inequalities implied by the four implications holding.

Formally, the individual likelihood contribution of a consumer who eventually chooses option \(j\) is given by

\[
L^i(\theta) = \log \int \left( \frac{1}{\tilde{h}(\tilde{w}_j) \forall k \in S} \right) \\
\times \prod_{k \in S_- \cup \{0\}} \mathbb{P}(Z_k^s \geq w_j \cap U_k \leq w_j) \\
\times \prod_{k \in S_+} \mathbb{P}(Z_k^s \geq \tilde{w}_j \cap U_k \leq \tilde{w}_j) \\
\times \prod_{k \in A(\tilde{w}_j) \setminus S} \mathbb{P}(Z_k^s \leq \tilde{w}_j) dH(\eta, \nu_j, \varepsilon_j),
\]

where \(H(\eta, \nu_j, \varepsilon_j)\) is the joint CDF of the shocks that form the effective values \(\tilde{w}_j\) and \(w_j\), and the utility \(u_j\) of the chosen option. Depending on whether the consumer chose the outside option or an alternative, either only the outside option shock \(\eta\) or the taste shocks \((\nu_j, \varepsilon_j)\) determine these values. \(1(\cdot)\) denotes the indicator function that captures that the consumer cannot have stopped scrolling before having discovered all alternatives she clicked on. \(S_- = \{k : k \in S, h_k < h_j\}\) is the set of clicked alternatives discovered before \(j\) and \(S_+\) is the set of clicked alternatives discovered after \(j\).

### 3.4.2 Smooth Likelihood Simulation

The individual likelihood contribution (8) requires does not admit a closed-form solution. Hence, computing it requires likelihood simulation techniques, which introduces two challenges.

The first challenge arises because simulating the integral requires calculating a probability of the form \(\mathbb{P}(Z_k^s \geq q \cap U_k \leq q)\) many times for different constants \(q\). Generally, computing this
probability would require using a numerical integration routine because the shock $\nu_j$ enters both $Z^*_j$ and $U_j$, such that the two random variables are not independent.

Proposition 7 in Appendix D.1 decomposes this probability into functions that can be computed using standard numerical methods, allowing me to compute this part of the likelihood without a computationally costly numerical integration routine.

The second challenge arises because naive Monte Carlo integration will lead to kinks and jumps in the likelihood function, making it difficult to solve (7) numerically. Specifically, such a procedure would simulate the integral by averaging the inner probability across draws $r = 1, \ldots, N_r$ for $\eta^r$ or $(\nu^r_j, \varepsilon^r_j)$ from the respective distributions. However, the set of alternatives a consumer discovers, $A(\tilde{w}^r_j)$, depends on the draw through the stopping implication. As a result, a tiny change in the parameter values can make a consumer discover one more alternative. This can create a jump in the likelihood because it changes the set of alternatives defining the last part of the inner probability in (7). Making matters worse, the effective value $\tilde{w}_j = \min\{\xi, \varepsilon_j\}$ has a kink at $\xi = \varepsilon_j$, which can exacerbate jumps and introduces additional kinks in the likelihood function.

I circumvent these issues by partitioning the relevant probability space into separate regions. Each region is defined so that the conditional likelihood is smooth in the parameters for every region. This is achieved by constructing the partition so that, in every region, (i) the number of alternatives the consumer discovers is fixed, and (ii) $\varepsilon_j$ is either greater or smaller than $\xi$. I then simulate the conditional likelihoods for each region separately and combine them into the unconditional likelihood. Because the conditional likelihoods and the probabilities of the different regions are smooth, this procedure yields a smooth likelihood contribution. Appendix D.2 formally defines the partition and provides further details on the simulation procedure.

Besides leading to a smooth likelihood function, partitioning the probability space also helps avoid regions where the likelihood of the data is zero. These regions are particularly common in the SD model because consumers must have discovered all alternatives they searched, a condition enforced by the indicator function in the likelihood contribution (8). By avoiding computations for draws that violate this condition, the procedure substantially reduces estimation time.

3.5 Parameter Identification and Normalizations

I first discuss the case where the data contains information on how far consumers scrolled. Although such information is rarely available, this case is instructive because it reveals the conditional moments that allow identifying the model parameters. I then show that the same conditional moments are determined in the data even without information on how many alternatives consumers discovered. Hence, the same identification arguments continue to apply.
3.5.1 With Data on How Far Consumers Scrolled

Conditional on discovery, the model reduces to a Weitzman model. Hence, if the data contains information on how far consumers scrolled, the same identification arguments apply for $\beta_0$, $\beta$, and $c_s$ with moments that condition on the discovered alternatives. For example, larger search costs imply that consumers are less likely to search the alternatives they discovered on the list. This means that the average number of clicks consumers make across the positions they have revealed identifies the search costs $c_s$. For the identification of the other search parameters, I refer to Ursu et al. (2024), who provide a recent review of the empirical Weitzman model and the respective identification arguments.

Given that these search parameters are identified by conditional moments, data on where consumers stopped discovering identifies the discovery parameters $c_d$ and $\rho$. Intuitively, consumers stopping scrolling earlier on the list implies that the discovery costs $c_d$ are large, and vice versa. Moreover, discovering only the first few positions but rarely scrolling further implies a smaller $\rho$, where consumers expect the alternatives they discover further down the list to be worse on average. Appendix G.3 shows this more formally by mapping the probability of stopping discovery at different positions to the discovery parameters.

3.5.2 Without Data on How Far Consumers Scrolled

Without data on how far consumers scrolled, these identification arguments no longer apply directly. A key concern is how to separately identify the search and discovery parameters. For example, an increase in either search or discovery costs will induce consumers to end discovery sooner and search fewer products. Without observing the number of clicks conditional on how far consumers scrolled, it so far remains unclear how the data would allow separately identifying the two costs.

However, as I now show, data on consumers’ clicks is sufficient to nonparametrically identify the probability of stopping discovery at different positions and to pin down the moments conditional on discovery. Hence, these moments are effectively present in the data, even without information on how many alternatives consumers discovered. As a result, the same identification arguments still apply, even in the absence of this information.

Intuitively, the probability of consumers stopping discovery at a given position is identified by the data if there is an observable pattern that can only be explained by consumers stopping discovery at that position. In the SD model, this pattern is given by the position effects, provided the ranking is randomized. Section 3.3 established that consumers stopping discovery generates position effects in the SD model. The ranking being randomized further ensures that higher click rates on the top positions are not driven by consumers’ preferences. Hence, the SD model can rationalize the observed position effects only through consumers stopping discovery. Proposition 5 in Appendix C formalizes this intuition by showing that the probability of stopping discovery at the different positions can be expressed as a function of differences
in the position-specific click rates. As these click rates can be estimated without data on how far consumers scrolled, this means that the stopping probabilities continue to be identified even without information on how far consumers scrolled.

When the stopping probabilities are identified in the data, so are the moments conditional on discovery. This follows from consumers not being able to search or choose alternatives they have not yet discovered. For example, consumers who stop scrolling before reaching the last position cannot search the product in this position. This means that the total number of clicks observed in the last position, combined with the likelihood that consumers reach it, fully determines the number of clicks among those who do. As a result, once the probability of reaching the position and the click frequency for the last position are given by the data, so is the click rate conditional on reaching the position. Proposition 6 in Appendix C establishes this result formally, and generalizes it to other positions through a recursive relation. Consequently, the moments conditional on discovery can be recovered from data that provides no direct information on how far consumers scrolled, such that the same identification arguments apply as in the case when these moments are directly available.

3.5.3 Shock Variances

The shock variances are not estimated. Instead, I set \( \sigma_\nu = 1 \) which is a true normalization (see Ursu et al., 2024). As highlighted by Morozov et al. (2021) and Yavorsky et al. (2021), the second standard deviation \( \sigma_\varepsilon \) is not a true normalization, but can be difficult to identify. I find a similar result in my model: jointly estimating \( \sigma_\varepsilon \) with the other parameters does not reliably yield consistent estimates. Hence, I follow Morozov et al. (2021) and set \( \sigma_\varepsilon = 1 \). Moreover, I analyze the sensitivity of the results in Appendix E. Specifically, I show that the consumer welfare effects, the estimated discovery costs, and the model’s ability to fit the data are not sensitive to the choice of \( \sigma_\varepsilon \). The reason for this insensitivity is that the estimates determining the net benefits of the different search actions over immediately taking the outside option—which ultimately determine consumers’ choices—are not very sensitive to \( \sigma_\varepsilon \). However, in line with Morozov et al. (2021), the results also reveal that the estimated search costs are highly sensitive to the choice of \( \sigma_\varepsilon \), which is why I refrain from reporting search costs in dollar terms.

3.5.4 Monte Carlo Simulation

I conduct Monte Carlo simulation studies to confirm that parameters can be estimated with the present data. I first generate searches and purchases for different parameter values, and then verify whether the estimation procedure can recover these parameter values from these simulated data. Appendix D.4 presents the results, revealing the estimation procedure recovers all parameters, including the discovery and search costs that are backed out post-estimation.
3.6 Parameterizing Discovery and Search values

In principle, it would be possible to estimate the discovery costs directly. This would require computing the discovery value \( z^d(1) \) for every parameter vector that the optimization routine will try. However, computing \( z^d(1) \) is costly because it requires taking many draws to approximate the attribute distribution and numerically solving for the root of (5) to obtain \( \Xi \).\(^{20}\)

By estimating a parameter \( \tilde{z}^d = z^d(1) \) instead of \( c_d \), I avoid having to do this computation many times during estimation. This approach works because, given consumers’ beliefs and the other parameters, \( z^d(1) \) uniquely determines \( c_d \) through (5). Hence, given estimates for \( \tilde{z}^d \) and the other parameters, I can back out \( c_d \) after the estimation by inverting (5). Barring small numerical differences that might arise from having to find the root numerically, the resulting estimate for \( c_d \) will be the same as an estimate obtained by directly estimating \( c_d \) and computing \( z^d(1) \) during estimation. Appendix G.3 provides further details on this procedure.\(^{21}\)

I also apply the same technique to the search costs to avoid having to numerically solve for a root during estimation. Instead of estimating the search costs \( c_s \), I estimate part of the search value, \( \xi \), and then back out \( c_s \) post-estimation by applying (4).

3.7 Sample Selection

Given that the data only contains sessions with at least one click, I follow Compiani et al. (2024) to account for this selection. Specifically, I condition the likelihood contributions on the event that the consumer makes at least one search, which is equivalent to dividing the likelihood contribution by the likelihood of the consumer making at least one click. To account for the sample selection when evaluating model fit, I use fit measures conditional on consumers searching at least one alternative throughout.\(^{22}\)

4 Estimation Results and Model Fit

I estimate the model using 100 simulation draws on consumer search sessions that observed the randomized ranking. To limit the computational burden, I restrict the estimation sample to the fifty largest destinations.\(^{23}\)

\(^{20}\)An exception is the case where search values are normally distributed, as described in the replication package to Greminger (2022).

\(^{21}\)For other positions, no such procedure is necessary because the discovery value for \( h > 1 \) is given by \( z^d(h) = z^d(1) + \rho \log(h) \) such that it can be easily computed given \( z^d(1) \) and \( \rho \).

\(^{22}\)Not accounting for the sample selection would lead to underpredicting the number of clicks compared to the ones observed in the data because the model predicts a share of consumers not searching at all.

\(^{23}\)I also follow Ursu (2018) by only including sessions with at least 30 hotel listings in the results and omitting opaque offers from this analysis.
| Parameter                              | Estimate  | Standard error |
|---------------------------------------|-----------|----------------|
| Price (in $100)                       | -0.242*** | (0.006)        |
| Star rating                           | 0.215***  | (0.006)        |
| Review score                          | 0.033***  | (0.008)        |
| No reviews                            | 0.098     | (0.038)        |
| Location score                        | 0.073***  | (0.003)        |
| Chain                                 | -0.018    | (0.008)        |
| On promotion                          | 0.089***  | (0.008)        |
| Outside option                        | 5.057***  | (0.035)        |
| $d$                                    | 5.469***  | (0.040)        |
| $\rho$                                | -0.093*** | (0.005)        |
| $\xi$                                 | 2.081***  | (0.020)        |
| Discovery costs ($)                   | 0.059     |                |
| $c_d \times 100$                      | 0.014     |                |
| $c_s$                                 | 0.007     |                |
| Log likelihood                        | -48,735.168 |               |
| N consumers                           | 11,467    |                |

Notes: Parameter estimates obtained using 100 simulation draws. Asymptotic standard errors are shown in parentheses. The Discovery costs are recovered using 10M draws. Statistical significance is indicated by * p < 0.1, ** p < 0.05, *** p < 0.01.

4.1 Parameter Estimates

Table 2 reports the parameter estimates and asymptotic standard errors, revealing that all parameter estimates have the expected sign.

The discovery cost estimate suggests that an average consumer is willing to pay 6¢ to reveal another alternative. Although small, these discovery costs prevent consumers from discovering all options, creating scope for rankings to affect their choices. The model correctly captures that it is unlikely that the next hotel discovered will be booked. As a result, the expected benefits of discovering an additional hotel are low, and consumers are unwilling to pay even small discovery costs to keep scrolling.24

4.2 Model Fit

I evaluate the model’s fit by comparing the model-implied position-specific click and booking probabilities with the ones in the estimation sample. The results in Figure 4 reveal that the model fits the decrease in clicks and bookings across positions remarkably well, confirming that the small implied discovery costs are sufficient for the model to fit the position effects in the data. Additional fit measures in Appendix D.3 further reveal that the parsimonious model specification also manages to fit various other moments.

24As I highlight in Section 3.5, the estimates for $c_s$ highly depend on the choice of $\sigma_\epsilon$, while estimates for $c_d$ depend little on this choice. Hence, the relative size of the costs should not be directly compared.
To effectively quantify the trade-offs between different rankings, the model should fit how an alternative’s position effect depends on its price—a crucial factor determining differences across rankings (see Section 2.3). To analyze whether this is the case, I re-estimate the linear probability model from Section 2.2 on data simulated with the estimated model. The results in Figure 5 reveal that the model fits the position effect across the different price percentiles remarkably well, confirming that the model accurately captures this crucial factor.25

25The overall magnitude of position effects differs from those in Figure 3 due to the different samples.
5 Ranking Comparison

With the model fit established, I now develop several ranking algorithms and compare their effects using the estimated model.

5.1 Ranking Algorithms

I focus on ranking algorithms that aim to maximize one of three metrics—conversions, revenues, or consumer welfare—by sorting the available alternatives on the list. Table 3 provides an overview of the rankings constructed by the algorithms I compare.

| Algorithm | Description |
|-----------|-------------|
| ER        | Expedia Ranking |
| UBR       | Utility-Based Ranking |
| R1R       | Rank-1 Ranking |
| BUR       | Bottom-Up Ranking |
| PDR       | Price-Decreasing Ranking |

### \text{Table 3} – Counterfactual Rankings

Developing ranking algorithms to maximize any metric is a challenging task. While a simple brute-force algorithm that tests all possible rankings is guaranteed to find the optimal one, it quickly becomes infeasible to execute. For example, with just 20 alternatives, there are already more than two quintillion rankings the algorithm would have to test.\(^{26}\) For the same reason, platforms also cannot determine the optimal ranking through simple A/B testing, making effective ranking algorithms valuable tools to achieve different objectives.

To simplify the analysis, I focus on the case where the platform does not disclose changes to the ranking. This assumption is common in research on ranking algorithms (e.g., Chu et al., 2020; Derakhshan et al., 2022; Compiani et al., 2024). However, the rationale underlying these algorithms remains largely the same even when consumers learn about the ranking change.\(^{27}\) While it is difficult to formally prove that the same properties continue to hold in this case, I leverage the model to additionally quantify the different rankings’ effects when consumers learn about the ranking change. The results in Appendix G.6 show that consumers learning about the ranking change further amplifies the different rankings’ intended effects. Hence, I conclude that the proposed algorithms remain effective in achieving their respective objectives even in this case.

5.1.1 Consumer Welfare Maximization

Maximizing consumer welfare can be an objective for platforms operating in a competitive environment and concerned about (long-term) customer churn and growth. Moreover, the

\(^{26}\)Generally, there are \(N!\) possible rankings for \(N\) alternatives.

\(^{27}\)In a recent working paper, Fong et al. (2024) find that consumers do not immediately adjust their search behavior to a new ranking, but may learn about the algorithm over time with repeated interactions.
consumer-welfare-maximizing ranking provides regulators with a benchmark to assess the potential adverse consumer welfare effects of different rankings.

To maximize consumer welfare, a ranking should help consumers find better-matching alternatives, reduce the discovery costs they pay, or do both simultaneously. Intuitively, this can be achieved by promoting high-utility alternatives, allowing consumers to find them without incurring high discovery costs. Proposition 3 confirms this intuition by establishing that an algorithm that ranks alternatives by utility maximizes consumer welfare in the SD model. Appendix A provides the formal proof.

**Proposition 3.** Ranking alternatives in decreasing order of the expected list utility $u_j^e = x_j^e \beta$ maximizes consumer welfare and the conversion rate.

Proposition 3 further establishes that this “Utility-Based Ranking” (UBR) also maximizes the conversion rate. The result follows directly from the fact that the ranking determines which products consumers discover. By promoting high-utility alternatives, the UBR minimizes the likelihood that consumers end their search before discovering a product they would be willing to buy, while also maximizing the chance that they find their preferred option.

### 5.1.2 Revenue Maximization

Next, I introduce ranking algorithms designed to maximize total revenues from the list. By maximizing total revenues, these algorithms also maximize the platform’s profits, provided it takes a commission as a percentage of revenues. The reduced-form evidence indicated that lower-priced hotels have larger position effects, meaning that increasing revenues requires balancing the demand and price effects highlighted in Section 2.3.

This presents a complex optimization problem, and unlike in the case of consumer welfare maximization, there is no simple ranking that provably solves it. The difficulty arises because the ordering of alternatives in other positions determines the revenues an alternative will have in a particular position. As a result, simple algorithms that avoid comparing all possible rankings by determining how to fill each position in isolation will not perform well unless this influence is negligible.

To overcome this challenge, I introduce a heuristic ranking algorithm that constructs the “Bottom-up Ranking” (BUR). As the name suggests, the algorithm starts ranking alternatives from the bottom up. The first step is to iterate over each of the available alternatives and compute the total revenues when that alternative is shown in the last position, while the alternatives above are sorted using the UBR. The second step is to select the alternative that maximizes total revenues computed in the first step and fix it to the last position. Then, the algorithm returns to the first step, but now determines the alternative for the second-to-last position, and so on. With this iterative procedure, constructing the BUR for a consumer requires computing total

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28 The revenue-based rankings can be readily adjusted for the case where a platform earns more by selling certain products. The trade-offs in ranking objectives in this case will depend on the utility offered by those alternatives.
revenues $\sum_{k=1}^{N} (N - k)$ times, where $N$ is the number of alternatives the consumer can discover. For example, with 20 alternatives, this requires 190 revenue comparisons, substantially fewer than the quintillions required for the brute-force algorithm.

Starting to fill positions from the bottom, instead of from the top, is motivated by the fact that the demand and revenues of an alternative in a particular position is unaffected by the ordering of alternatives discovered in previous positions—only their identity has an influence. As a result, filling in positions from the bottom up can circumvent much of the influence of the ordering of other alternatives when iteratively deciding which alternatives to display in each position. For example, suppose some product offers a sufficiently large utility to induce a consumer to immediately choose it upon discovering it. In this case, the consumer does not reveal the third position, independent of whether this high-utility alternative is displayed in the first or second position. Hence, when first determining which alternative to display in the third position, the ordering of the alternatives in the first two is irrelevant for the revenues in the third position. In contrast, whether the high-utility alternative is shown in the second or third position will influence whether the consumer chooses the alternative in the first position because the consumer might not discover the high-utility alternative in the third position. As a result, the revenues of the alternative in the first position is directly affected by how the alternatives in the remaining positions are sorted. Consequently, an algorithm filling positions from the top down will be influenced by how the alternatives below the current position are sorted.

I compare this bottom-up ranking algorithm to an alternative heuristic algorithm that constructs the “Rank-1 Ranking” (R1R). This algorithm sorts alternatives based on the revenues they generate in the first position—the position that generates the most purchases and, therefore, is the most relevant. The first step in this algorithm is to iterate over and calculate each alternative’s revenues when shown in the first position, while the other alternatives are sorted using the Utility-Based Ranking. The second step is to sort all alternatives based on the revenues calculated in the first step.

The Rank-1 Ranking is fast to construct because the first step requires computing each alternative’s revenues only once. With $N$ alternatives, this requires only calculating $N$ times the revenues of a single alternative. It also emulates a simple algorithm based on alternatives’ past revenues in a particular position—a type of algorithm likely used in practice. Specifically, a platform could easily implement a version of this algorithm without any demand model; it would only need to show the different alternatives in the first position, and then rank them based on the revenues they generated in that position.

To measure the importance of the position effect heterogeneity this paper documents, I further compare these heuristics with a “Price-Decreasing Ranking” (PDR) that sorts alternatives by their price. Proposition 4 proves that this ranking maximizes revenues in the SD model when position effects are homogeneous, rendering it a useful benchmark for assessing the importance of position effect heterogeneity. The proof in Appendix A shows that the result follows from
the fact that when position effects are homogeneous, the conversion rate does not depend on
the ranking, making it optimal to promote expensive alternatives based on the price effect.

**Proposition 4.** The Price-Decreasing Ranking (PDR) maximizes revenues when position ef-
fects are homogeneous.

### 5.2 Counterfactual Results

To compare the different rankings, I use the model to quantify their effects by simulating con-
sumers’ choices. To compute consumer welfare more efficiently, I build on the extended even-
tual purchase theorem of Greminger (2022) to obtain an expression for consumer welfare that
circumvents the need to simulate different search paths (see Appendix G.4). Moreover, I use
a simulation procedure similar to the one for the likelihood contributions to precisely calculate
the small choice probabilities for each alternative (see Appendix G.5).

I quantify the consumer welfare and revenue effects of the proposed rankings relative to
a neutral benchmark that favors no particular objective—the randomized ranking. As an ad-
ditional benchmark, I also include Expedia’s own ranking algorithm as observed in the data.
The comparison with this ranking gives an indication of how the proposed algorithms could
improve on the status quo during the sample period. 29

To be able to compare the rankings to Expedia’s ranking, I use the sample of sessions
that observed this ranking for the counterfactual analysis. 30 To further limit the computational
burden, I randomly sample 10,000 sessions from this sample.

#### 5.2.1 Relative to a Randomized Ranking

Table 4 shows the effects of the different rankings relative to the neutral benchmark. The ER,
UBR, BUR, R1R, and PDR all manage to increase revenues over the randomized ranking. As
intended, the R1R and BUR increase revenues the most, with the BUR outperforming the R1R
and Expedia’s own ranking. Despite being designed to benefit consumers, the UBR also leads
to a substantial increase in platform revenues of 11.14%. It achieves this revenue increase by
maximizing the number of bookings. The two heuristics that target revenues instead balance
the demand with the price effect, inducing consumers to book more expensive hotels. This
allows them to generate even larger revenue increases of up to 17.97%, but reduces the number
of bookings relative to the conversion-maximizing UBR.

Turning to consumer welfare effects, the Utility-Based Ranking increases the average con-
sumer welfare by a modest 7¢. This increase is small because most consumers are not predicted

29Expedia’s algorithm was not trained on the demand system I am imposing with my model. Nonetheless, the
estimated model closely fits the data, suggesting that Expedia’s ranking should continue to work as intended
within the model-implied demand system.

30Whereas purchases are oversampled in this sample, using the model estimated on the sample with the randomized
ranking to quantify the effects of all rankings, including Expedia’s, ensures that the comparison uses the same
population throughout.
Table 4 – Ranking Effects (Over Randomized Ranking)

|                        | ER  | UBR | R1R | BUR | PDR |
|------------------------|-----|-----|-----|-----|-----|
| **Platform**           |     |     |     |     |     |
| Total revenues (%)     | 4.19| 11.14| 15.40| 17.97| 3.75|
| Number of transactions (%) | 4.45| 14.53| 10.74| 14.13| -4.87|
| Avg. price of booking (%) | -0.25| -2.96| 4.21 | 3.37 | 9.06|
| **Consumers**          |     |     |     |     |     |
| Consumer welfare ($, average) | 0.02| 0.07| 0.05| 0.06| -0.02|
| Consumer welfare ($, cond. on booking) | 3.11| 10.31| 8.27| 8.59| -4.86|
| Discovery costs ($, cond. on booking) | -0.06| -0.18| -0.14| -0.15| 0.08|

Notes: Changes relative to a randomized ranking obtained by averaging across 100 randomizations.

Comparing the effects of the two revenue-targeting heuristics reveals that the BUR performs better than the R1R in both metrics. It does so by promoting more high-utility alternatives to further increase conversions (14.13% vs. 10.74%), which also benefits consumers. Hence, while being more involved to construct, starting to rank alternatives from the bottom provides an effective way for platforms to increase revenues relative to simpler algorithms, while also benefitting consumers.

The results for the Price-Decreasing Ranking reveal the importance of the position effect heterogeneity I document. The PDR would maximize revenues if position effects were homogeneous, implying that there would be no effect on conversions. However, the results in Table 4 reveal that the PDR performs worst among all tested rankings: it increases revenues only by 3.75% and substantially decreases consumer welfare. Hence, the simple heuristic that abstracts from position effect heterogeneity and only promotes based on price leads to a ranking that benefits neither the platform nor consumers.

Combined, these results suggest that the proposed Bottom-Up Ranking is an effective means for a platform to increase its revenues, while also benefitting consumers. By considering how consumers use the list to discover more alternatives, the ranking manages to outperform simpler heuristics that do not sufficiently consider the effects on conversions. Although this entails promoting high-utility alternatives, the Bottom-Up Ranking does not maximize consumer welfare or conversions, unlike the Utility-Based-Ranking. Nonetheless, the results indicate that it does not come at great cost to consumers, suggesting only limited trade-offs between the different objectives.

I further analyze the way the different rankings affect consumers. Rankings can affect
consumers in the SD model by determining the discovery costs they pay and the best utility they discover before choosing an option. To disentangle the two effects, I report the change in discovery costs paid by consumers who eventually book a hotel in the last row of Table 4. These cost changes range from a reduction of 18¢ for the UBR, to an increase of 8¢ for the PDR. These small cost changes are in line with the small discovery cost estimates. Moreover, they make up only a small part of the entire welfare change, highlighting that rankings mainly affect consumers by determining the hotels they discover and eventually choose, rather than helping them find their preferred alternative earlier.

5.2.2 Relative To Revenue Maximum

While the comparison so far revealed that the proposed Bottom-Up Ranking performs well compared to various other rankings, it is not guaranteed to maximize revenues. Hence, it is possible that the rankings in the comparison are simply ineffective at increasing revenues, meaning that another ranking could still substantially increase the revenues relative to the BUR. To analyze whether this is the case, I additionally compare the BUR’s revenues to the maximum possible. To make this comparison feasible, I reduce the number of available alternatives by randomly selecting up to seven alternatives for each session, allowing me to obtain the revenue-maximizing ranking by iterating over all possible rankings. The results in Appendix G.2 show that the BUR decreases revenues by less than 0.5% from the maximum possible, confirming that it is highly effective at increasing revenues.

6 Comparison with the Weitzman Model

The Weitzman (WM) model is an established alternative approach to quantify the effects of rankings and other changes to the search environment (see Ursu et al., 2024). The SD model I estimate in this paper generalizes the WM model by introducing that consumers first need to discover an alternative before being able to search it. As Greminger (2022) highlights, this difference is not only conceptual but also matters empirically: abstracting from product discovery can introduce biases in the search cost and preference estimates because it requires assuming that consumers observe the entire list page—an assumption unlikely to hold unless there are only few alternatives on the list. I now extend these results by showing how explaining position effects through product discovery also allows the SD model to better fit this key factor in the data.

6.1 Parametrization and Estimation

I compare the empirical search and discovery model with a baseline Weitzman model (e.g., Ursu, 2018). To keep the models as similar as possible, I use the same general utility specification as in the search and discovery model. Unlike in the SD model, consumers in the WM
model are aware of all list utilities $u^i_j$ upon arriving on the list and there is no notion of product discovery. Without product discovery, the WM model generates position effects through higher search costs for lower positions. Formally, search costs determine the search value $\xi(h)$ defined in (4), which now depends on the position $h$. As search costs increase, $\xi(h)$ decreases, leading to fewer searches and purchases at lower positions. To estimate these position-specific search costs, I impose a non-linear functional form on how search costs depend on the position. This functional form parallels the one I impose in the SD model and allows capturing the non-linear decrease in clicks and bookings by estimating two parameters.

To estimate the WM model, I leverage the fact that it is a special case of a general SD model, allowing me to use the same simulated maximum likelihood approach developed in Section 3. Using this approach has the advantage that it does not require observing the search order, keeping the data requirements comparable between the two models. Appendix F provides further details.

### 6.2 Results for the Weitzman Model

I estimate the WM model using the same estimation sample as for the SD model and evaluate model fit by comparing the model-implied position effects across the different price percentiles. The results in Figure 6 show that, similar to the SD model, the WM model fits position effects in clicks remarkably well. Unlike in the SD model, however, the shape of their heterogeneity is not implied by the mechanism producing position effects. Instead, by changing the search cost estimates or the specification of the shock distributions, the WM model could, in principle, produce the opposite result. Hence, the WM model offers no clear mechanism explaining this result.

For bookings, Figure 6 shows that the WM model substantially underpredicts position effects for all price percentiles. As only bookings and not clicks generate demand for the different hotels, this result implies that the WM model substantially underestimates the position effects that ultimately determine the trade-offs in ranking objectives.

Figure 7 reveals the reason for this result. The panels show the position-specific percentage of clicks that result in a booking for the estimation sample and data simulated from the respective models. The first panel shows that this percentage is stable across positions in the data, as also noted by Ursu (2018). In contrast, in the estimated WM model, the post-search purchase probability at the bottom position is nearly three times higher than at the top. As a result, the WM model overpredicts bookings at lower positions despite matching the clicks at those positions, creating the contrast shown in Figure 7.

31 Ursu (2018), Jiang et al. (2021), Morozov (2023), and Chung et al. (2024) provide alternative estimation approaches for the WM model. All these approaches require observing the search order.
**6.3 Rationale and Comparison**

This result is a direct implication of the WM model and not specific to the empirical specification I estimate. In the WM model, consumers are only willing to search an alternative at the bottom of the page if it is promising enough to warrant paying the increased search cost. Hence, for an alternative to be searched in a lower position, it must offer a larger list utility, making it more likely that the consumer will choose it after searching. Appendix F.4 provides a formal proof for this argument.

This model implication makes it difficult for the WM model to simultaneously fit the position effects in clicks and bookings observed in the data. When the WM model fits the position effects in clicks, it necessarily underestimates them in bookings, as in Figure 6. Vice versa, for the WM model to fit the position effects in bookings, it would need to distort where consumers click to offset that the model-implied post-search purchase probabilities contradict the data.

The SD model does not have the same implication and, as shown in the right panel of Figure 7, generates a constant post-search purchase probability. This results from the SD model explaining position effects through a different mechanism: product discovery. With this mechanism, an alternative’s position influences its clicks and purchases by determining the likelihood of it being discovered. Importantly, the probability of discovering an alternative depends on the utility of the alternatives discovered before it, rather than on the alternative’s own list utility.
Hence, unlike the WM model, the SD model does not require alternatives in lower positions to offer a larger list utility for consumers to search them. If an alternative’s list utility is large enough for a consumer to search it in the first position, the consumer would also search it in any other position, provided she scrolls far enough to discover it. Consequently, the SD model can fit the constant post-search purchase probabilities, allowing it to simultaneously fit position effects in clicks and bookings (see Figure 5).

The empirical comparison of the two models uses parsimonious specifications that are designed to keep the models comparable to each other and to prior work estimating the Weitzman model. Whereas alternative specifications are possible, the discussed rationale applies independent of the functional forms or distributional assumptions imposed.\textsuperscript{32} Hence, I conclude that explaining position effects through product discovery allows the SD model to better fit the data, including moments that are highly relevant when determining the effects of different rankings.

7 Conclusions

This paper studies and quantifies the trade-offs between different ranking objectives. Using data with exogenous ranking variation, I provide reduced-form evidence of a key factor shaping these trade-offs: cross-product heterogeneity in position effects. I then develop a novel structural model and show that it effectively captures this factor. Moreover, I develop ranking algorithms for different objectives and compare their effects in a counterfactual analysis. The results suggest that the trade-offs between ranking objectives are limited, and that the proposed heuristic to maximize revenues provides an effective way to simultaneously increase the platform’s revenues and help consumers find better-matching alternatives.

Whereas I use the proposed empirical framework to study the effects of ranking algorithms, a promising avenue for future work is to allow sellers to influence their rank. For example, the platform could offer slots at the top of the list that sellers would want to compete for to ensure consumers discover them. The proposed empirical framework could then be used to compare the effects of different ways to organize this competition.

Another promising avenue for future research is to extend the proposed framework and apply it to data tracking how consumers discover products more broadly. For example, consumers may also visit other platforms or use price aggregators to discover more products. The proposed framework can be adapted to incorporate such discovery technologies, allowing future work to apply it in a broader context.

\textsuperscript{32} Making the WM model more flexible by introducing heterogeneity in various dimensions or abandoning the rational expectations assumption would likely allow it to better fit the data. However, in that case, the model would have to use the additional flexibility to fit the constant post-search purchase probabilities. An SD model with the same degree of flexibility would not have the same restriction, such that it would be able to improve model fit in other dimensions.
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Appendices

A  Proofs of Propositions

This appendix provides proofs for the three propositions presented in the main text.

A.1  Proof of Proposition 1

To prove Proposition 1, I first derive a Lemma that provides general expressions for the position effect in searches and demand.

Lemma 1. Let $\tilde{W}_h = \max_{k: h_k \leq h} \tilde{W}_k \geq z^d(h)$ denote the maximal effective value discovered up to position $h$. Conditional on its observable attributes, the position effect for the demand for some alternative $j$ in position $h$ is given by

$$\Delta d_j(h) = P(\tilde{W}_{h-1} \in (z^d(h), z^d(h-1)]) P(\tilde{W}_j > \tilde{W}_{h-1} | \tilde{W}_{h-1} \in (z^d(h), z^d(h-1)])$$

$$+ P(\tilde{W}_{h-1} \leq z^d(h)) P(\tilde{W}_j > z^d(h)) P(\tilde{W}_j > z^d(h)),$$  \hspace{1cm} (9)

where $W_k$ is the effective value of the alternative $k$ that is shown besides $j$ in either position $h$ or $h+1$.

Similarly, the position effect in searches is given by

$$\Delta s_j(h) = P(\tilde{W}_{h-1} \in (z^d(h), z^d(h-1)]) P(Z_j^s > \tilde{W}_{h-1} | \tilde{W}_{h-1} \in (z^d(h), z^d(h-1)])$$

$$+ P(\tilde{W}_{h-1} \leq z^d(h)) P(Z_j^s > z^d(h)) P(\tilde{W}_j > z^d(h)).$$  \hspace{1cm} (10)

The Lemma is derived as follows. The stopping and search rules imply that the consumer stops in position $h$ whenever $\tilde{W}_h \geq z^d(h)$, i.e., whenever the maximal effective value discovered so far exceeds the discovery value. Hence, by partitioning the probability space, the position effect in purchases can be written as

$$\Delta d_j(h) = d_j(h) - d_j(h+1)$$

$$= P(\tilde{W}_{h-1} \in [z^d(h), z^d(h-1)]) P(\tilde{W}_j > \tilde{W}_{h-1} | \tilde{W}_{h-1} \in [z^d(h), z^d(h-1)]) +$$

$$P(\tilde{W}_{h-1} \leq z^d(h)) [P(\tilde{W}_j > z^d(h)) (1 - P(\tilde{W}_k \leq z^d(h))) + 1],$$  \hspace{1cm} (11)

where

$$C = P(\tilde{W}_j \leq z^d(h)) P(\tilde{W}_j \geq \tilde{W}_{h+1} | \tilde{W}_j \leq z^d(h), \tilde{W}_h \leq z^d(h)) -$$

$$P(\tilde{W}_k \leq z^d(h)) P(\tilde{W}_j \geq \tilde{W}_{h+1} | \tilde{W}_j \leq z^d(h), \tilde{W}_k \leq z^d(h), \tilde{W}_h \leq z^d(h)).$$  \hspace{1cm} (12)
Because \( \mathbb{P}(\tilde{W}_j \geq \tilde{W}_{h+1}|\tilde{W}_j \leq z^d(h), \tilde{W}_k > z^d(h)) = 0 \), we get \( C = 0 \) and immediately obtain equation (9). As consumers always click a discovered alternative \( j \) whenever \( \bar{z}^*_i \geq \bar{w}_h \), the expression for position effects in clicks can be derived the same way.

Proposition 1 then follows from these expressions because the sizes of the two position effects of \( A \) depend on the distribution of \( \tilde{W}_j = u^e_j + \nu_j + \min\{\xi, \varepsilon_j\} \) and the distribution of \( Z^*_j = u^e_j + \nu_j + \xi \). If larger values of \( Z^*_j \) or \( \tilde{W}_j \) become more likely, then the respective position effect is larger. Hence, the position effects increase in \( u^e_j = x^e_j \beta \).

### A.2 Proof of Proposition 3

Because there are a finite number of alternatives, a finite number of possible rankings exists. This guarantees that an optimal ranking exists. Hence, to show that a utility-based ranking maximizes consumer welfare and the conversion rate, it is enough to show that an improvement exists whenever alternatives are not ranked in decreasing order of \( u^e_j \).

To show whether an improvement exists, I use that consumer welfare is given by

\[
\mathbb{E} \left[ \sum_{h=0}^{\bar{h}} 1(\tilde{W}_{h-1} < z^d(h-1))1(\tilde{W}_h > z^d(h)) \times \sum_{j \in A_h} 1(\tilde{W}_j \geq \tilde{W}_h)\tilde{W}_j \right] - \\
\mathbb{E} \left[ \sum_{h=0}^{\bar{h}} 1(\bar{w}_h < z^d(h))c_d \right],
\]

where \( \bar{w}_h = \max\{\bar{w}_0, \ldots, \bar{w}_h\} \) is the maximal effective value discovered up to position \( h \) (see Appendix G.4).

Suppose the first claim does not hold, i.e., a ranking where \( u^e_A < u^e_B \), with \( h_A = h \) and \( h_B = h + 1 \) for two alternatives \( A \) and \( B \) maximizes welfare.\(^{33}\) In this case, switching the two alternatives leads to a change in consumer welfare that follows from the two parts in equation (13).

The first part in (13) changes with three possible cases for the realized effective values:\(^{34}\)

1. \( \bar{w}_A > z^d(h), \bar{w}_B > z^d(h) \) : the consumer stops before discovering the second product such that the realized change is \( \Delta = \bar{w}_B - \bar{w}_A \).
2. \( \bar{w}_A > z^d(h), \bar{w}_B < z^d(h) \) : the consumer never books \( B \) such that \( \Delta = \bar{w}_A - \bar{w}_A = 0 \).
3. \( \bar{w}_A < z^d(h), \bar{w}_B > z^d(h) \) : the same logic applies as in 2. such that \( \Delta = 0 \).

Because \( u^e_A < u^e_B \), larger realizations of \( \bar{w}_B \) are more likely such that the first case implies that the first part in equation (13) increases if \( A \) and \( B \) are switched.

The second part in equation (13) also increases with the switch; \( u^e_A < u^e_B \) immediately implies that the probability of stopping on position \( h \) increases, making it less likely to pay the

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33 Whenever \( u^e_B < u^e_A \) and \( h_B > h_A + 1 \), then there must be some \( \hat{A} \) and \( \hat{B} \) such that \( u^e_{\hat{B}} < u^e_{\hat{A}} \) and \( h_{\hat{B}} = h_{\hat{A}} + 1 \).

34 Alternatives discovered before \( h \) and after \( h + 1 \) do not need to be considered for this analysis, as the probability of reaching \( h \) and the probability of continuing beyond \( h + 1 \) are not affected by switching \( A \) and \( B \).
additional discovery costs.

Hence, the switch increases consumer welfare, which implies that whenever a ranking does not order alternatives in decreasing order of \( u_j^e \), an improvement exists.

To prove the second claim, suppose again the opposite; a ranking where \( u_A^e < u_B^e \), with \( h_A = h \) and \( h_B = h + 1 \) maximizes conversions. Switching the two alternatives leads to a change in the conversion rate equal to\(^{35}\)

\[
P(U_0 \geq z^d(h))[P(\hat{W}_B \geq U_0) - P(\hat{W}_A \geq U_0)] .
\] (14)

\( u_A^e < u_B^e \) then directly implies that larger values \( \hat{w}_B \) are more likely than those of \( \hat{w}_A \) such that this is positive. Hence, the switch increases conversions such that an improvement exists.

### A.3 Proof of Proposition 4

Similar to the proof for the consumer-welfare maximizing ranking, I prove this proposition by showing that under any alternative ranking, there exists a switch that increases revenues. I again use the notation that \( B \) is the alternative being moved up.

Proposition 1 implies that position effects are only homogeneous in the SD model when alternatives are homogeneous in the expected list utilities \( u_j^e \). This implies that switching two alternatives only shifts demand from \( A \) to \( B \) and leaves the demand for other alternatives unaffected. Hence, the total change in revenues following a switch is given by

\[
\Delta R = (p_B - p_A) \Delta d_A .
\] (15)

The expression shows that for any ranking that is not decreasing in price such that \( p_B > p_A \) is possible, there exists a switch that increases revenues as long as there are position effects such that \( \Delta d_A = \Delta d_B > 0 \). If there are no position effects, then \( \Delta R = 0 \) such that any ranking, including the Price-Decreasing Ranking, maximizes revenues.

\(^{35}\)With \( u_0 < z^d(h) \), the consumer either books a hotel or discovers the hotel in position \( h + 1 \) such that switching the two alternatives does not influence the purchase probability.
Further Evidence of Position Effects

Table 5 presents the parameter estimates for the main regression (1). As in the main text, the coefficient estimates are scaled to represent changes in percentage points. Columns 1 and 4 show the results of a baseline model that does not include the interaction term and, hence, assumes that position effects are homogeneous. Columns 2 and 5 show the main results. Columns 3 and 6 show the results for the specification that additionally includes hotel fixed effects.

The remainder of this appendix presents results for alternative specifications. Throughout, the results indicate that the main findings are robust to these alternative specifications. First, I replicate the analysis of Figures 2 and 3 for a Probit model and a linear probability model that parametrizes position effects more flexibly. The results are shown in Figures 8 to 11.

Table 6 presents coefficient estimates for another linear probability model where the position effect is specific to the first three positions and then follows a linear specification for the remaining hotels. This specification is given by

$$P(Y_{ij} = 1 | z_{ij}, pos_{ij}) = x'_j \beta_1 + w'_i \beta_2 + \sum_{q=1}^{3} 1(pos_{ij} \leq h)(\gamma_h + x'_j \theta_h) -$$

$$1(pos_{ij} \geq 4)(pos_{ij} - 3)(\gamma_4 + x'_j \theta_4) + \tau_d. \quad (16)$$

In this specification, $\gamma_h$ and $\theta_h$ capture the position effect on position $h$. To see this, consider, for example, the effect of decreasing $pos_{ij}$ from $h = 2$ to $h = 1$. (16) and the definition of the position effect in (2) implies that this effect is given by

$$\text{Position effect}_{ij} = (\gamma_1 + \gamma_2) + x'_j(\theta_1 + \theta_2) - \gamma_1 - x'_j \theta_1 = \gamma_2 + x'_j \theta_2. \quad (17)$$

Hence, $\gamma_2$ and $\theta_2$ capture the expected change in $Y_{ij}$ when moving from the second to the first position. Similarly, $\gamma_4$ and $\theta_4$ capture the expected change in $Y_{ij}$ when moving across positions beyond $h = 3$. For example, changing $pos_{ij}$ from $h = 5$ to $h = 4$ implies

$$\text{Position effect}_{ij} = -(4 - 5 - 3)(\gamma_4 + x'_j \theta_4) = \gamma_4 + x'_j \theta_4. \quad (18)$$

Finally, I also estimate the following specification, which allows position effects to be fully

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36 Standard errors are clustered on a consumer query level, capturing that search behavior can induce correlation in the error terms. A large draw in one alternative can mean that consumers are less likely to click on or book another alternative, suggesting a potential negative correlation in the error terms.

37 Several hotels are displayed only to a single consumer and therefore are excluded from this specification. Only price and whether the hotel is on promotion vary across different search sessions, such that the coefficients in $\beta_1$ cannot be estimated for other characteristics. The interaction between hotel characteristics and position can still be estimated because it is identified by within-hotel variation of the position.
flexible across all positions:

\[
P(Y_{ij} = 1|z_{ij}, pos_{ij}) = x'_j \beta_1 + w'_i \beta_2 + \sum_{q=h}^{33} 1(pos_{ij} = h)(\gamma_h + x'_j \theta_h) + \tau_d. \tag{19}
\]

In this specification, \(\gamma_h\) and \(\theta_h\) capture the position effect on position \(h\) relative to the bottom position \(h = 34\). \(^{38}\)

Figures 12 and 13 present the estimates for the main parameters \(\theta_h\) for positions \(h \leq 15\). For clicks, the results are consistent with the parsimonious specification from the main text: price mutes position effects, while location score—a desirable attribute that also has a strong effect in the parsimonious specification—amplifies position effects. For the other variables, the effects are not statistically significant, indicating insufficient variation of these attributes in the data.

Given the small booking probabilities and many parameters to estimate, differences in position-specific position effects across different hotels are difficult to identify, as evidenced by the coefficients \(\gamma_h\) not being statistically significant for the less flexible specification in Table 6. Nonetheless, the results from the extremely flexible specification continue to imply that lower-priced hotels have larger position effects conditional on other attributes.

\(^{38}\)I drop sessions with more than 34 hotels to avoid estimating position effects for positions that are rarely observed.
|                | (1)   | (2)   | (3)   | (4)   | (5)   | (6)   |
|----------------|-------|-------|-------|-------|-------|-------|
| Position       | 0.1864*** | 0.1424*** | 0.1427*** | 0.0116*** | 0.0028 | 0.0028 |
|                | (0.0019) | (0.0121) | (0.0123) | (0.0005) | (0.0028) | (0.0029) |
| Price          | -0.0125*** | -0.0173*** | -0.0190*** | -0.0011*** | -0.0017*** | -0.0017*** |
|                | (0.0002) | (0.0004) | (0.0004) | (0.0000) | (0.0001) | (0.0001) |
| On promotion   | 1.1578*** | 1.4961*** | 1.5318*** | 0.1261*** | 0.1436*** | 0.1463*** |
|                | (0.0497) | (0.1100) | (0.1229) | (0.0130) | (0.0287) | (0.0332) |
| Star rating    | 1.6211*** | 2.1556*** | 0.1051*** | 0.127*** |
|                | (0.0317) | (0.0657) | (0.0079) | (0.0163) |
| Review score   | 0.0810** | 0.0287 | 0.0366*** | 0.0794*** |
|                | (0.0351) | (0.0813) | (0.0082) | (0.0193) |
| No reviews     | -0.2488 | -0.7767** | 0.0872** | 0.1412* |
|                | (0.1622) | (0.3839) | (0.0345) | (0.0825) |
| Chain          | 0.2227*** | 0.3105*** | 0.0248** | 0.0641*** |
|                | (0.0459) | (0.0966) | (0.0113) | (0.0240) |
| Location score | 0.4381*** | 0.5602*** | 0.0529*** | 0.0556*** |
|                | (0.0168) | (0.0321) | (0.0036) | (0.0071) |
| Position × Price | -0.0003*** | -0.0003*** | -0.0000*** | -0.0000*** |
|                | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Position × Star rating | 0.0318*** | 0.0270*** | 0.0011 | 0.0005 |
|                | (0.0028) | (0.0029) | (0.0007) | (0.0007) |
| Position × Review score | -0.0028 | -0.0044 | 0.0025*** | 0.0024*** |
|                | (0.0035) | (0.0035) | (0.0008) | (0.0008) |
| Position × No reviews | -0.0295* | -0.0338** | 0.0032 | 0.0026 |
|                | (0.0164) | (0.0166) | (0.0035) | (0.0036) |
| Position × Chain | 0.0053 | 0.0047 | 0.0023** | 0.0017 |
|                | (0.0041) | (0.0042) | (0.0010) | (0.0010) |
| Position × Location score | 0.0071*** | 0.0083*** | 0.0002 | 0.0004 |
|                | (0.0013) | (0.0013) | (0.0003) | (0.0003) |
| Position × On promotion | 0.0201*** | 0.0209*** | 0.0010 | 0.0010 |
|                | (0.0048) | (0.0049) | (0.0012) | (0.0013) |

Notes: Coefficient estimates are scaled to represent changes in terms of percentage points. Estimates for query characteristics are omitted. Standard errors are shown in parentheses and are clustered at the query level. Star ratings are adjusted so that the position effect from the first row is for a hotel with 1 star and other characteristics equal to the minimum observed value. Statistical significance is indicated by *** \( p < 0.01 \), ** \( p < 0.05 \), * \( p < 0.1 \).
**Figure 8 – Heterogeneous Position Effects: Probit**

Notes: This figure replicates Figure 2 for a Probit model.

**Figure 9 – Heterogeneous Position Effects: Probit**

Notes: This figure replicates Figure 3 with estimates for a Probit model.

**Figure 10 – Heterogeneous Position Effects: Cubic**

Notes: This figure replicates Figure 2 with estimates from a linear probability model that adds $pos_i^2$, $pos_i^2 x_j$, $pos_i^3$ and $pos_i^3 x_j$ to the baseline specification.

**Figure 11 – Heterogeneous Position Effects: Cubic**

Notes: This figure replicates Figure 2 with estimates from a linear probability model that adds $pos_i^2$, $pos_i^2 x_j$, $pos_i^3$ and $pos_i^3 x_j$ to the baseline specification. Position effects are computed at $pos_i = 6$. 
|                           | (1)               | (2)               | (3)               | (4)               | (5)               | (6)               |
|---------------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| position                  |                   |                   |                   |                   |                   |                   |
| Position ≤ 1              | 2.4100***         | 5.3516***         | 5.3388***         | -0.0053           | 0.2025            | 0.2111            |
| Position ≤ 2              | 1.2778***         | 0.9898            | 0.9858            | 0.0080            | -0.0132           | -0.0611           |
| Position ≤ 3              | 2.9015***         | 2.5541***         | 2.2869***         | 0.1536***         | 0.0218            | 0.0079            |
| Position ≥ 4 × (Position - 3) | 0.1274***       | 0.0517***         | 0.0582***         | 0.0848***         | 0.0012            | 0.0021            |
| Price                     | -0.0124***        | -0.0144***        | -0.0162***        | -0.0011           | 0.0015***         | 0.0013***         |
| On promotion              | 1.1428***         | 1.2757***         | 1.3161***         | 0.1254***         | 0.1155***         | 0.1166***         |
| Star rating               | 1.6156***         | 1.9467***         | 0.1048***         | 0.1142***         |                   |                   |
| Review score              | 0.0921***         | 0.2555***         | 0.0371***         | 0.0596***         |                   |                   |
| Chain                     | 0.2335***         | 0.4413***         | 0.2053**          | 0.2088            |                   |                   |
| Location score            | 0.4420***         | 0.4471***         | 0.0531***         | 0.0628***         |                   |                   |
| position                  |                   |                   |                   |                   |                   |                   |
| Position ≤ 1 × I × Price  |                   |                   |                   |                   |                   |                   |
| Position ≤ 2 × I × Price  |                   |                   |                   |                   |                   |                   |
| Position ≤ 3 × I × Price  |                   |                   |                   |                   |                   |                   |
| Position ≥ 4 × (Position - 3) × Price |          |                   |                   |                   |                   |                   |
| Price                     |                   |                   |                   |                   |                   |                   |
| On promotion              |                   |                   |                   |                   |                   |                   |
| Star rating               |                   |                   |                   |                   |                   |                   |
| Review score              |                   |                   |                   |                   |                   |                   |
| Chain                     |                   |                   |                   |                   |                   |                   |
| Location score            |                   |                   |                   |                   |                   |                   |
| position                  |                   |                   |                   |                   |                   |                   |
| Position ≤ 1 × I × No reviews |                   |                   |                   |                   |                   |                   |
| Position ≤ 2 × I × No reviews |                   |                   |                   |                   |                   |                   |
| Position ≤ 3 × I × No reviews |                   |                   |                   |                   |                   |                   |
| Position ≥ 4 × (Position - 3) × No reviews |                   |                   |                   |                   |                   |                   |
| Star rating               |                   |                   |                   |                   |                   |                   |
| Review score              |                   |                   |                   |                   |                   |                   |
| Chain                     |                   |                   |                   |                   |                   |                   |
| Location score            |                   |                   |                   |                   |                   |                   |
| position                  |                   |                   |                   |                   |                   |                   |
| Position ≤ 1 × I × On promotion |                   |                   |                   |                   |                   |                   |
| Position ≤ 2 × I × On promotion |                   |                   |                   |                   |                   |                   |
| Position ≤ 3 × I × On promotion |                   |                   |                   |                   |                   |                   |
| Position ≥ 4 × (Position - 3) × On promotion |                   |                   |                   |                   |                   |                   |

**Notes:** Coefficient estimates are scaled to represent changes in terms of percentage points. Estimates for query characteristics are omitted. Star ratings are adjusted so that the position effect from the first row is for a hotel with 1 star and other characteristics equal to the minimum observed value. Statistical significance is indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are shown in parentheses and are clustered at the query level.
FIGURE 12 – Flexible Heterogeneous Position Effects for Clicks

Notes: This figure shows the parameter estimates $\theta_h$ in specification (19) for the first 15 positions. A positive estimate implies that the attribute amplifies the position effect.

FIGURE 13 – Flexible Heterogeneous Position Effects for Bookings

Notes: This figure shows parameter estimates $\theta_h$ in specification (19) for the first 15 positions. A positive estimate implies that the attribute amplifies the position effect.
C Parameter Identification

This appendix provides the formal propositions proving that the model parameters can be identified even without data on how far consumers scrolled. The first proposition establishes that the stopping probabilities are identified by the position-specific click probabilities. The second proposition shows that the relevant conditional moments are uniquely determined by the stopping probabilities and the unconditional moments.

C.1 Identification of Stopping Probabilities

Proposition 5. Suppose there are \( N \) alternatives randomly shown in \( N \) positions, and let \( q_h = \mathbb{P}(\text{Click in position } h) \) denote the probability of clicking in position \( h \) across consumers. The stopping probability in the SD model then is given by

\[
P(\text{Stop discovery on position } h) = m(q_1, \ldots, q_N),
\]

where the function \( m() \) has a known form.

To prove this proposition, I first derive two conditions required for the stopping probabilities to be identified by the data. Intuitively, the two conditions guarantee that only the stopping probabilities produce position effects and that there are position effects whenever consumers do not discover all alternatives. After establishing the two conditions, I show that they apply in the SD model.

To simplify exposition, I introduce the following notation: \( q_h = \mathbb{P}(\text{Click in position } h) \), \( \Delta q_h = q_h - q_{h-1} \), \( D_h \) denotes the event of a consumer ending discovery on position \( h \), \( R_h \) denotes the event of a consumer discovering at least position \( h \), \( R_h^c \) denotes the complement event of a consumer stopping before reaching position \( h \), and \( S_{jh} \) denotes the event of a consumer searching alternative \( j \) in position \( h \).

With \( N \) alternatives randomly shown across \( N \) positions, the expected difference in clicks across two positions is the average across the click-probabilities for each alternative when it is shown in the respective positions. Formally, this is given by

\[
\Delta q_h = \frac{1}{N} \left[ \sum_j \mathbb{P}(S_{jh}) - \mathbb{P}(S_{jh+1}) \right],
\]

which is an average across the \( N \) possible products that could be shown in the respective positions.

Consumers cannot search products they did not discover such that \( \mathbb{P}(S_{jh} | R_h^c) = 0 \). Hence, conditioning on reaching position \( h \) and differentiating the two cases of stopping on position \( h \)
or reaching $h + 1$, the expected difference in clicks can be written as

$$N \Delta q_h = \mathbb{P}(R_h) \left[ \mathbb{P}(D_h|R_h) \sum_j \mathbb{P}(S_{jh}|D_h) \right] + \mathbb{P}(R_{h+1}|R_h) \left[ \sum_j \mathbb{P}(S_{jh}|R_{h+1}) - \sum_j \mathbb{P}(S_{jh+1}|R_{h+1}) \right].$$

(22)

Now suppose that the following two conditions hold for all positions $h$:

1. $\Delta q_h = q_h \iff \mathbb{P}(D_h|R_h) = 1$: whenever there are no clicks in the next position ($q_{h+1} = 0$), consumers who reach position $h$ never discover $h + 1$.

2. $\Delta q_h = 0 \iff \mathbb{P}(D_h|R_h) = 0$: whenever there is no difference in clicks across the two positions, consumers who reach position $h$ always continue to discover $h + 1$.

Applying the first condition and setting $\Delta q_h = q_h$ and $\mathbb{P}(D_h|R_h) = 1$ in (22) yields

$$\mathbb{P}(D_h|R_h) \mathbb{P}(S_{jh}|D_h) = q_h.$$

This is because $\mathbb{P}(D_h|R_h) = 1$ implies that $\mathbb{P}(R_{h+1}|R_h) = 1 - \mathbb{P}(D_h|R_h) = 0$. Similarly, applying the second condition and setting $\Delta q_h = 0$ and $\mathbb{P}(D_h|R_h) = 0$ in (22) yields

$$\sum_j \mathbb{P}(S_{jh}|R_{h+1}) - \sum_j \mathbb{P}(S_{jh+1}|R_{h+1}) = 0.$$

Substituting these two expressions in (22) then yields

$$N \Delta q_1 = \mathbb{P}(D_h|R_h) N q_h = \mathbb{P}(D_h|R_h) N \frac{1}{N} \left[ \sum_j \mathbb{P}(S_{jh}|D_h) \right]$$

(23)

$$\Rightarrow \mathbb{P}(D_h|R_h) = \frac{N \Delta q_h}{\sum_j q_j}.$$

(24)

This relation shows that the probability of stopping on a particular position $h$ conditional on reaching it is nonparametrically identified as long as the position-specific click probabilities can be estimated. The unconditional stopping probabilities then are given by the recursive relation

$$\mathbb{P}(D_h) = \mathbb{P}(D_h|R_h) \mathbb{P}(R_h) + 0$$

$$= \frac{N \Delta q_h}{\sum_j q_j} \left( 1 - \sum_{q=1}^{h-1} \mathbb{P}(D_q) \right),$$

(25)

where I use that the probability of consumers stopping on position $h$ conditional on not having reached is always zero. This recursive relation uniquely pins down the unconditional stopping probabilities for all positions $h$ starting from $h = 1$. At $h = 1$, $\mathbb{P}(D_h) = 0$ by the assumption that the first discovery is free. Given $\mathbb{P}(D_0)$, (25) yields $\mathbb{P}(D_1)$ from the conditional stopping probability. Given $\mathbb{P}(D_1)$, (25) yields $\mathbb{P}(D_2)$ from the conditional stopping probability, and so on. Hence, once the conditional stopping probabilities are identified, so are the unconditional stopping probabilities.

It remains to show that the two conditions hold in the SD model. The first condition holds as long as consumers cannot search an alternative without discovering it, which is the case in the
SD model. This guarantees that \( q_{h+1} = 0 \) whenever \( h+1 \) is not discovered. The random ranking then guarantees that there is a non-zero probability of clicking on an alternative in position \( h+1 \) when that position is revealed, which proves that \( \Delta q_h = 0 \) if and only if \( \mathbb{P}(D_h|R_h) = 0 \).

The second condition holds because the SD model guarantees that an alternative is searched when shown in some position whenever it will also be searched when shown in the previous position. This follows immediately from the two search implications that provide the conditions under which an alternative is searched, given an effective value for the chosen option. Given that \( w_j \leq \tilde{w}_j \), the requirement for an alternative to be searched in earlier positions is weaker than the requirement for it to be searched in later positions. As a result, the second condition also holds in the SD model.

### C.2 Identification of Conditional Moments

**Proposition 6.** Moments on clicks and purchases conditional on discovery are uniquely determined by the stopping probabilities and the unconditional moments.

Let \( M \) be an average quantity of interest determined by either clicks or purchases, and let \( M_h \) be the respective position-specific counterparts. For example, \( M \) could be the number of clicks consumers make on average and \( M_h \) the clicks consumers make on average in position \( h \). The unconditional moments then are \( \mathbb{E}[M] = \sum_h \mathbb{E}[M_h] \) and the conditional moments are \( \mathbb{E}[M_h|D_h] \), where \( D_h \) again denotes the event of ending discovery on position \( h \). Throughout, I assume that sufficient data is available so that \( \mathbb{E}[M] \), \( \mathbb{E}[M_h] \) and \( \mathbb{P}(D_h) \) (through Proposition 5) are precisely estimated and, hence, can be treated as known. The conditional moments \( \mathbb{E}[M_h|D_h] \) then are identified if \( \mathbb{E}[M_h|D_h] \) is uniquely determined by these known moments for all positions \( h \).

I now show that this is indeed the case through a recursive relation. The fact that consumers cannot click or choose alternatives from positions they have not discovered implies that \( \mathbb{E}[M_k|D_h] = 0 \) for all \( k < h \). As a result, the law of total probability implies the following:

\[
\mathbb{E}[M_h] = \sum_{k \geq h} \mathbb{E}[M_h|D_k] \mathbb{P}(D_k).
\] (26)

In the last available position, denoted by \( \hat{h} \), this relation simplifies to \( \mathbb{E}[M_{\hat{h}}] = \mathbb{E}[M_{\hat{h}}|D_{\hat{h}}] \mathbb{P}(D_{\hat{h}}) \). Hence, \( \mathbb{E}[M_{\hat{h}}|D_{\hat{h}}] \) is fully determined by \( \mathbb{E}[M_{\hat{h}}] \) and \( \mathbb{P}(D_{\hat{h}}) \). Given \( \mathbb{E}[M_{\hat{h}}|D_{\hat{h}}] \), \( \mathbb{E}[M_{\hat{h}-1}|D_{\hat{h}-1}] \) then is also determined through (26), which then allows determining the conditional moment for \( \hat{h} - 2 \), and so on. Hence, the recursive relation (26) uniquely determines all conditional moments from the stopping probabilities and the unconditional moments.
D  Estimation Details

This appendix provides additional details on the estimation approach. First, it provides the result that facilitates computing the probability of searching an alternative without choosing it. Then, it provides details on the partitioning of the probability space that leads to a smooth likelihood function. Finally, it reports additional fit measures for the estimated model and results from Monte Carlo Simulation studies.

D.1 Probability of Search and Non-Purchase

The probability of searching an alternative \( k \) without purchasing it enters the likelihood as

\[
P(Z_s^k \geq w_j \cap U_k \leq w_j) \]

where \( w_j \) is the effective value of the eventually chosen option \( j \) and a fixed value. By expressing it as the CDF of a standard normal and the CDF of a bivariate normal distribution, Proposition 7 provides a way to calculate this probability using standard numerical methods, circumventing the need for a computationally costly numerical integration routine.\(^{39}\)

**Proposition 7.** If the two shocks are independent with \( \nu_j \sim N(0, 1) \) and \( \varepsilon_j \sim N(0, \sigma^2_\varepsilon) \), then

\[
P(Z_k^s \geq q \cap U_k \leq q) = \Phi \left( \frac{q - u_k^e}{\sigma} \right) - \Phi \left( \frac{q - u_k^e}{1} \cap Y \leq q - \xi - u_k^e \right)
\]

where

\[
u = x_k^\prime \beta,
\]

\[
Y \sim N(0, 1), \quad Y_1, Y_2 \sim N(0, \sigma^2_\varepsilon)
\]

for some constant \( q \), where \( u_k^e = x_k^\prime \beta \), \( Y \) follows a standard normal distribution, \( [Y_1, Y_2] \) follows a bivariate normal distribution with correlation \( -1 \), \( \tilde{\sigma} = 1 + 1 / \sigma^2_\varepsilon \).

This result follows from the assumption that the shocks are normally distributed and independent. Under these assumptions, \( P(Z_k \geq q \cap U_k \leq q) \) can be written as

\[
P(Z_k^s \geq q \cap U_k \leq q) = \int_{q - u_k^e - \xi}^{\infty} \Phi \left( \frac{q - u_k^e - \nu}{\sigma_\varepsilon} \right) \phi(\nu) \, d\nu
\]

\[
= \int_{-\infty}^{\infty} \Phi \left( \frac{q - u_k^e}{\sigma_\varepsilon} \right) \phi(\nu) \, d\nu - \int_{-\infty}^{q - u_k^e - \xi} \Phi \left( \frac{q - u_k^e - \nu}{\sigma_\varepsilon} \right) \phi(\nu) \, d\nu.
\]

Using results 10,010.8 and 10,010.1 for normal integrals from Owen (1980), the expression then immediately follows.

---

\(^{39}\)To calculate the bivariate normal CDF, I use the method by Drezner and Wesolowsky (1990) as implemented in the Julia StatsFuns.jl package.
D.2 Partitioning the Probability Space

I calculate the likelihood contribution in (7) as

\[ P(\text{observed choices of } i) = \sum_{R_k \in R} P(\text{observed choices of } i| R_k) P(R_k), \tag{30} \]

where \( R = \bigcup_k R_k \) is a partition of the probability space of \((\eta, \nu_j, \varepsilon_j)\), the shocks for the chosen option. The partition is defined so that two conditions hold for any region \( R_k \): (i) the number of alternatives the consumer discovered remains fixed, and (ii) \( \varepsilon_j \) is either above or below the threshold \( \xi \).

Recall that the set of alternatives a consumer discovers, \( A(\tilde{w}_j) \), is determined by the effective value of the chosen (inside or outside) option, \( \tilde{w}_j \). Hence, I can keep the number of alternatives the consumer discovered fixed by constructing regions for the effective value of the chosen option. Given the stopping rule, the following partition of the real line yields intervals such that \( A(\tilde{w}_j) \) is fixed for all \( \tilde{w}_j \) from the same interval:

\[ B = (-\infty, z^d(|J|)] \cup (z^d(|J|), z^d(|J| - 1)] \cup \ldots \cup (z^d(1), \infty]. \tag{31} \]

Using these intervals and additionally partitioning on \( \varepsilon_j > \xi \), I calculate the individual likelihood contributions as

\[ L^i(\theta) = \sum_{b \in B} P(\tilde{W}_j \in b \cap \varepsilon_j \leq \xi) \mathbb{E}[p(\tilde{W}_j)| \tilde{W}_j \in b \cap \varepsilon_j \leq \xi] + \sum_{b \in B} P(\tilde{W}_j \in b \cap \varepsilon_j > \xi) \mathbb{E}[p(\tilde{W}_j)| \tilde{W}_j \in b \cap \varepsilon_j > \xi], \tag{32} \]

where \( p(\tilde{w}_j) \) denotes the product of the integral in (8). As it has no closed-form solution, I use Monte Carlo integration to compute \( \mathbb{E}[p(\tilde{W}_j)| \tilde{W}_j \in b \cap \varepsilon_j \leq \xi] \), i.e., I take draws \( r = 1, \ldots, N_i \) from distributions truncated so that the draws satisfy the respective conditions. This then produces a smooth likelihood because \( p(\tilde{w}_j^r) \), \( P(\tilde{W}_j \in b \cap \varepsilon_j > \xi) \) and \( P(\tilde{W}_j \in b \cap \varepsilon_j \leq \xi) \) are all smooth functions.

If the outside option is chosen, \( \tilde{w}_j = \beta_0 + \eta \) such that simulating the expression can be done by taking draws \( \eta^r \) from its distribution, truncated so that \( \beta_0 + \eta \in b \) holds.

If instead an alternative \( j > 0 \) is chosen, the expression further depends on the condition \( \varepsilon_j \geq \xi \). This case can be simulated using draws generated with the following sequential procedure:

1. Take a draw \( \varepsilon_j^r \) from its distribution truncated on \( \varepsilon_i \leq \xi \).
2. Take a draw \( \nu_j^r \) from its distribution truncated on \( \tilde{w}_j(\varepsilon_j^r) = u_j^s + \nu_j + \varepsilon_j^r \in b \).
3. Calculate \( \tilde{w}_j^r \) using draws \( \nu_j^r \) and \( \varepsilon_j^r \), and compute the inner probability \( p(\tilde{w}_j^r) \).

Based on draws generated by this procedure, the expression can be calculated as the weighted
average

\[ P(\varepsilon_j \leq \xi) \sum_r P(\tilde{W}_j(\varepsilon^r_j) \in b)p(\tilde{w}^r_j). \]  

(33)

Because the only difference is the condition for \( \varepsilon_j \), \( P(\tilde{W}_j \in b \cap \varepsilon_j > \xi) \) can be calculated using the same steps.

D.3 Additional Model Fit Measures

Table 7 reports additional model fit measures based on the same simulation procedure as used in Figure 4. The results reveal that the model predicts moments that are close to those observed in the estimation sample. Notably, the model closely matches the average number of clicks and bookings, as well as the positions at which these clicks and bookings occur. The predicted averages of the attributes of hotels consumers search and eventually book also broadly fit the data, suggesting that the model also captures which alternatives consumers search and choose.

|              | Bookings |        | Clicks |        |
|--------------|----------|--------|--------|--------|
|              | Data     | Predicted | Data | Predicted |
| N (per consumer) | 0.055 | 0.059 | 1.134 | 1.157 |
| Mean position | 13.468 | 13.398 | 13.305 | 13.252 |
| Price        | 145.166 | 152.853 | 162.208 | 154.405 |
| Star rating  | 3.495 | 3.653 | 3.508 | 3.622 |
| Review score | 3.965 | 3.951 | 3.917 | 3.943 |
| No reviews   | 0.009 | 0.017 | 0.018 | 0.018 |
| Location score | 3.788 | 3.811 | 3.611 | 3.774 |
| Chain        | 0.667 | 0.636 | 0.643 | 0.639 |
| On promotion | 0.413 | 0.429 | 0.359 | 0.414 |

Notes: This table compares moments in the estimation sample with those predicted by the model. The moments are the average for the number of clicks and bookings per consumer; the average position at which consumers clicked or booked a hotel; and the averages for the different attributes of hotels that consumers searched or chose. The simulated search paths were generated with 10,000 draws for each consumer, conditional on searching at least one alternative.
D.4 Monte Carlo Simulation Studies

I run two Monte Carlo simulation studies to confirm that parameters can be identified with the present data. To this end, I first simulate data for two different sets of parameter values. I chose these sets of parameters because they generate averages for the number of clicks and bookings that roughly fit those observed in the data. Then, I use the proposed estimation approach to estimate the model on these simulated data.

For the observable product characteristics and the ranking, I use the hotel characteristics from the estimation sample with the randomized ranking. This ensures that the variation in these observable characteristics is the same as in the estimation sample. To reduce the computational burden, I randomly sample 5,000 search sessions, rather than using the entire the estimation sample.

Table 8 reports the results. The results show that the estimation procedure is able to recover the parameters well in both cases. Importantly, the search and discovery costs are also recovered well, confirming that the proposed approach to back these out after the estimation to save on computation time works as intended.

| TABLE 8 – Monte Carlo Simulation: Search and Discovery Model |
|-----------------|-----------------|-----------------|-----------------|
|                 | Simulation 1 ($\sigma_e = 1$) |                 | Simulation 2 ($\sigma_e = 2$) |
|                 | True | Estimate | Std. Error | True | Estimate | Std. Error |
| Price (in $100) | -0.300 | -0.297 | (0.009) | -0.200 | -0.198 | (0.007) |
| Star rating     | 0.300 | 0.294 | (0.009) | 0.400 | 0.416 | (0.009) |
| Review score    | 0.200 | 0.202 | (0.012) | 0.050 | 0.043 | (0.012) |
| No reviews      | 0.300 | 0.278 | (0.084) | 0.200 | 0.245 | (0.059) |
| Location score  | 0.150 | 0.152 | (0.005) | -0.100 | -0.106 | (0.004) |
| Chain           | 0.100 | 0.089 | (0.012) | 0.200 | 0.190 | (0.012) |
| On promotion    | 0.200 | 0.174 | (0.011) | 0.100 | 0.107 | (0.012) |
| Outside option  | 6.500 | 6.458 | (0.059) | 6.000 | 6.055 | (0.059) |
| $\tilde{z}_d$   | 7.000 | 7.019 | (0.083) | 7.000 | 7.137 | (0.087) |
| $\rho$          | -0.100 | -0.120 | (0.017) | -0.200 | -0.226 | (0.019) |
| $\xi$           | 2.000 | 2.000 | (0.028) | 3.500 | 3.558 | (0.040) |
| $c_d \times 100$| 0.008 | 0.008 | 0.092 | 0.089 |
| $c_s$           | 0.008 | 0.008 | 0.032 | 0.030 |
| Log likelihood  | -19530.928 | -34072.321 | |
| N consumers     | 5,000 | 5,000 | |
| No. clicks (average) | 1.081 | 1.867 |
| No. bookings (average) | 0.058 | 0.115 |

Notes: Each estimation is performed with 100 simulation draws. Observable characteristics are from a random sample of sessions from the estimation sample. Asymptotic standard errors are calculated from the inverse of the Hessian matrix. Discovery costs are calculated using 10M draws of effective values.
E Comparison of Specifications

This appendix evaluates the impact of using alternative specifications for the model.

E.1 Distributions of Idiosyncratic Shocks

First, I evaluate the impact of using different values for $\sigma_\varepsilon$ and the upper bound in the distribution of $\eta_i$. To this end, I estimate each of these specifications using the same sample as in the main analysis, simulate how many and where clicks and bookings occur, and predict the revenue and the consumer welfare effects of implementing either the utility-based or the bottom-up ranking over a randomized ranking. To compute the consumer welfare effects, I use the method from Appendix G.4.

The results of this comparison are presented in Table 9. They reveal that most parameter estimates are not that sensitive to the choice of $\sigma_\varepsilon$. The exceptions are the estimates for $\beta_0$, $\Xi$, $\xi$, and $c_s$ in dollar terms, which all increase as $\sigma_\varepsilon$ increases. However, the differences $\Xi - \beta_0$ and $\xi - \beta_0$ remain virtually unchanged. These differences capture the net benefits of the different search actions. As they are not very sensitive to $\sigma_\varepsilon$, the consumer welfare effects also are not very sensitive to this choice.

The relative effects of the UBR and the R1R are also quite stable across the different specifications, as are the revenue effects. Throughout, the UBR gets to about 69-75% of the revenue effect of the R1R, whereas the R1R gets about 69-75% of the consumer welfare effect of the UBR.

Given these results, I choose $\sigma_\varepsilon = 1$—the common choice in prior work for this error variance (Ursu et al., 2024)—for the main specification and conclude that the results are not very sensitive to this choice.

The last column of Table 9 additionally compares a specification where $\eta_i \sim \text{Uniform}(0, 5)$, which again yields results that are qualitatively similar to the main specification. However, the average consumer welfare effects become somewhat smaller, which follows from fewer consumers being predicted to click on any alternative—a moment that is not observed in the data. Importantly, however, the relative effects of the UBR and the R1R remain roughly the same, such that I conclude that the results are not very sensitive to increasing the upper bound of the distribution of the outside option.
| Parameter estimates | $\sigma _{\varepsilon }=0.5$ | Main | $\sigma _{\varepsilon }=5$ | $\sigma _{\varepsilon }=20$ | $b=5$ |
|---------------------|------------------|------|------------------|------------------|------|
| Price (in $100)    | -0.245           | -0.242 | -0.242            | -0.242           | -0.241 |
| Star rating        | 0.215            | 0.215 | 0.216             | 0.216            | 0.215 |
| Review score       | 0.038            | 0.033 | 0.036             | 0.035            | 0.032 |
| No reviews         | 0.116            | 0.098 | 0.108             | 0.108            | 0.096 |
| Location score     | 0.076            | 0.073 | 0.075             | 0.075            | 0.073 |
| Chain              | -0.024           | -0.018 | -0.022            | -0.022           | -0.018 |
| On promotion       | 0.093            | 0.089 | 0.092             | 0.092            | 0.088 |
| Outside option     | 4.318            | 5.057 | 11.604            | 36.463           | 5.052 |
| $\tilde{z}^d$      | 4.779            | 5.469 | 12.062            | 36.920           | 5.499 |
| $\rho$             | -0.104           | -0.093 | -0.102            | -0.102           | -0.101 |
| $\xi$              | 1.343            | 2.081 | 8.631             | 33.490           | 2.082 |
| $\tilde{z}^d-\beta_0$ | 0.461          | 0.412 | 0.458             | 0.457            | 0.447 |
| $\xi-\beta_0$      | -2.975           | -2.977 | -2.973            | -2.973           | -2.970 |
| Discovery costs ($)| 0.059            | 0.060 | 0.063             | 0.064            | 0.059 |
| Click costs ($)     | 0.227            | 2.824 | 35.433            | 160.847          | 2.823 |
| Log likelihood      | -48,560.220      | -48,735.168 | -48,521.103      | -48,516.029     | -48,736.553 |

**Fit: bookings**

| N, model (cond. on click) | 0.062 | 0.059 | 0.057 | 0.057 | 0.059 |
| N, data                  | 0.055 | 0.055 | 0.055 | 0.055 | 0.055 |
| Mean position, model     | 13.604 | 13.398 | 13.500 | 13.501 | 13.395 |
| Mean position, data      | 13.468 | 13.468 | 13.468 | 13.468 | 13.468 |

**Fit: clicks**

| N, model              | 1.168 | 1.157 | 1.167 | 1.167 | 1.158 |
| N, data               | 1.134 | 1.134 | 1.134 | 1.134 | 1.134 |
| Mean position, model  | 13.390 | 13.252 | 13.467 | 13.468 | 13.269 |
| Mean position, data   | 13.305 | 13.305 | 13.305 | 13.305 | 13.305 |

**Effects of UBR**

| $\Delta$ total revenues (%) | 11.427 | 11.140 | 9.644 | 9.548 | 11.081 |
| $\Delta$ consumer welfare ($, average) | 0.082 | 0.073 | 0.079 | 0.078 | 0.015 |
| $\Delta$ consumer welfare ($, cond. on click) | 9.457 | 9.682 | 9.415 | 9.412 | 11.327 |
| $\Delta$ consumer welfare ($, cond. on booking) | 9.562 | 10.312 | 10.232 | 10.111 | 11.621 |

**Effects of RIR**

| $\Delta$ total revenues (%) | 15.137 | 15.402 | 13.846 | 13.826 | 15.283 |
| $\Delta$ consumer welfare ($, average) | 0.062 | 0.053 | 0.055 | 0.055 | 0.011 |
| $\Delta$ consumer welfare ($, cond. on click) | 7.825 | 7.686 | 7.226 | 7.199 | 9.029 |
| $\Delta$ consumer welfare ($, cond. on booking) | 7.816 | 8.273 | 7.754 | 7.678 | 9.424 |

**Notes:** The main specification uses $\sigma _{\varepsilon }=1$ and $\eta _{i} \sim \text{Uniform}(0,1)$. The other specifications are the same, except for either $\sigma _{\varepsilon }$ or the distribution of $\eta _{i} \sim \text{Uniform}(0,b)$. The fit measures are averages across 10,000 draws per consumer, conditional on at least one click occurring. The reported welfare effects for the different rankings are for the short term and calculated using 10,000 draws of effective values. The welfare effects are all relative to a randomized ranking, obtained by averaging across 100 randomizations.
E.2 Functional Form for Beliefs and Number of Alternatives Discovered

To evaluate the impact of the functional form for beliefs, specified in (6), I further estimate the model with the following linear specification for $h > 1$:

$$\mu_u(h) = \mu_u(1) + \rho h.$$  \hfill (34)

Figure 14 shows the position-specific booking and click probabilities predicted by the model under this linear specification. The results show that with the linear specification, the model does not capture that clicks and bookings decrease at a decreasing rate across positions.

To evaluate the impact of the assumptions that consumers discover the first alternative for free and that they discover alternatives one by one, I also estimate two specifications that relax these assumptions. The results in Figures 15 and 16 show that the model does not fit the position effects observed in the data in both cases.

![Figure 14 – Model Fit Under the Linear Belief Specification](image)

Notes: Click and booking probabilities averaged across 10,000 draws per consumer, conditional on consumers searching at least one hotel. The shaded area indicates the 95th percentile of the minimum and maximum number of clicks or bookings across draws and consumers.
**Figure 15 – Model Fit When Consumers Initially Discover 3 Alternatives**

Notes: Click and booking probabilities averaged across 10,000 draws per consumer, conditional on consumers searching at least one hotel. The shaded area indicates the 95% percentile of the minimum and maximum number of clicks or bookings across draws and consumers.

**Figure 16 – Model Fit When Consumers Discover 3 Alternatives at a Time**

Notes: Click and booking probabilities averaged across 10,000 draws per consumer, conditional on consumers searching at least one hotel. The shaded area indicates the 95% percentile of the minimum and maximum number of clicks or bookings across draws and consumers.
F  Details on the Weitzman Model

In this appendix, I present additional details for the Weitzman (WM) model estimated in Section 6. First, I provide details on parametrization. Second, I show the estimation approach I apply. Third, I present the full parameter estimates. Finally, I provide a formal derivation of the result that the WM model implies that the post-search purchase probability increases in position.

F.1 Specification for the Standard Weitzman Model

The general utility specification for the WM model is the same as for the SD model (see 3 ). However, I adjust the distribution of the shocks so that they better fit specifications used in prior work (e.g., Ursu, 2018; Ursu et al., 2024). Specifically, I assume \( \eta \sim N(0, \sigma_\eta) \) and \( \varepsilon_j \sim N(0, \sigma_\varepsilon) \), and estimate \( \sigma_\varepsilon \). The estimation of \( \sigma_\varepsilon \) is possible in this case because the position on the list acts as a search cost shifter (see Yavorsky et al., 2021).

I further introduce position-specific search costs by assuming that the search value depends on the position through the following functional form: \( \xi(h) = \xi + \rho \log(h) \). As in the SD model, I estimate the parameters \( \xi \) and \( \rho \), while the assumed shape allows the model to fit the non-linear decrease in clicks and bookings across positions. By the same logic as I discussed in Section 3.6, this way of estimating the model is equivalent to imposing a functional form on how search costs depend on the position and estimating cost parameters.

F.2 Likelihood for the Weitzman Model

The WM model is a special case of the SD model in which consumers observe all list utilities \( u_j = x'_j \beta + \nu_j \) at the beginning of search. In this case, the likelihood can be calculated by adjusting the likelihood contribution in (8) to consumers discovering all alternatives. The individual likelihood contribution for this case is given by

\[
L'(\theta) = \log \int \prod_{k \in S} \mathbb{P}(Z_k^* \geq \tilde{w}_j \cap U_k \leq \tilde{w}_j) \times \prod_{k \in J \setminus S} \mathbb{P}(Z_k^* \leq \tilde{w}_j) dH(\eta, \nu_j, \varepsilon_j).
\]  (35)

The expression results from the fact that the consumer is aware of all products on the list, such that the stopping and the search and early discovery implications do not apply. Similar to the SD model, the expression can be calculated.

Besides not requiring to observe the search order, this estimation approach for the WM model is also easier to implement and computationally less demanding than the approaches proposed by Jiang et al. (2021) and Chung et al. (2024). This is because it effectively integrates at most over two dimensions \( (\nu_j, \varepsilon_j) \), instead of over as many dimensions as the number of searches each consumer makes.
As in the SD model, I condition the likelihood contribution to searching at least once.

F.3 Estimation Results

Table 10 presents the full parameter estimates for the WM model. Note that these parameter estimates are not directly comparable to the parameter estimates for the SD model, given the differences in the distributions of the shocks.

Figure 17 complements the results in the main text by replicating Figure 4 for the WM model. It confirms that the WM model fits the position-specific click-probabilities, but over-predicts bookings for positions further down the page.

| Estimate | Std. error |
|----------|------------|
| Price (in $100) | -0.256*** (0.006) |
| Star rating | 0.223*** (0.006) |
| Review score | 0.037*** (0.007) |
| No reviews | 0.103*** (0.037) |
| Location score | 0.079*** (0.003) |
| Chain | -0.011 (0.008) |
| On promotion | 0.090*** (0.008) |
| Outside option | 5.812*** (0.059) |
| $ \xi $ | 1.777*** (0.023) |
| $ \rho $ | -0.140*** (0.003) |
| $ \sigma_e $ | 0.696*** (0.011) |

Log likelihood -48,855.066
N consumers 11,467

Notes: Parameter estimates obtained using 100 simulation draws. Asymptotic standard errors are shown in parentheses. Statistical significance is indicated by * p < 0.1, ** p < 0.05, *** p < 0.01.

F.4 Post-Search Purchase Probabilities in the Weitzman Model

The Weitzman model rationalizes the observed position effects by introducing position-specific search costs. This implies that the probability of choosing an alternative conditional on having searched it necessarily increases in position. I now formally prove this result by deriving the position-specific post-search purchase probability for the WM model.

Let $ \bar{w}_{-j} = \max_{k \in J \setminus j} \bar{w}_j $ denote the maximum effective value across all alternatives except for some alternative $ j $. The search and discovery implications then require $ z_j^s \geq \bar{w}_{-j} $ for $ j $ to be searched, whereas the choice implication requires $ u_j \geq \bar{w}_{-j} $ for $ j $ to be chosen. Hence, the
probability of choosing $j$ conditional on having searched it in position $h_j$ is given by

$$
P(\text{choose } j | \text{search } j) = P(u_j \geq w_{-j} | z^*_j \geq w_{-j})
= P(x'j\beta + \nu_j + \varepsilon_j \geq w_{-j} | x'j\beta + \nu_j + \xi(h_j) \geq w_{-j}).
$$

(36)

This expression depends on the position $h_j$ through the implicit function $\xi(h)$, defined in (4). Moreover, note that the implicit function $\xi(h)$ determines the number of clicks in a position, with a smaller $\xi(h)$ implying fewer clicks in position $h$. Hence, to capture the observed position effects in clicks, $\xi(h)$ needs to decrease in $h$. However, the conditional choice probability in (36) reveals that for smaller $\xi(h)$, the list utility $u'_j = x'_j\beta + \nu_j$ needs to be larger for $j$ to be searched. As a result, the conditional choice probability increases in the position $h$ as long as the WM model produces position effects in clicks.
G Additional Derivations and Results

G.1 Weakly Increasing $\mu(h)$

In this appendix, I show that any functional form that implies that $\mu(h)$ weakly increases in $h$ contradicts the data. Hence, even if the model were estimated without the restriction that $\mu(h)$ weakly decreases in $h$, it would necessarily produce estimates that imply that the assumption holds. To show this, I first establish the following proposition:

**Proposition 8.** If $\mu(h)$ weakly increases in $h$ and the ranking is randomized, then there are no position effects on positions $h > 1$ for consumers who take the outside option.

The proposition makes a prediction for the case when $\mu(h)$ is weakly increasing in $h$. This prediction contradicts the data because there are position effects for consumers who take the outside option, including for positions $h > 1$. Specifically, re-running the analysis from Section 2.2 while excluding the first position continues to produce significant position effects. Hence, a weakly increasing $\mu(h)$ contradicts the data. Moreover, note that when consumers know that they are facing a randomized ranking, $\mu(h)$ will be constant. Hence, the proposition also implies that consumers do not adjust their beliefs immediately to the randomized ranking; otherwise, the position effects would disappear for consumers who take the outside option.

To prove the proposition, note that the optimal policy continues to be based on the three reservation values independent of how $\mu(h)$ depends on $h$. The only difference when $\mu(h)$ increases in $h$ is that the expression for $z^d(h)$ becomes more complex because it will depend on future periods (see Greminger, 2022). Nonetheless, $z^d(h)$ will continue to in- or decrease in $h$ depending on how $\mu(h)$ in- or decreases in $h$.

The proposition then follows from the stopping rule. This rule implies that consumers who take the outside option continue discovering as long as $U_0 > z^d(h)$. As a result, if $\mu(h)$ and, hence, $z^d(h)$ weakly increase in $h$, consumers who take the outside option always discover either only the first—which is discovered for free—or all available alternatives. This already implies the result because position effects can only arise in the SD model through consumers stopping discovery before reaching the last position, unless the ranking is not randomized.

G.2 Comparing Heuristics for Revenue-Maximization

This appendix compares the different heuristics with the revenue-maximizing ranking when consumers search following the estimated model. To compute the revenue-maximizing ranking, I use a brute-force algorithm that iterates over all possible rankings. To make this feasible, I reduce the number of alternatives for each consumer to at most seven and focus on the same random sample used in the counterfactual analysis.

Table 11 presents the results, showing that the Bottom-Up Ranking performs remarkably well: revenues decrease by less than 0.5% from the maximum. The Utility-Based Ranking
(UBR) and the Rank-1 Ranking (R1R) reduce revenues more substantially, with the R1R performing somewhat better than the UBR, but still reducing revenues by up to 8.2%.

The Price-Decreasing Ranking (PDR) performs by far the worst, reducing revenues by up to 12.5%. As this ranking maximizes revenues when position effects are homogeneous (Proposition 4), this result highlights the importance of accounting for position effect heterogeneity when designing rankings.

| Table 11 – Evaluation Heuristics |
|----------------------------------|
| UBR    | BUR   | R1R   | PDR   |
| 4 alternatives | -8.78 | -0.13 | -7.50 | -11.47 |
| 5 alternatives | -9.49 | -0.25 | -8.17 | -12.46 |
| 6 alternatives | -9.23 | -0.39 | -7.70 | -12.43 |
| 7 alternatives | -8.72 | -0.47 | -7.03 | -12.16 |

Notes: Revenue changes in percent relative to the revenue-maximizing ranking obtained through brute force.

G.3 The Discovery Value, Consumers’ Beliefs, and Discovery Costs

In this appendix, I first show how the expression for the discovery value in the main text follows from Greminger (2022). Then, I show how the probability of stopping discovery at different positions pins down the discovery values $z_d(h)$. Finally, I show how the discovery parameters $c_d$ and $\rho$ are uniquely determined by these discovery values and how $c_d$ can be recovered after estimating $\tilde{z}_d$ and the other parameters.

G.3.1 Position-Specific Discovery Values

Greminger (2022) shows that the position-specific discovery value $z_d(h)$ is implicitly defined by

$$c_d = \int_{z^d(h)}^{\infty} \left[ 1 - \tilde{G}_h(t) \right] dt,$$

where $\tilde{G}_h$ is the CDF of the effective value $U_l^j(h) + \min\{\xi, \varepsilon_j\}$. The distribution of this term is determined by consumers’ beliefs over the list utility and the shock. Moreover, in Online Appendix EC.2, Greminger (2022) shows that this is equivalent to $z_d(h) = \mu(h) + \Xi(h)$, where $\Xi(h)$ is implicitly defined by

$$c_d = \int_{\Xi(h)}^{\infty} \left[ 1 - G_h(t) \right] dt,$$

and $G_h$ now is the CDF of the demeaned effective value $\tilde{V}_j(h) = U_l^j(h) - \mu(h) + \min\{\xi, \varepsilon_j\}$.

The variance and the shape of the distribution of these demeaned effective values does not change with positions. This is because consumers know the distributions of the two shocks.
and the overall distribution of attributes. Moreover, consumers only expect the mean of $U_j^l(h)$ to depend on the position on the list, whereas the shape of the distribution remains constant. Hence, the distribution of the demeaned effective value does not change across the positions such that $\Xi(h)$ is constant. As a result, the discovery value $z^d(h)$ is given by $z^d(h) = \mu(h) + \Xi$, which is the expression given in the main text.

G.3.2 Stopping Probabilities Uniquely Determine $z^d(h)$

Given the search parameters, the probabilities of stopping discovery across the different positions determine the discovery value through the stopping rule. To see this, consider the case with only two alternatives, $A$ and $B$. In this case, the respective probability is given by

$$\mathbb{P}(\text{Stop discovery on position 1}) = \frac{1}{2} \sum_{j \in \{A,B\}} \mathbb{P}(\max\{\hat{W}_j, U_0\} \geq z^d(2)),$$

which is an expectation over the random ranking. Apart from $z^d(2)$, the search parameters (e.g., $\beta$) in (39) are already determined. Hence, the stopping probability identified from the data fully determines $z^d(2)$ through (39). With more than two alternatives, the logic remains the same and the respective probability of stopping discovery on a position determines the associated discovery value.

G.3.3 Discovery Values Uniquely Determine $c_d$ and $\rho$

The overall level of the discovery values $z^d(h)$ uniquely determines $c_d$ when consumers know the overall attribute distribution. Intuitively, the discovery values capture the net benefits of discovering more alternatives. These net benefits are determined by consumers’ beliefs about the alternatives they will discover and the discovery costs. Hence, the discovery values could be large because consumers expect to discover good alternatives or because the cost of discovering alternatives is small. Whereas it is generally not possible to distinguish the two from the data, the assumption that consumers know the overall distribution they are sampling from fixes consumers’ beliefs to the attribute distribution in the data. Given these beliefs, the discovery value fully determines the discovery costs $c_d$. The procedure described in the next section shows this more formally.

Differences in $z^d(h)$ across positions $h$ then uniquely determine the belief parameter $\rho$. For example, the functional form (6) that I impose implies

$$\Delta z^d(h) = z^d(h) - z^d(h-1) = \mu(h) - \mu(h-1) = \rho \frac{\log (h-1)}{\log(h)},$$

Fixing beliefs by assuming rational expectations is the common approach in empirical search models. For example, virtually all studies that estimate a Weitzman model assume that consumers know the distribution of the shock that will be revealed when searching an alternative.
which pins down \( \rho \) given the difference in the discovery values across the positions. Note, however, that this functional form is not necessary for the identification of \( \rho \) because \( z_d(h) \) is identified for each position \( h > 1 \) by the data. Hence, in principle, more flexible functional forms for the beliefs about the ranking could be used.

Combined, this shows that \( c_d \) and \( \rho \) are uniquely determined by the discovery values given the other parameters. Hence, whenever the discovery values are identified, \( c_d \) and \( \rho \) are also identified. Moreover, given some estimate for \( \tilde{z}_d \) and the other parameters, \( c_d \) can be recovered from \( \tilde{z}_d \) without having to estimate it directly.

### G.3.4 Post-estimation Recovery of \( c_d \) from \( z_d \)

To recover \( c_d \) given estimates for \( \tilde{z}_d = z_d(1) \) and the other parameters, I apply the following procedure:

1. Obtain an estimate \( \hat{\mu}_X \) for \( \mu_X = \mathbb{E}[X_j] \) from the data.
2. Substitute (6) in \( \frac{1}{|J|} \sum_{h=1}^{|J|} \mu(h) = \hat{\mu}_X \beta \) to obtain an estimate \( \hat{\mu}_1 \) given the estimate \( \hat{\rho} \). In my application, I set \( |J| = 34 \), which is the maximum number of positions in the data.
3. Obtain \( \hat{\Xi} \) from \( \hat{\mu}_1 \) and \( \hat{\rho} \) through \( \hat{\tilde{z}} = \mu_1 + \Xi \) implied by the definition of the discovery value and the functional form of the beliefs.
4. Compute the estimate \( \hat{c}_d \) from \( \hat{\Xi} \) by applying the definition of \( \Xi \) given in (5), which is equivalent to the following:

\[
    c_d = \mathbb{E} \left[ \max \{0, \tilde{W}_j - \hat{\mu}'_X \beta - \hat{\Xi} \} \right].
\]

To compute the right-hand side, I use the following standard Monte Carlo integration procedure:

(a) Take \( N_{c_d} \) draws \((x^q, \nu^q, \varepsilon^q)\) from the empirical attribute distribution across all positions and the assumed distributions of the two taste shocks.

(b) For each \((x^q, \nu^q, \varepsilon^q)\), compute \( \tilde{w}^q = x^q \hat{\beta} + \nu^q + \min \{\hat{\xi}, \varepsilon^q\} \) for each draw.

(c) Compute \( \hat{c}_d \) as the average of \( \max \{0, \tilde{w}^q - \hat{\mu}'_X \hat{\beta} - \hat{\Xi} \} \) across draws.

Note that by directly sampling from the attribute distribution in the last step, I avoid having to impose parametric assumptions on the distribution of product attributes. Moreover, by computing \( c_d \) from \( \tilde{z}_d \) instead of estimating it directly, this procedure avoids having to do the costly computation of \( \Xi \) given \( c_d \) during estimation.

### G.4 Calculating Consumer Welfare

This appendix provides an expression for the expected consumer welfare that simplifies the proof of Proposition 3. Moreover, the expression provides a way to compute expected consumer welfare that circumvents the need to simulate search paths. The derivation of the expression builds on the eventual purchase theorem and follows almost the same steps as the derivations in
EC.1.2. in the online appendix of Greminger (2022). The main adjustment is that the discovery value depends on the position and that welfare is calculated conditional on observable hotel attributes.

Define \( \bar{\omega}_h \equiv \max \{ \bar{\omega}_0, \ldots, \bar{\omega}_h \} \) as the maximum of values discovered up to position \( h \), with \( \bar{\omega}_j = x'_j \beta + \nu_j + \min \{ \xi, \varepsilon_j \} \) being the effective value defined in Section 3.2. Moreover, let \( \bar{\omega}_0 = \max_{j \in A_0} \bar{\omega}_j \) denote the maximum value in the initial awareness set, \( \hat{h} \) the maximum position to discover, and \( A_h \) the set of alternatives that are discovered up to position \( h \). To simplify notation, let \( y_j = x'_j \beta + \nu_j \) denote the pre-search part of utility and \( 1(\cdot) \) the indicator function.

The consumer continues discovering whenever \( \bar{\omega}_h < z^d(h) \). Hence, given realizations \( \nu_j \) and \( \varepsilon_j \) for all hotels, the discovery costs that the consumer pays are given by

\[
\sum_{h=0}^{\hat{h}} 1(\bar{\omega}_h < z^d(h)) c_d . \tag{42}
\]

The consumer also stops discovering whenever \( \bar{\omega}_h > z^d(h) \), conditional on which the consumer searches any alternative that is discovered and satisfies \( z^*_j > \bar{\omega}_h \). Hence, expected consumer welfare without discovery costs is given by

\[
\sum_{h=0}^{\hat{h}} 1(\bar{\omega}_{h-1} < z^d(h-1)) 1(\bar{\omega}_h > z^d(h)) \times \left( \sum_{j \in A_h} 1(\bar{\omega}_j \geq \bar{\omega}_h)(y_j + \varepsilon_j) - 1(y_j + \xi \geq \bar{\omega}_h) c_s \right) \tag{43}.
\]

Using that \( c_j = \mathbb{E}[1(\varepsilon_j \geq \xi) 1(\varepsilon_j - \xi)] \) and taking expectations over the whole expression yields

\[
\mathbb{E} \left[ \sum_{h=0}^{\hat{h}} 1(\bar{\omega}_{h-1} < z^d(h-1)) 1(\bar{\omega}_h > z^d(h)) \times \left( \sum_{j \in A_h} 1(\bar{\omega}_j \geq \bar{\omega}_h)(Y_j + \varepsilon_j) - 1(Y_j + \xi \geq \bar{\omega}_h) 1(\varepsilon_j \geq \xi)(\varepsilon_j - \xi) \right) \right] . \tag{44}
\]

As \( 1(y_j + \xi \geq \bar{\omega}_h) 1(\varepsilon_j \geq \xi) \) implies \( 1(\bar{\omega}_j \geq \bar{\omega}_h) \), the second part simplifies to \( 1(\bar{\omega}_j \geq \bar{\omega}_h)(y_j + \min \{ \varepsilon_j, \xi \} ) = 1(\bar{\omega}_j \geq \bar{\omega}_h) \bar{\omega}_j \). Combining this with (42) then yields that expected
consumer welfare is given by

$$
\mathbb E \left[ \sum_{h=0}^{\hat{h}} 1(\bar{W}_{h-1} < z^d(h-1))1(\bar{W}_h > z^d(h)) \times \sum_{j \in A_h} 1(\bar{W}_j \geq \bar{W}_h)\bar{W}_j \right] - \mathbb E \left[ \sum_{h=0}^{\hat{h}} 1(\bar{W}_h < z^d(h))c_d \right].
$$

(45)

G.5 Calculating the Product-Specific Demand

The product-specific demand in the SD model does not admit a closed-form solution and, hence, requires simulation. The following provides a more precise way to compute these product-specific demands. The procedure builds on the same idea as the computation on the likelihood. By the same logic, it also requires fewer draws and is more precise than a simple Monte Carlo integration, i.e., it avoids wasting draws in regions that are irrelevant for the demand calculation.

The probability of a consumer eventually choosing option $j$ given parameters in $\theta$ is given by

$$
d_j(\theta) = \int_{-\infty}^{\infty} \mathbb P(U_0 \leq \tilde{w}_j) \mathbb P\left( \max_{k \in A(\tilde{w}_j)} \bar{W}_k \leq \tilde{w}_j \right) dH_j(\tilde{w}_j).$$

(46)

This expression immediately follows when combining the stopping and the choice implication discussed in Section 3.4. The integral in the expression can be calculated by partitioning the probability space in the same way as for the likelihood. The only difference is that the inner probability now depends on

$$
\tilde{p}(\tilde{w}_j^r) = \prod_{k \in A(\tilde{w}_j^r)} \mathbb P(\bar{W}_k \leq \tilde{w}_j^r) = \prod_{k \in A(\tilde{w}_j^r)} \mathbb P(Z_k^* \leq \tilde{w}_j^r \cup U_k \leq \tilde{w}_j^r),
$$

(47)

and on $\mathbb P(U_0 \leq \tilde{w}_j^r)$.

Whereas calculating $\mathbb P(U_0 \leq \tilde{w}_j^r)$ is straightforward, calculating $\tilde{p}(\tilde{w}_j^r)$ requires calculating a probability of the form $\mathbb P(Z_k^* \leq q \cup U_k \leq q)$, where $q$ is some constant. This probability can be written as

$$
\mathbb P(Z_k^* \leq q \cup U_k \leq q) = \mathbb P(Z_k^* \leq q) + \mathbb P(Z_k^* \geq q)\mathbb P(U_k \leq q \cap Z_k^* \geq q).
$$

(48)

$\mathbb P(Z_k^* \leq q)$ then can be computed as it is the CDF of $\nu_k$. The second part is the same as (28) in Appendix D.1 and can be computed accordingly.
G.6 Long-Term Ranking Effects

This appendix provides results for a counterfactual analysis where consumers adjust their beliefs after the change in ranking. For this analysis, it is necessary to first obtain consumers’ updated beliefs after the ranking changed.

In the model, consumers expect to discover alternatives with mean pre-search utilities given by equation (6). When they adjust beliefs to the new rankings, these beliefs will be true such that they can be recovered from the data after reordering hotels. Specifically, I first compute $u^e_j$ for all consumers and alternatives in the sample using the preference estimates. Then, I recover beliefs by estimating the following linear regression:

$$u^e_{ij} = \gamma_0 + \gamma_1 \log(pos_{ij}) + \varepsilon_{ij} ,$$  \hspace{1cm} (49)

where $pos_{ij}$ is the position of alternative $j$ in the new ranking for consumer $i$. This yields an estimate for the new beliefs through $\rho = \log(-\gamma_1)$ and $\tilde{z}^d = \gamma_0$.

Table 12 reports the estimates for the beliefs.\textsuperscript{41} Standard errors are small such that beliefs are estimated precisely. Moreover, the reported estimates for $\rho$ are in line with the rankings: they suggest that consumers expect alternatives to get worse at a substantially faster rate under the Utility-Based Ranking than under the two heuristics.

Given the updated beliefs under the different rankings, I now can compute the effects of the different rankings when consumers adjust their beliefs. Table 13 shows the main effects when consumers update their beliefs. Throughout, the long-term effects are more pronounced than the short-term effects reported in Table 4. Hence, Expedia and consumers benefit even more from the respective rankings in the long term. Given these results, I conclude that the proposed rankings continue to serve their intended objectives even when consumers adjust their beliefs.

Because the effects of the UBR increase more strongly in the long term, the results also imply that the differences between the revenue-based rankings and the utility-based ranking increases. However, the revenue-based rankings continue to provide substantial welfare gains over the randomized ranking and are not detrimental to consumer welfare even when consumers adjust their beliefs.

\textsuperscript{41}As the PBR and UBR lead consumers to expect better alternatives as they scroll down the list, I do not compute these results and focus only on the main rankings.
### TABLE 12 – Estimates of Adjusted Beliefs

|    | ER  | UBR | R1R  | BUR  |
|----|-----|-----|------|------|
| $\rho$ | -0.047 | -0.160 | -0.126 | -0.133 |
|     | (0.000) | (0.000) | (0.000) | (0.000) |
| $z^d$ | 5.343 | 5.655 | 5.560 | 5.581 |
|     | (0.001) | (0.001) | (0.001) | (0.001) |

*Notes:* Standard errors in parentheses.

### TABLE 13 – Long-Term Ranking Effects

|                      | ER  | UBR  | R1R  | BUR  |
|----------------------|-----|------|------|------|
| Total revenues (%)   | 1.31| 15.75| 18.96| 20.19|
| Consumer welfare ($) | 0.02| 0.08 | 0.05 | 0.06 |

*Notes:* Changes relative to a randomized ranking obtained by averaging across 100 randomizations.
H Data

The original dataset from Kaggle.com contains 9,917,530 observations on a hotel-session level. Following Ursu (2018), I exclude sessions with at least one observation satisfying any of the following criteria:

1. The implied tax paid per night either exceeds 30% of the listed hotel price (in $), or is less than $1.
2. The listed hotel price is below $10 or above $1,000.
3. There are less than 50 consumers looking for hotels at the same destination throughout the sample period.
4. The consumer observed a hotel in positions 5, 11, 17, or 23, i.e., the consumer did not have opaque offers (Ursu (2018) provides a detailed description of this feature in the data).

The final dataset contains 4,503,128 observations. This number differs from the one in Ursu (2018) by 85 observations. This difference stems from three sessions (IDs 79921, 94604, 373518). For these sessions, the criteria evaluation above yields different result due to differences in the numerical precision. Specifically, I evaluate the criteria with double precision calculations, whereas Ursu (2018) uses the Stata default, single precision.

Completing information on the dataset, Table 14 provides a detailed description of each variable.

| Hotel-level                        | Session-level                                                      |
|------------------------------------|-------------------------------------------------------------------|
| Price (in $)                       | Number of items                                                  |
| Gross price in USD                 | How many hotels in list for consumer, capped at first page         |
| Star rating                        | Number of clicks                                                  |
| Number of hotel stars              | Number of clicks by consumer                                      |
| Review score                       | Made booking                                                     |
| User review score, mean over sample period | Dummy whether consumer made a booking                             |
| No reviews                         | Trip length (in days)                                             |
| Dummy whether hotels has zero reviews (not missing) | Length of stay consumer entered                                  |
| Chain                              | Booking window (in days)                                          |
| Dummy whether hotel is part of a chain | Number of days in future that trip starts                         |
| Location score                     | Number of adults                                                  |
| Expedia’s score for desirability of hotel’s location | Number of adults on trip                                         |
| On promotion                       | Number of children                                                |
| Dummy whether hotel on promotion   | Number of children on trip                                        |
|                                    | Number of rooms in hotel                                          |

Table 14 – Description Variables