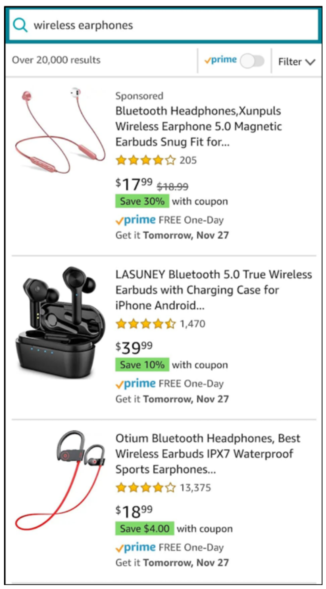
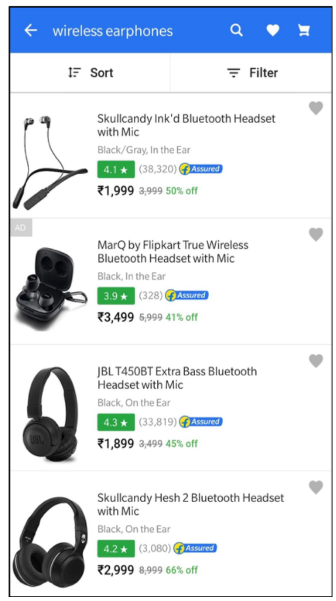
Online Appendix: The Impact of "Retail Media" on Online Marketplaces: Insights from a Field Experiment

1 Sponsored Listings on Mobile Apps



(a) Amazon



(b) Flipkart

Figure 1: Sponsored Listings on Mobile Apps

2 Theoretical Analysis

Here, we provide a detailed version of the stylized theoretical model of advertising on an online marketplace we presented earlier in the main text.

2.1 Model

Our effort is to develop a simplified model that can capture the main forces at play and communicate the main insights. The model has three types of players: the marketplace, heterogeneous sellers, and consumers. We assume that there are three sellers, one selling a product of high relevance to consumers (denoted by H), and two selling products of lower relevance to the consumers (denoted by L_1 and L_2); this reflects the reality that typically low-relevance sellers are more in number than high-relevance sellers. Let V_H, V_{L_1} and V_{L_2} denote the expected utilities of H, L_1 and L_2, respectively, where $0 < V_{L_1} = V_{L_2} = V_L < V_H < 1$. This deterministic utility measures the expected relevance of the listing with respect to the search query (e.g., the quality of the product and how well it matches the consumers' needs). A consumer's utility from the product $i \in \{H, L_1, L_2\}$ is given by $u_i = V_i + \epsilon_i$, where ϵ_i is an idiosyncratic i.i.d. shock, $\epsilon_i \sim \text{Uniform}[-1, 1]$. We assume that on viewing a listing the consumer learns the type of the seller as H or L, i.e., learns V_i and also learns the realization of ϵ_i. We normalize the consumer's utility from an outside option to zero.

A consumer searches for a product on the marketplace. In response, the marketplace displays the three sellers in an ordered list to the consumer. Clearly, H is most relevant to the consumer. L_1 and L_2 are equally relevant, but less so than H. When there exists information asymmetry between the platform and the sellers, the platform may misidentify the type of sellers. We assume that, from the three products, the platform can correctly identify H with probability $\kappa \in [\frac{1}{3}, 1]$. Therefore, κ can be interpreted as a parameter that measures the amount of information asymmetry between the platform and the sellers, with smaller κ implying greater information asymmetry.

If there is no advertising, in response to a consumer query, the platform ranks H above L_1 and L_2 with probability $\kappa \in [\frac{1}{3}, 1]$, or it makes an error and ranks H below at least one of the L-type listings with probability $1 - \kappa$. Specifically, let $\sigma(xyz)$ denote the probability of ranking listing x at the first position, y at the second position and z at the third position. Then, $\sigma(HL_iL_j) = \frac{\kappa}{2}$, $\sigma(L_iHL_j) = \frac{1-\kappa}{4}$ and $\sigma(L_iL_jH) = \frac{1-\kappa}{4}$ for $i, j \in \{1, 2\}$ and $i \neq j$. $\kappa = 1$ implies there is no information asymmetry while $\kappa = \frac{1}{3}$ implies maximum information asymmetry.

If there is advertising, the marketplace sells the first position as a sponsored slot to the sellers at a fixed price per click (P). Sellers have to opt in to be displayed in the sponsored slot. If multiple sellers opt in, then the platform chooses the seller with the highest expected relevance to show in the sponsored slot. (We use the opting in at fixed ad price mechanism to be faithful to the mechanism used by Flipkart. We note that our analytical results will remain qualitatively unchanged if we use an auction-based mechanism for allocating the sponsored slot, in which the seller with the highest bid is allocated the slot. Therefore, our results are valid in settings beyond Flipkart.) The sellers that do not get the sponsored slot are ranked in the organic slots (the second and the third positions) in order of their predicted relevance (which, as described, is imperfect in the presence of information asymmetry). Here, we make two assumptions based on the practices of our data partner Flipkart. First, we assume that one product is placed in the list only once, i.e., if a product is placed in the sponsored slot (i.e., the first slot), then it cannot also be placed in an organic slot (i.e., the second and third slots). Second, we assume that when the platform sells the sponsored slot, the seller information revealed from selling the slot is not used while deciding the organic rankings.[1]

Specifically, we assume that if L_1 gets placed in the ad slot, then H is placed higher than L_2, i.e., in the second slot (which is an organic slot), with the same probability that H would not be placed below *both* L-type listings in the case of no ads, which is given by

$$\sigma(HL_1L_2) + \sigma(HL_2L_1) + \sigma(L_1HL_2) = \kappa + \frac{(1-\kappa)}{4}.$$

If H gets placed in the ad slot, then each L is placed in the second slot with probability 1/2. For the auction, we assume that the reservation price is set equal to zero. We also assume that the profit margins of all sellers are equal to one.

We characterize the consumer's search behavior as follows. The consumer does not incur any cost to view the listing at the first position and thus evaluates it with probability one. However, she incurs an evaluation cost, $s > 0$, to view and evaluate the listing at the second position. As there is one high-relevance listing and two low-relevance listings, we assume that if the first listing is H, the consumer's expected utility from clicking on the next listing is given by V_L. If the first listing is L_1 or L_2, her expected utility from clicking on the next listing is given by $\hat{V}$, where $\hat{V} = \frac{V_H+V_L}{2}$ if there is no sponsored slot, and $\hat{V} = (\kappa + \frac{1-\kappa}{4})V_H + \frac{3(1-\kappa)}{4}V_L$ if there is a sponsored slot. This is because, conditional on an L being ranked first and if there is no sponsored slot, H is ranked at the second and third positions with equal probability,[2] while if there is a sponsored slot, H is ranked at the second position with probability $(\kappa + \frac{1-\kappa}{4})$. The consumer views the second listing if her expected marginal benefit of evaluating the second listing is greater than the marginal search cost. We assume that the consumer's marginal search cost of evaluating the listing at the third position

[1] At Flipkart, the customer experience team is separate from the ad products team (this is for various reasons, such as avoiding conflicts of interest). Our conversations with managers at multiple e-commerce marketplaces indicate that this is the case at most marketplaces. Of late, there is an effort at marketplace firms to jointly rank organic and sponsored results. Recent work studies this problem (Long et al., 2022; Yang et al., 2023).

[2] $\frac{\sigma(L_iHL_j)}{\sigma(L_iHL_j)+\sigma(L_iL_jH)} = \frac{\sigma(L_iL_jH)}{\sigma(L_iHL_j)+\sigma(L_iL_jH)} = \frac{1-\kappa}{4} / \frac{1-\kappa}{2} = \frac{1}{2}$ for $i, j \in \{1, 2\}$ and $i \neq j$.

is so high that she never views the third listing.[3]

After evaluating the listings, the consumer makes her click decision. Specifically, if she evaluated only the first listing then she decides whether to click it or not, and if she evaluated the first two listings then she decides which one to click or not to click anything. We assume that γ_i is the probability of conversion conditional on click of a listing of type $i \in \{H, L\}$, and that $0 < \gamma_L < \gamma_H < 1$; for simplicity, we assume that for any listing the other listings do not affect the conversion probability post click.

2.2 Analysis and Results

We now solve the model. The proof for all the lemmas and propositions are provided below in Section 2.3. Let δ^i denote the probability of evaluating the second listing if the type of the first listing is $i \in \{H, L\}$. Then, $\delta^H = \Pr(V_L - u_H > s)$ and $\delta^L = \Pr(\hat{V} - u_L > s)$, where $\hat{V}$ could be different with and without the sponsored listing.

Note that $\delta^L > \delta^H$ and $\frac{d\delta^i}{ds} < 0$ for $i \in \{H, L\}$. Let $\theta_i = \Pr(u_i > 0)$ denote the probability of click on listing $i \in \{H, L\}$ when only i, the first listing, is evaluated, and $\theta_{ij} = \Pr(u_i > \max\{u_j, 0\})$ denote the probability of click on listing i when both listings $i, j \in \{H, L\}$ are evaluated, where $\theta_H > \theta_L$ and $\theta_{HL} > \theta_{LL} > \theta_{LH}$. Let β_k^{jl} and π_k^{jl} denote the probability of click and the probability of conversion, respectively, of the listing at position $k \in \{1, 2\}$ when $j \in \{H, L\}$ occupies the first and $l \in \{H, L\}$ occupies the second position. The expressions for all δ, θ, β and π are derived in Appendix A. We assume $0 < \gamma_L < \gamma_H < 1$ such that $\pi_1^{HL} > \pi_1^{LH}$ and $\pi_2^{HL} < \pi_2^{LH}$.

[3]We note that our focus is on the optimal advertising decision of the sellers given the consumer behavior, and we are making certain simplifying assumptions about consumer behavior and beliefs — specifically, that consumers start searching from the top position downwards, and if they see a product of type L in the first position then they assume the second position has a product of type H and L with equal probability. Our assumptions can be interpreted as assuming that consumers are boundedly rational, which has been assumed in various previous studies on position auctions such as in Jerath et al. (2011), and has been assumed and argued more generally such as in Gabaix and Laibson (2006) and Ho et al. (2006), among many others. Furthermore, while we do not do the same here (and do not consider it necessary), we note that Jerath et al. (2011) show in Section 5.2 in their paper that boundedly rational behavior by consumers can be fully rationalized in equilibrium by introducing beliefs of consumers on other constructs, such as firm margins.

The value of advertising per click for the two types of listings is as follows:

$$v_H = \gamma_H \left\{ 1 - \frac{(1+3\kappa)}{4} \frac{\beta_2^{LH}}{\beta_1^{HL}} \right\}, \tag{1}$$

$$v_L = \gamma_L \left\{ 1 - \frac{(1+3\kappa)}{4} \frac{\beta_2^{HL}}{\beta_1^{LH}} + \frac{3(1-\kappa)}{4} \frac{(\beta_2^{LL} - \beta_2^{HL})}{\beta_1^{LL}} \right\}. \tag{2}$$

When $v_H > v_L$, H is more likely to opt-in for advertising and pay the ad price, and vice versa. The following lemma states how κ affects the incentives of the two types of listings.

Lemma 1 $\frac{dv_i}{d\kappa} < 0 \ \forall \ \kappa \in [\frac{1}{3}, 1]$, *where* $i \in \{H, L\}$

Lemma 1 states that both types have a higher valuation for advertising when information asymmetry is higher, i.e., as κ decreases. This happens for the high type because as information asymmetry increases, the probability of it being ranked at the third position increases, where it gets no views. This creates a higher incentive for the high type to advertise when κ is lower. As for the low types, the incentive increases because, with lower κ, the two low types can occupy the first two positions more frequently, which increases the returns to obtaining the first position (which is the sponsored slot).

We now compare the valuations of the high- and low-relevance sellers to determine which one gets the sponsored slot. We present the key result in the following proposition. We define the following quantities that are used in the proposition:

$$\underline{r} = \left. \frac{1 - \frac{\beta_2^{HL}}{2\beta_1^{LH}} + \frac{\beta_2^{LL} - \beta_2^{HL}}{2\beta_1^{LL}}}{1 - \frac{\beta_2^{LH}}{2\beta_1^{HL}}} \right|_{\kappa = \frac{1}{3}}, \overline{r} = \left. \frac{1 - \frac{\beta_2^{HL}}{\beta_1^{LH}}}{1 - \frac{\beta_2^{LH}}{\beta_1^{HL}}} \right|_{\kappa = 1}$$

$$\text{and } \overline{\kappa} = 1 - \frac{4\beta_1^{LL}(\gamma_H(\beta_1^{HL} - \beta_2^{LH})\beta_1^{LH} - \gamma_L \beta_1^{HL}(\beta_1^{LH} - \beta_2^{HL}))}{3(\gamma_L \beta_1^{HL}(\beta_1^{LL}\beta_2^{HL} - \beta_1^{LH}(\beta_2^{HL} - \beta_2^{LL})) - \gamma_H \beta_2^{LH}\beta_1^{LH}\beta_1^{LL})}.$$

Note that $\underline{r} \leq \overline{r}$.

Proposition 1 *Assume that* $\underline{r} < \frac{\gamma_H}{\gamma_L} < \overline{r}$. *Then for* $\kappa \in \left[\frac{1}{3}, \overline{\kappa}\right]$ *(high information asymmetry), the high-relevance listing is displayed in the sponsored slot (i.e.,* $v_H > v_L$*), whereas for* $\kappa \in (\overline{\kappa}, 1]$ *(low information asymmetry) a low-relevance listing is displayed in the sponsored slot (i.e.,* $v_L > v_H$*).*

For completeness, we also state the following: if $\frac{\gamma_H}{\gamma_L} \leq \underline{r} < \overline{r}$, a low-relevance listing is always

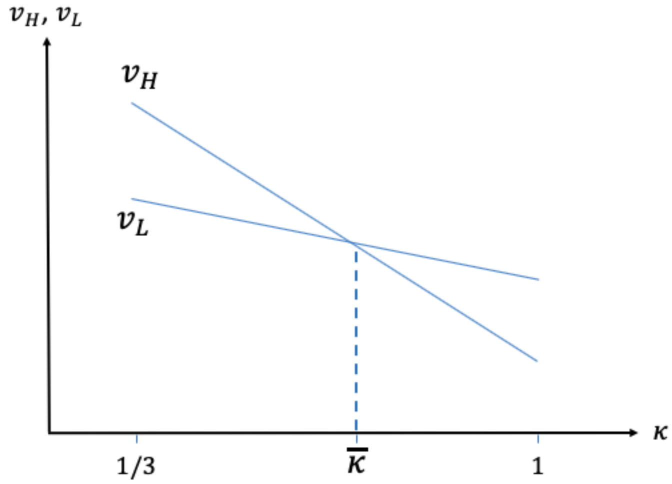


Figure 2: Incremental value of being placed in the sponsored slot for high- and low-relevance sellers with respect to κ

displayed in the sponsored slot (i.e., $v_L > v_H \ \forall \ \kappa$), and if $\underline{r} < \overline{r} \leq \frac{\gamma_H}{\gamma_L}$, the high-relevance listing is always displayed in the sponsored slot ($v_H > v_L \ \forall \ \kappa$).

Now consider the statement of the proposition. Suppose $\frac{\gamma_H}{\gamma_L} < \overline{r}$, i.e., when γ_H is not too large as compared to γ_L. Then, for large enough κ, i.e., for low enough information asymmetry, the Ls value the sponsored slot higher than H (i.e., $v_L > v_H$). This is because if a low-relevance seller does not opt-in, it will be relegated to the third position with a high probability where it will get no conversions, whereas the high-relevance seller knows that even if it does not get the sponsored slot it will be placed in the second slot with high probability where it will get sufficient conversions; in other words, under low information asymmetry, a low-relevance seller is hurt more on not being placed in the sponsored slot and therefore values it more than the high-relevance seller.

From Lemma 1 we know that, as κ decreases (i.e., information asymmetry increases), sellers of both types of listings value the sponsored slot more. When $\frac{\gamma_H}{\gamma_L} > \underline{r}$, i.e., when γ_H is relatively large compared to γ_L, then v_H increases at a faster rate than v_L as κ decreases. Under this condition, the high type can have a higher incentive to advertise than the low type when information asymmetry is large enough. Indeed, when information asymmetry is large, if the high-relevance seller opts in for advertising it will obtain a large number of clicks and conversions while if it does not it may be placed in the third slot with a reasonable probability, where it will get no clicks or conversions.

On the other hand, if a low-relevance seller gets the sponsored slot it will be placed at the top but still not get many clicks and conversions (due to its low relevance) while on the other hand it has a reasonable probability of being placed in the second slot. Therefore, when information asymmetry is large, the high-relevance seller has more to lose from not getting the sponsored slot, and therefore has a higher valuation than the low-relevance seller. Figure 2 depicts such a scenario.

Based on the above proposition, we derive the following corollaries that compare outcomes when the marketplace allows sponsored listings versus when it does not. The aim of conducting this comparison is to obtain results that enable us to determine the empirical patterns that we expect to see in our data in the empirical analysis. We will assume for these corollaries that the conditions of Proposition 1 hold, such that the high-relevance (low-relevance) seller is displayed in the sponsored slot when information asymmetry is high (low) enough.

Corollary 1 ***Clicks and conversions on the first slot.*** *Under high (low) information asymmetry, if the first slot displays a sponsored listing, it gets more (fewer) clicks and conversions than if it displayed an organic listing.*

Corollary 2 ***Clicks and conversions on the second slot.*** *Under high (low) information asymmetry, if the first slot displays a sponsored listing, the second slot gets fewer (more) clicks and conversions than if the first slot displayed an organic listing.*

From Proposition 1, we know that if information asymmetry is high, then the H-type seller obtains the first slot (which is the sponsored slot). If this slot were not for a sponsored ad, an L-type seller would have a high likelihood of being displayed in this slot. Therefore, if the first slot displays a sponsored ad listing, this listing will be of the H-type, which implies that it will get more expected clicks and conversions than if there were no sponsored listings. This also implies that fewer consumers proceed to the second slot, which will now display an L-type seller. With low information asymmetry, the reasoning is exactly the reverse — an L-type seller obtains the first slot when this is a sponsored slot, and is less likely to obtain it if there are no sponsored slots, leading to the predictions on clicks and conversions in the two positions in the corollaries.

Next, we state a corollary regarding the total click and conversion performance with and without a sponsored listing at the top slot.

Corollary 3 ***Total effect on clicks and conversions.*** *Under high (low) information asymmetry, if the first slot displays a sponsored listing, the overall click and conversion performance at two positions together increases (decreases). In both cases, the magnitude of the effect becomes smaller as the consumer search cost, s, decreases.*

When there is high information asymmetry, the high-relevance listing occupies the sponsored slot, which leads to more clicks and conversions. However, this also lowers the clicks and conversions from the succeeding position, thus nullifying some of the positive effect at the sponsored slot. Conversely, when there is low information asymmetry, the sponsored listing can hurt the search performance due to the selection of the low-relevance listing at the top position. However, if the consumers have low marginal search costs, then they continue with their search and purchase at a higher rate (compared to the case with no ads) from the next position. Note that Corollaries 1 and 2 show countervailing effects on the first and second slots, which implies that they might nullify each other in the overall effect of sponsored listings on clicks and conversions from a search, and so the overall effect can be small based on the search cost.

2.3 Derivations and Proofs

2.3.1 Expressions for δ, θ, β and π

We first derive the expressions for δ_H and δ_L.

$\delta^H = \Pr(V_L - u_H > s) = \Pr(\epsilon_H < V_L - V_H - s) = \frac{V_L - V_H - s + 1}{2}$, as $\epsilon_H \sim U[-1,1]$. Similarly,

$$\delta^L = \Pr(\hat{V} - u_{L_i} > s) = \Pr(\epsilon_{L_i} < \hat{V} - V_L - s) = \begin{cases} \frac{(\frac{V_H - V_L}{2}) - s + 1}{2} & \text{without the sponsored listing,} \\ \frac{(\frac{1+3\kappa}{4})(V_H - V_L) - s + 1}{2} & \text{with the sponsored listing} \end{cases}$$

$\forall\ i \in \{1,2\}$. We assume $s < 1 - (V_H - V_L)$ so that $\delta^H > 0$.

Next, we derive the expressions for θ_H, θ_L, θ_{HL}, θ_{LH} and θ_{LL}.

$\theta_i = \Pr(u_i > 0) = \Pr(\epsilon_i > -V_i) = \frac{1+V_i}{2}\ \forall\ i \in \{H, L_1, L_2\}$.

$\theta_{HL} = \Pr(u_H > \max\{u_{L_i}, 0\}) = \Pr(\epsilon_H - \epsilon_{L_i} > V_L - V_H, \epsilon_H > -V_H) = \frac{(1+V_H)(3+V_H-2V_L)}{8}$,

$\theta_{LH} = \Pr(u_{L_i} > \max\{u_H, 0\}) = \Pr(\epsilon_{L_i} - \epsilon_H > V_H - V_L, \epsilon_{L_i} > -V_L) = \frac{(1+V_L)(3-2V_H+V_L)}{8}$ and

$\theta_{LL} = \Pr(u_{L_i} > \max\{u_{L_j}, 0\}) = \Pr(\epsilon_{L_i} - \epsilon_{L_j} > 0, \epsilon_{L_i} > -V_L) = \frac{(1+V_L)(3-V_L)}{8}\ \forall\ i,j \in \{1,2\}$ and

$i \neq j$, as ϵ_k and $\epsilon_k - \epsilon_l$ has a joint density $\frac{1}{4}$ with support $[-1, 1]$ and $[\epsilon_k - 1, \epsilon_k + 1]$, respectively, where $k, l \in \{H, L_1, L_2\}$ and $k \neq l$.

Now we can derive the following expressions.

$$\pi_1^{HL} = \gamma_H \cdot \beta_1^{HL} = \gamma_H((1 - \delta^H)\theta_H + \delta^H \theta_{HL})$$
$$\pi_2^{HL_1} = \pi_2^{HL_2} = \pi_2^{HL} = \gamma_L \cdot \beta_2^{HL} = \gamma_L \cdot \delta^H \cdot \theta_{LH}$$
$$\pi_2^{LH} = \gamma_H \cdot \beta_2^{LH} = \gamma_H \cdot \delta^L \cdot \theta_{HL}$$
$$\pi_1^{LH} = \gamma_L \cdot \beta_1^{LH} = \gamma_L((1 - \delta^L)\theta_L + \delta^L \cdot \theta_{LH})$$
$$\pi_1^{LL} = \gamma_L \cdot \beta_1^{LL} = \gamma_L((1 - \delta^L)\theta_L + \delta^L \cdot \theta_{LL})$$
$$\pi_2^{LL} = \gamma_L \cdot \beta_2^{LL} = \gamma_L \cdot \delta^L \cdot \theta_{LL}$$

Note that all the βs and πs are positive.

2.3.2 Derivation of v_H and v_L

If H gets the sponsored slot, its payoff is given by π_1^{HL}. Instead, if L_i wins the auction, H's payoff is $(\kappa + \frac{1-\kappa}{4})\pi_2^{LH}$, as $\kappa + \frac{1-\kappa}{4}$ is the probability with which H is ranked higher than L_j, where $i, j \in \{1, 2\}$ and $i \neq j$. Then, taking the difference between these two payoffs we obtain:

$$v_H = \frac{\pi_1^{HL} - (\kappa + \frac{1-\kappa}{4})\pi_2^{LH}}{\beta_1^{HL}} = \gamma_H \Big(1 - \left(\kappa + \frac{1-\kappa}{4}\right) \frac{\beta_2^{LH}}{\beta_1^{HL}}\Big) > 0, \tag{3}$$

as $\kappa \leq 1$ and $\frac{\beta_2^{LH}}{\beta_1^{HL}} < 1$.

When the L-types get the sponsored slot, each L gets the sponsored slot with probability $\frac{1}{2}$, H occupies the second position with probability $\kappa + \frac{1-\kappa}{4}$ and the other L occupies the second position with probability $\frac{3(1-\kappa)}{4}$. If the L-types lose the slot to H, then the payoff of each L is given by $\frac{\pi_2^{HL}}{2}$, as they occupy the second position with probability $\frac{1}{2}$. If they get the sponsored slot, L gets a payoff of $\frac{\pi_1^{LH}}{2}$ when H occupies the second position. Instead, when an L occupies the second position, L gets a payoff of $\frac{\pi_1^{LL}}{2} + \frac{\pi_2^{LL}}{2}$. Then, v_L is given by the weighted sum of the values with

H and L at the second position.

$$v_L = (\kappa + \frac{1-\kappa}{4})\frac{(\frac{\pi_1^{LH}}{2} - \frac{\pi_2^{HL}}{2})}{\frac{\beta_1^{LH}}{2}} + \frac{3(1-\kappa)}{4}\frac{(\frac{\pi_1^{LL}}{2} + \frac{\pi_2^{LL}}{2} - \frac{\pi_2^{HL}}{2})}{\frac{\beta_1^{LL}}{2}} \tag{4}$$

$$= \gamma_L\Big(1 - \left(\frac{1+3\kappa}{4}\right)\frac{\beta_2^{HL}}{\beta_1^{LH}} + \frac{3(1-\kappa)}{4}\frac{(\beta_2^{LL} - \beta_2^{HL})}{\beta_1^{LL}}\Big) > 0,$$

as $\kappa \leq 1$, $\frac{\beta_2^{HL}}{\beta_1^{LH}} < 1$ and $\frac{\beta_2^{LL}}{\beta_2^{HL}} > 1$.

2.3.3 Proof of Lemma 1

We have

$$\frac{dv_H}{d\kappa} = -\frac{3\gamma_H\beta_2^{LH}}{4\beta_1^{HL}} < 0, \tag{5}$$

and

$$\frac{dv_L}{d\kappa} = -\frac{3\gamma_L\beta_2^{HL}}{4\beta_1^{LH}} - \frac{3\gamma_L(\beta_2^{LL} - \beta_2^{HL})}{4\beta_1^{LL}} < 0, \tag{6}$$

as $\beta_2^{LL} > \beta_2^{HL}$.

2.3.4 Proof of Proposition 1

We already know from Lemma 1 that both v_H and v_L monotonically decrease with κ. Therefore, if we have $v_L > v_H$ at $\kappa = 1$ and $v_H > v_L$ at $\kappa = \frac{1}{3}$, then there always exists $\overline{\kappa} \in (\frac{1}{3}, 1)$ such that $v_H \geq v_L \ \forall \ \kappa \in [\frac{1}{3}, \overline{\kappa}]$ and $v_L > v_H \ \forall \ \kappa \in (\overline{\kappa}, 1]$.

We have $v_L > v_H$ at $\kappa = 1$ iff:

$$\gamma_L\left(1 - \frac{\beta_2^{HL}}{\beta_1^{LH}}\right)\Bigg|_{\kappa=1} > \gamma_H\left(1 - \frac{\beta_2^{LH}}{\beta_1^{HL}}\right)\Bigg|_{\kappa=1}, \text{ or}$$

$$\frac{\gamma_H}{\gamma_L} < \frac{1 - \frac{\beta_2^{HL}}{\beta_1^{LH}}}{1 - \frac{\beta_2^{LH}}{\beta_1^{HL}}}\Bigg|_{\kappa=1}. \tag{7}$$

Similarly, $v_H > v_L$ at $\kappa = \frac{1}{3}$ iff:

$$\gamma_H\left(1 - \frac{\beta_2^{LH}}{2\beta_1^{HL}}\right)\Bigg|_{\kappa=\frac{1}{3}} > \gamma_L\left(1 - \frac{\beta_2^{HL}}{2\beta_1^{LH}} + \frac{\beta_2^{LL} - \beta_2^{HL}}{2\beta_1^{LL}}\right)\Bigg|_{\kappa=\frac{1}{3}}, \text{ or}$$

$$\frac{\gamma_H}{\gamma_L} > \left. \frac{\left(1 - \frac{\beta_2^{HL}}{2\beta_1^{LH}} + \frac{\beta_2^{LL} - \beta_2^{HL}}{2\beta_1^{LL}}\right)}{\left(1 - \frac{\beta_2^{LH}}{2\beta_1^{HL}}\right)} \right|_{\kappa = \frac{1}{3}} . \tag{8}$$

Without loss of generality, we assume $V_H = \frac{1}{2}$ to obtain analytical solutions. There exist parameter ranges where both (7) and (8) hold together. However, there does not exist any parameter range such that $v_H > v_L$ at $\kappa = 1$ and $v_L > v_H$ at $\kappa = \frac{1}{3}$.

2.3.5 Proof of Corollary 1

When L occupies the sponsored slot, then H occupies the second slot with probability $(\kappa + \frac{1-\kappa}{4})$, and the other L listing occupies with probability $\frac{3(1-\kappa)}{4}$. Therefore, the effect at the first position in the case with low information asymmetry is given by

$$\begin{aligned} &\left(\kappa + \frac{1-\kappa}{4}\right)\pi_1^{LH} + \frac{3(1-\kappa)}{4}\pi_1^{LL} - \left(\kappa\pi_1^{HL} + \frac{(1-\kappa)}{2}(\pi_1^{LH} + \pi_1^{LL})\right) \\ &= -\kappa(\pi_1^{HL} - \pi_1^{LH}) + \left(\frac{1-\kappa}{4}\right)(\pi_1^{LL} - \pi_1^{LH}) < 0, \end{aligned} \tag{9}$$

as $\pi_1^{LH} < \pi_1^{LL} < \pi_1^{HL}$.

When H occupies the sponsored slot, then the second slot is always occupied by L. The effect at the first position in the case with information asymmetry is given by

$$\begin{aligned} &\pi_1^{HL} - (\kappa\pi_1^{HL} + \frac{(1-\kappa)}{2}(\pi_1^{LH} + \pi_1^{LL})) \\ &= (1-\kappa)\pi_1^{HL} - \frac{(1-\kappa)}{2}(\pi_1^{LH} + \pi_1^{LL}) > 0, \end{aligned} \tag{10}$$

as $\pi_1^{LH} < \pi_1^{LL} < \pi_1^{HL}$.

2.3.6 Proof of Corollary 2

When L occupies the sponsored slot, the effect at the second position in the case with low information asymmetry is given by

$$\left(\kappa + \frac{1-\kappa}{4}\right)\pi_2^{LH} + \frac{3(1-\kappa)}{4}\pi_2^{LL} - \left(\kappa\pi_2^{HL} + \frac{(1-\kappa)}{2}(\pi_2^{LH} + \pi_2^{LL})\right) > 0, \tag{11}$$

as $\pi_2^{LH} > \pi_2^{LL} > \pi_2^{HL}$.

When H occupies the sponsored slot, the effect at the second position in the case of information asymmetry is given by

$$\pi_2^{HL} - (\kappa\pi_2^{HL} + \frac{(1-\kappa)}{2}(\pi_2^{LH} + \pi_2^{LL}) = (1-\kappa)\pi_2^{HL} - \frac{(1-\kappa)}{2}(\pi_2^{LH} + \pi_2^{LL}) < 0 \tag{12}$$

$\forall\ \kappa < \overline{\kappa}$, as $\pi_2^{HL} < \pi_2^{LL} < \pi_2^{LH}$.

2.3.7 Proof of Corollary 3

When L occupies the sponsored slot in the case of low information asymmetry, the overall effect on the two positions in the search is given by
$\Delta_\kappa^L = (\kappa + \frac{(1-\kappa)}{4})(\pi_1^{LH} + \pi_2^{LH}) + \frac{3(1-\kappa)}{4}(\pi_1^{LL} + \pi_2^{LL}) - \Big(\kappa(\pi_1^{HL} + \pi_2^{HL}) + \frac{(1-\kappa)}{2}(\pi_1^{LH} + \pi_2^{LH}) + \frac{(1-\kappa)}{2}(\pi_1^{LL} + \pi_2^{LL})\Big) < 0\ \forall\ \kappa > \overline{\kappa}$, as $\pi_1^{LH} < \pi_1^{HL}$ and $\pi_2^{LH} < \pi_2^{HL}$.

We have $\frac{\partial \Delta_\kappa^L}{\partial s} = \frac{1}{64}(2\gamma_L(\kappa(11 + V_H) - 3 - V_H)(1 + V_L) + \gamma_H(6 + V_H(4 + V_H) + 4V_L - 2V_HV_L + 3V_L^2 - \kappa(22 + V_H(20 + V_H) + 4V_H - 2V_HV_L + 3V_L^2))) < 0$.

When H occupies the sponsored slot in the case with high information asymmetry, the overall effect is given by $\Delta_\kappa^H = \pi_1^{HL} + \pi_2^{HL} - \Big(\kappa(\pi_1^{HL} + \pi_2^{HL}) + \frac{(1-\kappa)}{2}(\pi_1^{LH} + \pi_2^{LH}) + \frac{(1-\kappa)}{2}(\pi_1^{LL} + \pi_2^{LL})\Big) > 0$. Δ_κ^H is always positive as the introduction of the sponsored slot removes the possibility of two low types in the first two positions.

3 Randomization Checks

		Bucket 1	Bucket 2	Bucket 3	p-value
Total	Users	394,989	393,448	393,762	0.11
	Searches per user	3.41	3.41	3.40	0.16
Electronics	Users	269,148	268,464	268,206	0.93
	Searches per user	2.97	2.97	2.96	0.22
Footwear	Users	111,275	110,245	111,196	0.14
	Searches per user	2.16	2.16	2.15	0.56
Clothing	Users	128,295	127,355	127,242	0.50
	Searches per user	2.41	2.42	2.42	0.33

(a) Users and Searches Per User

		Bucket 1	Bucket 2	Bucket 3	p-value
Total	Click	0.0400	0.0402	0.0401	0.01
	Conversion	0.0024	0.0024	0.0024	0.59
Electronics	Click	0.0641	0.0645	0.0644	0.02
	Conversion	0.0034	0.0035	0.0035	0.54
Footwear	Click	0.0258	0.0258	0.0258	0.66
	Conversion	0.0014	0.0014	0.0015	0.26
Clothing	Click	0.0293	0.0293	0.0292	0.42
	Conversion	0.0021	0.0022	0.0021	0.45

(b) Impression-level Statistics (Two-week Period before Experiment)

Table 1: Balance Across Buckets

We conduct a randomization check by testing the balance in observations across the three buckets. Table 1(a) presents the statistics for number of users and searchers per user in our full sample. The top panel of the table, titled “Total”, includes all users who searched at least once in the any of the categories. The other panels only include users who searched at least once in Electronics, Footwear and Clothing, respectively. One can see that there is almost no difference in the number of users and searches per user across the buckets. The chi-square tests reveal that buckets are well balanced as we fail to reject the equality of observations at overall 5% significance level. We also analyze the impression-level click and conversion behavior of users in each bucket that we have from the two weeks before the experiment. We present the results in Table 1(b). We find that the two measures are almost identical across the three buckets, and fail to reject the null that all click and conversion means are equal at overall 5% significance level. (After Bonferroni correction to control for familywise error rate due to multiple hypothesis testing.) While we would have liked to compare the users on more dimensions, e.g., demographics, we do not have data on them.

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