

Web Appendices for
“The Effects of Search Interface on Consumer Preferences: Evidence from a
Randomized Experiment”

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A Propositions and Proofs

The propositions in this appendix are stated in terms of changes in partworths across attributes rather than relying on a specific model of exposure or learning. Their role is to characterize the comparative statics of how changes in the partworth vector β affect preference concentration and choice concentration. To connect these results to the search environment studied in the paper, we rely on the behavioral premise that removing filters reallocates attention away from repeatedly inspected, initially preferred attributes and toward previously lower-partworth, underexplored ones. Under attention-based mechanisms such as the mere exposure effect or cognitive ones such as the loser’s curse (see Section 6), greater exposure increases the partworth of an attribute, implying that previously less-preferred attributes tend to gain importance. For symmetry, we also consider the case where initially dominant attributes lose relative importance as attention becomes more broadly distributed. More generally, the propositions apply whenever changes in the search environment generate such shifts in relative partworths, regardless of the specific behavioral mechanism that produces them.

Suppose there are K product attributes indexed by $k = 1, \dots, K$. Attribute k may have several levels, but for simplicity we assume two levels; the results are generalizable. Let β_k denote the partworth for attribute k . Without loss of generality, we assume that the lower level of the attribute is set as the baseline, i.e., $\beta_k \geq 0$ for all k . The relative importance of attribute k , denoted by ω_k , is simply

$$\omega_k = \frac{\beta_k}{\sum_{l=1}^K \beta_l}$$

To study concentration in attribute importance, we use the Herfindahl-Hirschman Index (HHI) on normalized attribute importance weights to measure dispersion/concentration:

$$\mathcal{H}(\omega) = \sum_{k=1}^K \omega_k^2$$

Lower $\mathcal{H}(\omega)$ indicates lower concentration, i.e., a more even distribution of importance across attributes. Since $\omega_k = \beta_k / \sum_l \beta_l$, the HHI can equivalently be written as a function of the partworth vector β :

$$\mathcal{H}(\beta_1, \dots, \beta_K) = \frac{\sum_{k=1}^K \beta_k^2}{(\sum_{k=1}^K \beta_k)^2}$$

The key intuition underlying the results is an equalization effect. When filters are removed, exposure to attributes that consumers initially preferred less tends to increase, while exposure to heavily weighted attributes may decrease as attention becomes more broadly distributed across the attribute space. As a result, the relative differences among attribute partworths shrink, making the distribution of attribute importance more balanced. The proposition below formalizes this equalization mechanism by showing that increasing the weight of attributes whose importance lies below the overall concentration threshold—or decreasing the weight of attributes whose importance lies above that threshold—reduces the Herfindahl concentration of attribute preferences.

Our proofs proceed by analyzing the effect of changing one coordinate of β at a time while holding the remaining coordinates fixed, and then extending the logic along a path of sequential adjustments. This approach is sufficient because any broader reallocation of attention or learning-induced updating across attributes can be represented as a sequence of single-attribute partworth changes. Accordingly, let $\hat{\beta}_i$ denote the initial partworth of attribute i , and suppose that a change in exposure or learning shifts it to $\hat{\beta}_i + \delta_i$. The following proposition characterizes the conditions under which such a shift reduces the concentration of preferences across attributes.

Proposition 1: *Changing the partworth of attribute i from $\hat{\beta}_i$ to $\hat{\beta}_i + \delta_i$ decreases $\mathcal{H}(\beta)$ (i.e., makes preferences less concentrated across attributes) if:*

(i) $\delta_i > 0$ and $\omega_i < \mathcal{H}(\beta)$ for all $\beta_i \in [\hat{\beta}_i, \hat{\beta}_i + \delta_i]$,

or

(ii) $\delta_i < 0$ and $\omega_i > \mathcal{H}(\beta)$ for all $\beta_i \in [\hat{\beta}_i + \delta_i, \hat{\beta}_i]$.

Proof. Let $S = \sum_{k=1}^K \beta_k$ and $Q = \sum_{k=1}^K \beta_k^2$, so that $\mathcal{H}(\beta) = \frac{Q}{S^2}$. Holding β_{-i} fixed, the partial derivative with respect to β_i is

$$\frac{\partial \mathcal{H}}{\partial \beta_i} = \frac{2\beta_i S^2 - 2QS}{S^4} = 2 \frac{\beta_i S - Q}{S^3}$$

This derivative is negative if and only if $\beta_i < Q/S$, equivalently

$$\omega_i = \frac{\beta_i}{S} < \frac{Q}{S^2} = \mathcal{H}(\beta)$$

Likewise, $\partial \mathcal{H} / \partial \beta_i > 0$ if and only if $\omega_i > \mathcal{H}(\beta)$.

We first consider $\delta_i > 0$. When changing β_i from $\hat{\beta}_i$ to $\hat{\beta}_i + \delta_i$ (with all other β_{-i} fixed), the total change

in HHI is

$$\Delta \mathcal{H} = \int_{\hat{\beta}_i}^{\hat{\beta}_i + \delta_i} \frac{\partial \mathcal{H}}{\partial \beta_i} d\beta_i$$

If $\omega_i(\beta) < \mathcal{H}(\beta)$ for all $\beta_i \in [\hat{\beta}_i, \hat{\beta}_i + \delta_i]$, then $\partial \mathcal{H} / \partial \beta_i < 0$ throughout the integration interval, implying $\Delta \mathcal{H} < 0$. Similarly, if $\delta_i < 0$ and $\omega_i(\beta) > \mathcal{H}(\beta)$ for all $\beta_i \in [\hat{\beta}_i + \delta_i, \hat{\beta}_i]$, then $\partial \mathcal{H} / \partial \beta_i > 0$ throughout that interval, and hence

$$\Delta \mathcal{H} = - \int_{\hat{\beta}_i + \delta_i}^{\hat{\beta}_i} \frac{\partial \mathcal{H}}{\partial \beta_i} d\beta_i < 0$$

Therefore, increasing the partworth of an attribute whose share is below $\mathcal{H}$ (uniformly along the path), or decreasing the partworth of an attribute whose share is above $\mathcal{H}$ (uniformly along the path), reduces preference concentration. $\square$

We now turn to choice diversity. Suppose there are J products indexed by $j = 1, \dots, J$ on the (actual or simulated) market. Each product j is characterized by an attribute vector $\mathbf{x}^j = (x_1^j, \dots, x_K^j) \in \mathbb{R}^K$. Consumer utility for product j is linear in attributes: $U^j = \sum_{k=1}^K x_k^j \beta_k$. Let p^j be the choice probability for product j under a multinomial logit mapping of utilities, $p^j = \frac{\exp(U^j)}{\sum_{m=1}^J \exp(U^m)}$. We measure market concentration by the HHI on choice shares:

$$C(p) = \sum_{j=1}^J (p^j)^2 = \frac{\sum_{j=1}^J \exp(U^j)^2}{(\sum_{j=1}^J \exp(U^j))^2} = \frac{\sum_{j=1}^J \exp(2U^j)}{(\sum_{j=1}^J \exp(U^j))^2}$$

Lower $C(p)$ indicates lower market concentration, i.e., more homogeneous market shares. We again consider the change in β_i from $\hat{\beta}_i$ to $\hat{\beta}_i + \delta_i$. The following proposition states that increasing the partworths of less-preferred attributes and/or decreasing the partworths of more-preferred attributes will lead to a decrease in market share concentration as long as products with less (more) preferred attributes tend to be less (more) preferred overall.

Proposition 2. *Fix all partworths β_{-i} and change the partworth of attribute i from $\hat{\beta}_i$ to $\hat{\beta}_i + \delta_i$. This change decreases the concentration of choice shares, $C(p)$, if either: (i) $\delta_i > 0$ and attribute i is relatively more present among lower-share products, in the sense that*

$$\text{Cov}_p(p^j, x_i^j) < 0 \quad \text{for all } \beta_i \in [\hat{\beta}_i, \hat{\beta}_i + \delta_i],$$

or (ii) $\delta_i < 0$ and attribute i is relatively more present among higher-share products, in the sense that

$$\text{Cov}_p(p^j, x_i^j) > 0 \quad \text{for all } \beta_i \in [\hat{\beta}_i + \delta_i, \hat{\beta}_i].$$

where, $\text{Cov}_p(a^j, b^j) = \sum_{j=1}^J p^j a^j b^j - \left(\sum_{j=1}^J p^j a^j \right) \left(\sum_{j=1}^J p^j b^j \right)$ denote the covariance computed under the choice-share distribution p for any product-level variables a^j and b^j .

Proof. Let $S_1 = \sum_{j=1}^J \exp(U^j)$ and $S_2 = \sum_{j=1}^J \exp(2U^j)$, so that $C(p) = \frac{S_2}{S_1^2}$. Since $\partial U^j / \partial \beta_i = x_i^j$, the chain rule gives

$$\frac{\partial S_1}{\partial \beta_i} = \sum_{j=1}^J \exp(U^j) x_i^j, \quad \frac{\partial S_2}{\partial \beta_i} = 2 \sum_{j=1}^J \exp(2U^j) x_i^j$$

Differentiating $C = S_2/S_1^2$ yields

$$\frac{\partial C}{\partial \beta_i} = \frac{2}{S_1^3} \left[S_1 \sum_{j=1}^J \exp(2U^j) x_i^j - S_2 \sum_{j=1}^J \exp(U^j) x_i^j \right]$$

Because $p^j = \exp(U^j)/S_1$, we have

$$\exp(U^j) = p^j S_1, \quad \exp(2U^j) = (p^j)^2 S_1^2, \quad S_2 = S_1^2 \sum_{j=1}^J (p^j)^2 = S_1^2 C(p)$$

Substituting into the expression above gives

$$\frac{\partial C}{\partial \beta_i} = 2 \left[\sum_{j=1}^J (p^j)^2 x_i^j - C(p) \sum_{j=1}^J p^j x_i^j \right]$$

Hence the sign of the derivative is the sign of

$$\sum_{j=1}^J (p^j)^2 x_i^j - \left(\sum_{j=1}^J (p^j)^2 \right) \left(\sum_{j=1}^J p^j x_i^j \right) = \text{Cov}_p(p^j, x_i^j)$$

Therefore,

$$\text{sign} \left(\frac{\partial C}{\partial \beta_i} \right) = \text{sign} \left(\text{Cov}_p(p^j, x_i^j) \right)$$

Now consider changing β_i from $\hat{\beta}_i$ to $\hat{\beta}_i + \delta_i$. By the fundamental theorem of calculus,

$$\Delta C = \int_{\hat{\beta}_i}^{\hat{\beta}_i + \delta_i} \frac{\partial C}{\partial \beta_i} d\beta_i$$

If $\delta_i > 0$ and $\text{Cov}_p(p^j, x_i^j) < 0$ throughout the interval, then the derivative is negative and $\Delta C < 0$. If $\delta_i < 0$ and the covariance is positive throughout the interval, then the derivative is positive and again $\Delta C < 0$. Thus, increasing the partworth of attributes that are relatively more prevalent among low-share products, or decreasing the partworth of attributes concentrated among high-share products, reduces market-share concentration. $\square$

To illustrate the intuition, consider a simple choice set with two products j and k , where $x_i^j > x_i^k$. Let p^j and p^k denote their market shares, where $p^j + p^k = 1$. In this case, the covariance reduces to $\text{Cov}_p = p^j p^k (p^j - p^k)(x_i^j - x_i^k)$. Thus, the sign of the covariance depends on whether the product with a higher value of attribute i also has a higher market share. If $p^j > p^k$, then the product that has more of attribute i is already the more popular one, implying $\text{Cov}_p > 0$. Increasing β_i therefore increases $C(p)$, making market shares more concentrated. Conversely, decreasing β_i reduces the advantage of the dominant product and lowers concentration. If instead $p^j < p^k$, then the product with a higher value of attribute i is the less popular one, so $\text{Cov}_p < 0$. In this case, increasing β_i shifts choice probability toward the less popular product and reduces concentration. Thus, increasing the weight on attributes associated with low-share products (or decreasing the weight on attributes concentrated among high-share products) makes choice shares more balanced.

Generalizing to a choice set with any number of alternatives, we see that increasing the partworths of less-preferred attributes and/or decreasing the partworths of more-preferred attributes will lead to a decrease in market share concentration as long as products with less (more) preferred attributes tend to be less (more) preferred overall.

B Experimental Design

Price

☐ less than \$25

☐ \$25 - \$49.99

☐ \$50 - \$74.99

☐ \$75 - \$99.99

☐ \$100 - \$149.99

☐ \$150 - \$199.99

☐ \$200 - \$249.99

☐ \$250 - \$499.99

Customer Rating

☐ 5

☐ 4 & Up

☐ 3 & Up

☐ 2 & Up

☐ 1 & Up

Brand

☐ AfterShokz

☐ Anker

☐ Apple

☐ Audio-Technica

☐ Ausounds

☐ Beats by Dr. Dre

☐ Bose

☐ BuddyPhones

[show more](#)

Headphone Fit

☐ Over-the-Ear

☐ On-Ear

☐ In-Ear

Active Noise Cancelling

☐ Yes

Battery Life

☐ Less than 8 Hours

☐ 8 - 11 Hours

☐ 11 - 16 Hours

☐ 16 - 24 Hours

☐ 24 Hours or More

Color

☐ Black

☐ Gray

☐ White

☐ Red

☐ Yellow

☐ Multi

☐ Blue

☐ Pink

[show more](#)

Figure W1: Filtering Bar in Control Condition (All)

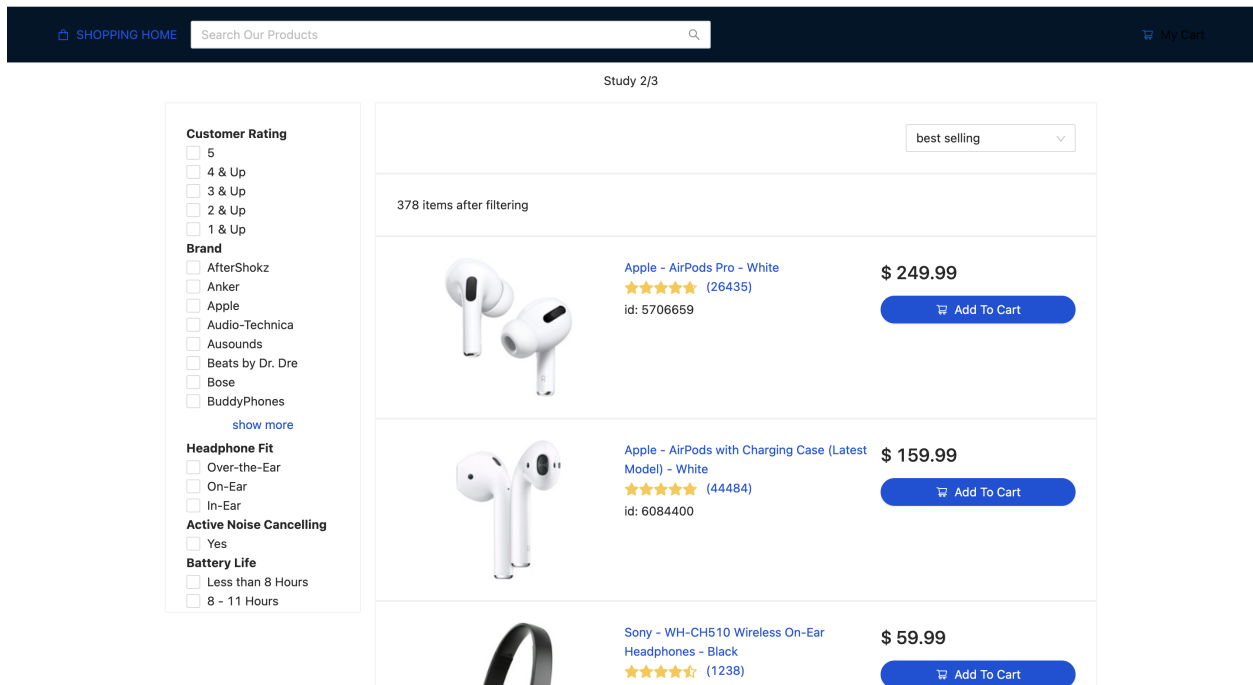


Figure W2: Homepage of the E-Commerce Website in Treated Condition 1 (All but Price)

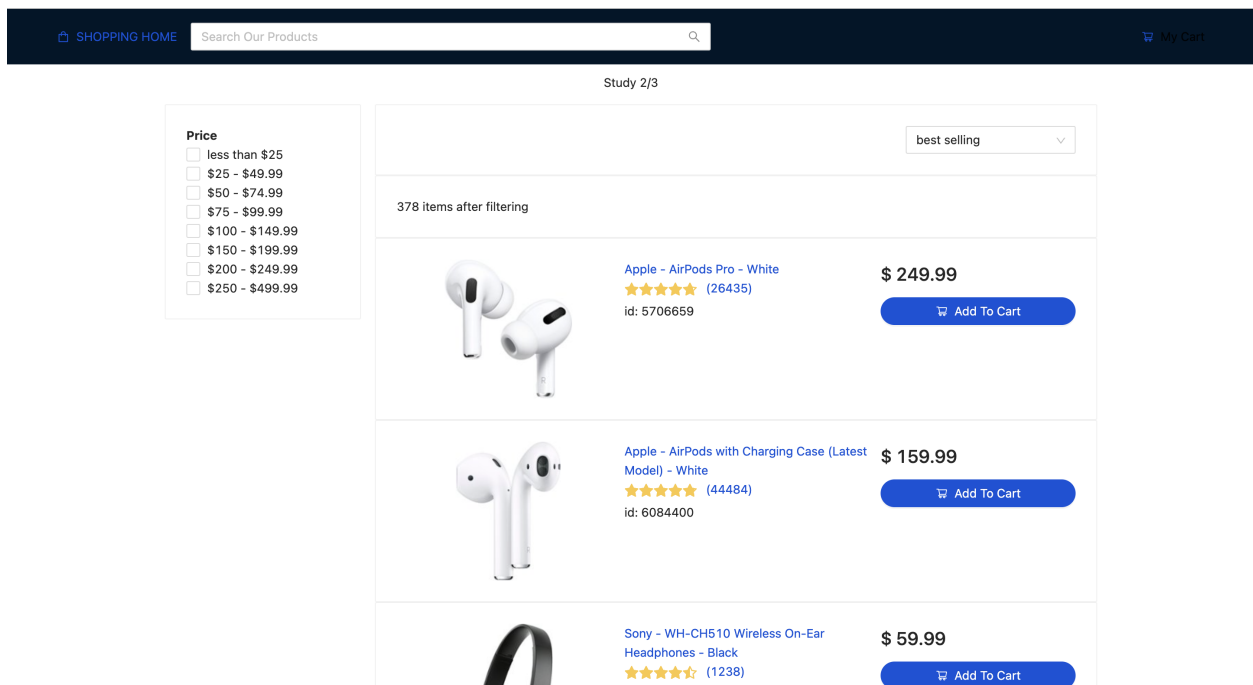


Figure W3: Homepage of the E-Commerce Website in Treated Condition 2 (Price Only)

Study 2/3

best selling

378 items after filtering



Apple - AirPods Pro - White

★★★★★ (26435)

id: 5706659

\$ 249.99

Add To Cart



Apple - AirPods with Charging Case (Latest Model) - White

★★★★★ (44484)

id: 6084400

\$ 159.99

Add To Cart



Sony - WH-CH510 Wireless On-Ear Headphones - Black

★★★★☆ (1238)

\$ 59.99

Add To Cart

Figure W4: Homepage of the E-Commerce Website in Treated Condition 3 (None)

Part 1 Survey:

1. (Ownership) Do you currently own a pair of wireless headphones? (yes or no)
2. (Ownership) Which brands of wireless headphones do you own? Please check as many as apply. (choice among 16 popular brands and “Other” for participants who own brands that are not included in the question)
3. (Familiarity) How familiar are you with each of the following headphone brands? (items include the top four brands considered in the conjoint study; measure on a scale from 1 (=Not at all) to 5 (=Extremely well))
4. (Familiarity) Please indicate how much you agree or disagree with the following statements (measurement on a scale from 1 (=strongly disagree) to 5 (=strongly agree))
 - Compared to the average person, I do not know much about headphones (inverse coded)
 - I am very familiar with headphones
 - I own several sets of wireless headphones
 - My friends own several sets of wireless headphones
 - I read articles related to headphones all the time
5. (Interest) How much do you agree or disagree with the statement that “I am very interested in headphones” (measurement on a scale from 1 (=strongly disagree) to 5 (=strongly agree))
6. (Preference) If you were to buy a pair of wireless headphones, please rate the importance of the following product attributes (items include brand, battery life, price, headphone fit, noise cancellation, consumer rating, sound quality; measure on a scale from 1 (=very unimportant) to 5 (=very important))
7. (Preference) What is the maximum amount you would be willing to pay (in U.S. dollars) for a pair of wireless headphones? (choice among 7 price intervals: less than \$25, \$25 – \$49.99; \$50 – \$74.99; \$75 – \$99.99; \$100 – \$149.99; \$150 – \$249.99; \$250 – \$499.99)

Table W1: Lookup Table for Conditional Price

Brand	Sony: \$0; Bose: \$80; Beats: \$80; Apple: \$120
Headphone Fit	In-ear: \$0; On-ear: \$50; Over-the-ear: \$100
Noise Cancellation	No: \$0; Yes: \$100
Battery Life	5hr: \$0; 10hr: \$0; 20hr: \$0; 30hr: \$0
Consumer Rating	3: \$0; 4: \$0; 5: \$0
Price Increments	low: -\$50; medium:\$0; high:\$50

Note: The base price is set to \$100.

C Survey Data Statistics

Table W2: Part 1 Survey Answers across Conditions

	(0) All	(1) All But Price	(2) Price Only	(3) None
Num. participants	307	279	295	288
Female (0/1)	0.56	0.56	0.56	0.57
Ownership				
Currently own (0/1)	0.80	0.85	0.86	0.81
Num. owned brands (all)	1.18 (1.02)	1.22 (0.96)	1.27 (1.01)	1.28 (1.01)
Num. owned brands (Top-4)	0.74 (0.71)	0.76 (0.72)	0.80 (0.72)	0.83 (0.70)
Knowledge	2.70 (0.69)	2.76 (0.70)	2.73 (0.73)	2.74 (0.71)
Interest	3.41 (0.93)	3.44 (0.90)	3.43 (0.93)	3.41 (0.97)
Familiarity				
Apple	3.95 (1.06)	3.95 (1.03)	3.98 (0.96)	4.11 (0.97)
Beats	2.54 (1.28)	2.68 (1.26)	2.56 (1.23)	2.61 (1.26)
Bose	2.31 (1.29)	2.56 (1.31)	2.37 (1.29)	2.53 (1.27)
Sony	2.90 (1.24)	2.89 (1.31)	2.99 (1.18)	3.02 (1.20)
Attribute Importance				
Brand	4.13 (0.82)	4.07 (0.85)	4.04 (0.81)	4.14 (0.80)
Battery life	3.47 (1.00)	3.40 (1.01)	3.40 (0.96)	3.48 (0.96)
Price	3.89 (0.82)	3.91 (0.81)	3.84 (0.89)	3.88 (0.87)
Headphone fit	4.39 (0.68)	4.40 (0.76)	4.39 (0.72)	4.44 (0.70)
Noise cancellation	4.02 (0.86)	3.94 (0.97)	3.91 (0.93)	4.08 (0.90)
Rating	4.15 (0.82)	4.13 (0.80)	4.15 (0.77)	4.24 (0.74)
Sound quality	4.54 (0.61)	4.56 (0.64)	4.57 (0.64)	4.62 (0.57)
Willingness-To-Pay (\$)				
< 25	0.029	0.018	0.014	0.014
25 – 49.99	0.091	0.093	0.115	0.104
50 – 74.99	0.117	0.140	0.125	0.111
75 – 99.99	0.130	0.122	0.115	0.080
100 – 149.99	0.238	0.233	0.227	0.257
150 – 249.99	0.267	0.251	0.268	0.281
250 – 499.99	0.127	0.143	0.136	0.153

Table W2 reports the results from the Part 1 survey relating to participants' product ownership, knowledge, interest, familiarity, attribute importance, and willingness to pay. Based on the ANOVA test, we find no significant difference across conditions for product ownership, knowledge, interest, familiarity, and attribute importance ($p > 0.2$). The last few rows of the table report the proportion of participants at different levels of willingness-to-pay, showing no significant differences across conditions ($p > 0.3$).

Table W3: Search Experience across Conditions

	(0) All	(1) All But Price	(2) Price Only	(3) None
I find the shopping website makes it easy to search for the headphones I want.	4.10 (0.72)*	4.07 (0.82)*	3.53 (1.03) [†]	3.51 (1.09) [†]
I like the way the shopping website looks.	3.78 (0.87)*	3.78 (0.83)*	3.59 (0.92) [†]	3.62 (0.88) [†]
My browsing behavior on the website is similar to how I usually search for product information on other e-commerce platforms.	4.16 (0.78)*	4.19 (0.84)*	4.03 (0.84) [†]	3.99 (0.88) [†]
The information on the website is useful for me to make a purchase decision.	4.01 (0.78)*	4.00 (0.80)*	3.88 (0.81) [†]	3.88 (0.84) [†]
This shopping website is similar to a real-life e-commerce website for buying headphones.	4.22 (0.77)*	4.17 (0.84)*	3.94 (0.95) [†]	3.88 (0.95) [†]
For the product that you checked out on the shopping website, how likely would you want to purchase it in reality?	3.79 (0.94)*	3.87 (0.85)*	3.70 (0.90)*	3.76 (0.94)*

Note: Numbers in parentheses indicate standard deviation across individuals assigned to the same condition. * indicates the experimental conditions (or tied) with the highest rating ($p < 0.05$). [†] indicates the conditions (or tied) with the lowest rating ($p < 0.05$).

D Classification of Self-Reported Decision Rules

One research assistant (with a background in economics) read each participant's answer and manually classified it into one of five possible primary decision rules, defined as follows:

- Compensatory rule; consumer selects the alternative with the highest overall evaluation on a set of choice criteria.
- Conjunctive rule; consumer establishes a minimum acceptable level for each choice criterion and accepts an alternative only if it equals or exceeds the minimum cutoff level for every criterion.
- Disjunctive rule; consumer establishes acceptable standards for each criterion and accepts an alternative if it exceeds the standard on at least one criterion.
- Elimination by aspects: consumer evaluates options based on a set of criteria or attributes and eliminates options that do not meet the criteria one by one.
- Lexicographic rule: consumer chooses alternatives with an order of preference on attributes. For example, a consumer might rank all hybrids over other fuel classes; within hybrids, they might next rank vehicles on crash test ratings, then on quality ratings, then on ride & handling, etc (Hauser et al., 2009).

All of the participants' primary decision rules can be labeled into one of the five options. Specifically, we find that only 7.3% of participants stated that they use compensatory decision rules while 82.7% stated a certain non-compensatory rule. This is consistent with the existing literature showing that people are more likely to adopt non-compensatory decision rules when they have to process a large amount of information in a limited time (Payne, 1982; Tversky et al., 1988; Billings and Scherer, 1988; Bettman et al., 1998). Across the four non-compensatory decision rules, we find that the elimination by aspects is the most frequently used (72%), followed by the lexicographic rule (19%) and then the conjunctive rule (9%). Only one participant stated a disjunctive rule.

We also examine whether the interface change affected the usage of decision rules reported by participants after search. We find that tendencies to adopt non-compensatory decision rules differ significantly across experimental conditions. The usage rate is 85.76% in "All," 80.70% in "All but Price," 85.30% in

“Price Only,” and 78.72% in “None.” Participants in the “None” condition have a significantly lower tendency to adopt non-compensatory preference rules compared to participants in the other three conditions ($p < 0.05$). That is, completely removing the filtering tool reduces the use of non-compensatory rules.

This pattern is theoretically consistent with IFT. Faceted filters reduce the cost of acting on strict attribute cutoffs, thereby reinforcing non-compensatory strategies that exploit pre-existing preferences. When filters are removed, the cost of implementing such rules rises because participants must expend more effort to screen alternatives manually. As a result, consumers shift toward more compensatory processing, weighing multiple attributes simultaneously. This finding also aligns with constructed-preference and bounded-rationality perspectives, which highlight that decision rules are context-dependent and adapt to interface structures that alter attention and effort costs (Payne et al., 1999; Gabaix, 2014).

E Bayesian Estimation Results

Table W4: In-Sample Choice Prediction Accuracy

	(0) All	(1) All But Price	(2) Price Only	(3) None
Pre-search	0.827 (0.107)	0.832 (0.106)	0.821 (0.111)	0.823 (0.117)
Post-search	0.844 (0.107)**	0.847 (0.110)*	0.838 (0.122)**	0.843 (0.117)**

Note: for each experimental condition in each column, ** (*) indicates the conjoint study for which our model has significantly higher prediction accuracy at $p < 0.05$ ($p < 0.1$).

Table W5: Partworth Estimates

Attribute	Level	μ	α_0 (All)	α_1 (All But Price)	α_2 (Price Only)	α_3 (None)
Brand	Apple	2.40 [2.18, 2.68]	-0.46 [-0.99, 0.06]	0.01 [-0.51, 0.52]	-0.29 [-0.76, 0.24]	-0.68 [-1.24, -0.16]
	Beats	-0.77 [-0.88, -0.68]	0.25 [0.07, 0.47]	0.02 [-0.18, 0.21]	0.10 [-0.11, 0.27]	0.30 [0.09, 0.53]
	Bose	-0.76 [-0.87, -0.66]	0.07 [-0.2, 0.28]	-0.05 [-0.25, 0.14]	0.18 [-0.01, 0.38]	0.29 [0.11, 0.47]
	Sony	-0.87 [-1.00, -0.75]	0.14 [-0.08, 0.37]	0.03 [-0.23, 0.27]	0.02 [-0.22, 0.23]	0.08 [-0.14, 0.34]
Fit	In	1.39 [1.19, 1.59]	-0.07 [-0.43, 0.33]	0.02 [-0.38, 0.4]	-0.39 [-0.78, -0.05]	-0.48 [-0.80, -0.10]
	On	-0.68 [-0.80, -0.58]	0.04 [-0.16, 0.22]	-0.11 [-0.30, 0.10]	0.04 [-0.14, 0.26]	0.12 [-0.07, 0.29]
Noise Cancel.	Over	-0.70 [-0.85, -0.56]	0.03 [-0.21, 0.25]	0.10 [-0.16, 0.33]	0.35 [0.13, 0.58]	0.37 [0.13, 0.57]
	No	-1.45 [-1.57, -1.31]	0.12 [-0.10, 0.30]	-0.19 [-0.40, 0.02]	-0.14 [-0.35, 0.06]	-0.20 [-0.38, 0.00]
Battery	Yes	1.45 [1.31, 1.57]	-0.12 [-0.30, 0.10]	0.19 [-0.02, 0.4]	0.14 [-0.06, 0.35]	0.20 [-0.00, 0.38]
	5hr	-3.70 [-3.92, -3.48]	0.71 [0.34, 1.20]	0.73 [0.17, 1.16]	0.51 [0.06, 0.96]	0.81 [0.38, 1.22]
	10hr	0.95 [0.86, 1.03]	-0.19 [-0.38, -0.05]	-0.19 [-0.36, -0.01]	-0.07 [-0.23, 0.08]	-0.21 [-0.37, -0.05]
	20hr	1.28 [1.20, 1.36]	-0.26 [-0.43, -0.1]	-0.22 [-0.38, -0.01]	-0.18 [-0.37, 0.01]	-0.24 [-0.41, -0.05]
Rating	30 hr	1.47 [1.37, 1.57]	-0.25 [-0.48, -0.07]	-0.31 [-0.57, -0.04]	-0.25 [-0.44, -0.04]	-0.36 [-0.55, -0.14]
	3	-2.45 [-2.58, -2.32]	0.19 [-0.11, 0.44]	0.11 [-0.15, 0.39]	0.01 [-0.30, 0.30]	0.02 [-0.31, 0.25]
	4	1.03 [0.96, 1.11]	-0.08 [-0.22, 0.09]	-0.11 [-0.25, 0.04]	-0.07 [-0.23, 0.10]	-0.03 [-0.17, 0.15]
Price $\times 0.01$	5	1.42 [1.35, 1.50]	-0.11 [-0.26, 0.06]	0.00 [-0.17, 0.14]	0.06 [-0.10, 0.23]	0.01 [-0.12, 0.19]
		-0.55 [-0.62, -0.47]	0.23 [0.08, 0.37]	0.09 [-0.05, 0.25]	0.14 [-0.02, 0.29]	0.14 [0.00, 0.03]

Note: partworths sum to zero across levels of each attribute. Price is treated as a continuous attribute. The 95% posterior confidence intervals are displayed after the posterior mean. The parameter μ is statistically significant for all of the attribute levels. For the parameter α , only those in bold are significantly different from zero ($p < 0.05$).

F Additional Experimental Results

Table W6: Treatment Effects on Attribute Importances

	(1) All But Price	(2) Price Only	(3) None
Brand (100%)	1.08 [1.03, 1.14]	-0.01 [-0.05, 0.04]	-0.63 [-0.67, -0.59]
Rating (100%)	0.01 [-0.06, 0.07]	0.60 [0.56, 0.65]	0.96 [0.91, 1.02]
Price (100%)	-0.62 [-0.66, -0.59]	-0.67 [-0.70, -0.63]	0.14 [0.10, 0.17]
Technical specs (100%)	-0.47 [-0.54, -0.39]	0.07 [0.01, 0.13]	-0.47 [-0.53, -0.42]

Note: for each variable and treated condition combination, the table reports the posterior mean and the 95% posterior confidence intervals. Only these in bold are significantly different from zero ($p < 0.05$). Here, we combine battery, fit, and noise cancellation into a single attribute, “technical specs,” for parsimony and generalizability.

Table W7: Likelihood of Using Each Search Action by Condition

	Control	Treated		
	(0) All	(1) All But Price	(2) Price Only	(3) None
Filtering	0.958*	0.935*	0.769	n.a.
Keyword search	0.147	0.115	0.539*	0.667*
Sorting	0.316	0.427*	0.627*	0.729*
By Price	0.218	0.344*	0.390*	0.587*
By Ascending Price	0.091	0.147*	0.169*	0.278*
By Descending Pricing	0.156	0.247*	0.302*	0.490*
By (Descending) Rating	0.169	0.190	0.437*	0.465*
Going to next page	0.726	0.688	0.824*	0.858*
Viewing PDP	0.756	0.771	0.858*	0.812
Clicking on PDP	0.726	0.756	0.817*	0.785
Overview	0.567	0.606	0.641	0.625
Technical specs	0.521	0.591	0.614*	0.569
Reviews	0.573	0.649	0.675*	0.688*
Images	0.609	0.591	0.678	0.639
Recommended products	0.228	0.204	0.292	0.250

Note: * indicates the treated condition that is significantly different from the control condition (0) ($p < 0.05$).

G Mediation Analysis

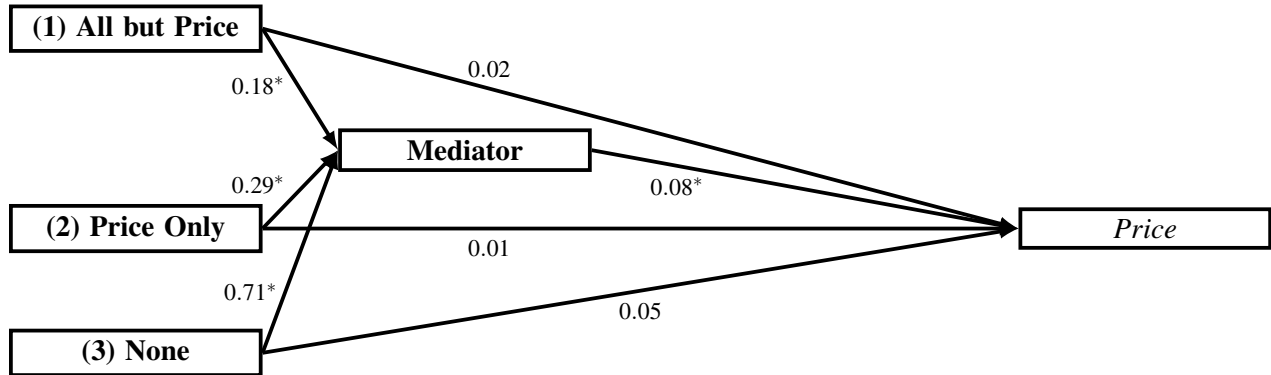


Figure W5: Mediating Effect of Sorting-by-Descending-Price on Purchased Price

Note: the baseline is the control condition ("All"). * $p < 0.05$.

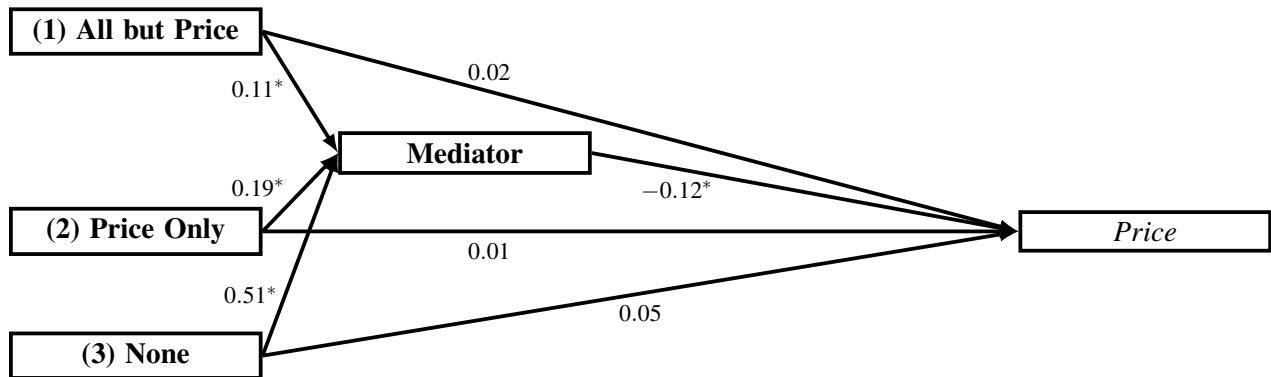


Figure W6: Mediating Effect of Sorting-by-Ascending-Price on Purchased Price

Note: the baseline is the control condition ("All"). * $p < 0.05$.

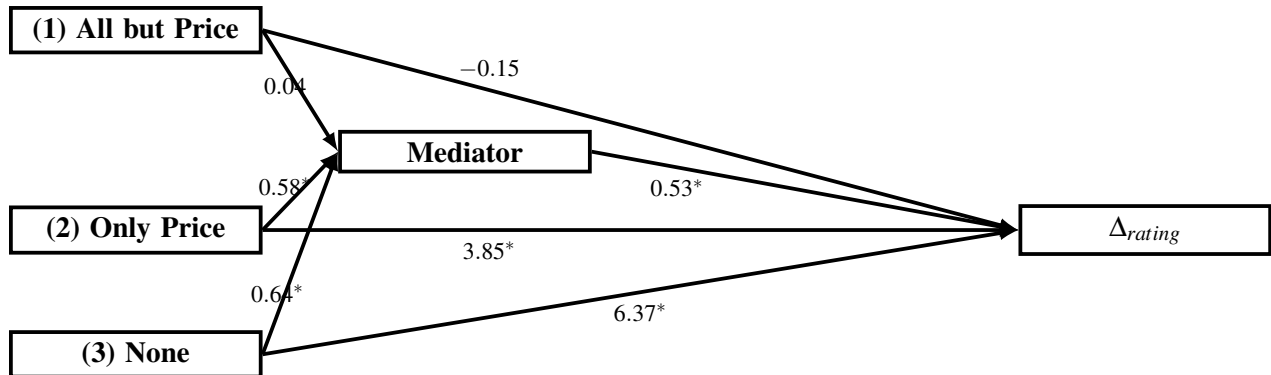


Figure W9: Mediating Effect of Sorting-by-Descending-Rating on Change in Rating Importance

Note: the mediator is whether the sorting-by-rating tool is used or not. The baseline is the control condition ("All"). * $p < 0.05$.

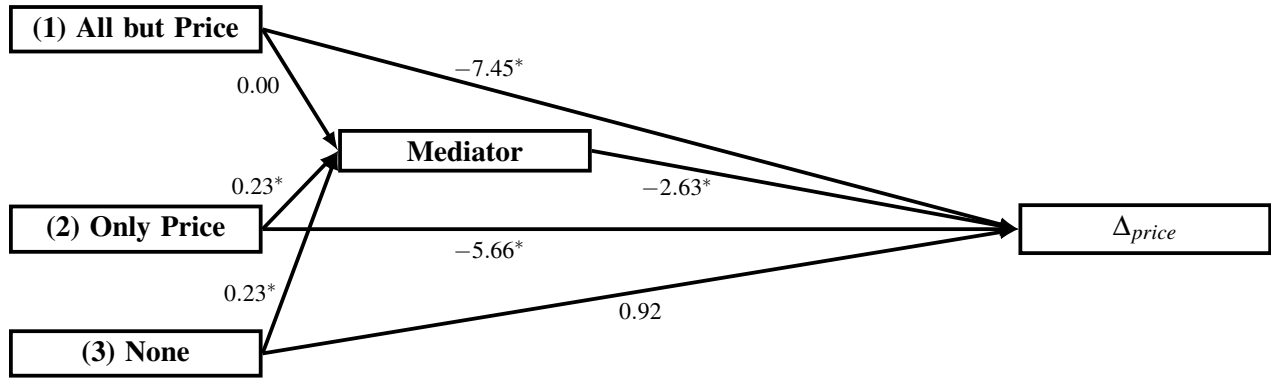


Figure W7: Mediating Effect of Time Spent on Product Detail on Change in Price Importance

Note: the mediator is the proportion of time spent on product detail pages relatively to the entire search time. The baseline is the control condition ("All"). $^*p < 0.05$.

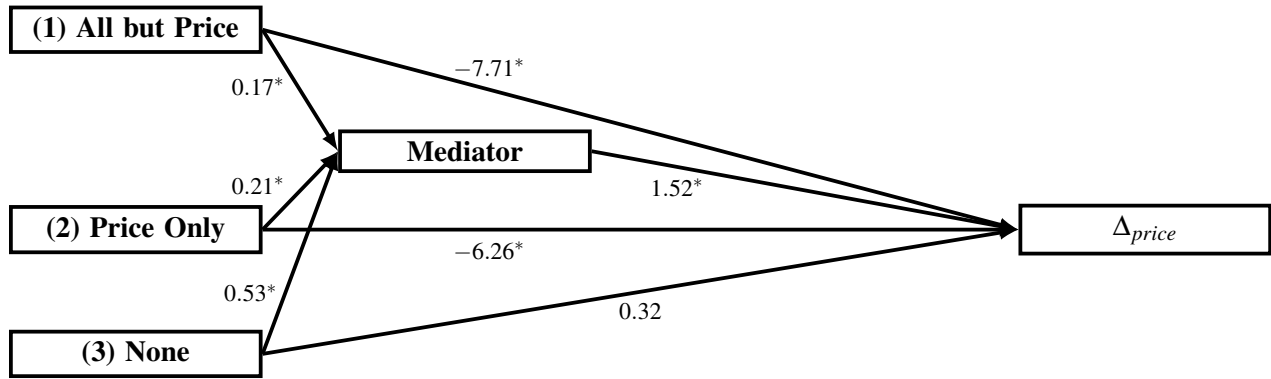


Figure W8: Mediating Effect of Sorting-by-Descending-Price on Change in Price Importance

Note: the baseline is the control condition ("All"). $^*p < 0.05$.

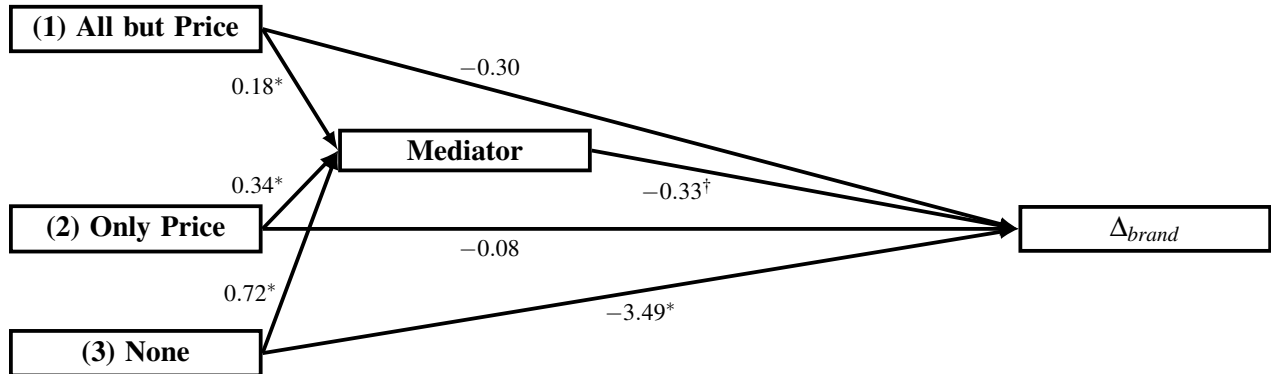


Figure W10: Mediating Effect of Use of Sorting Tools on Change in Brand Importance

Note: the mediator is the ratio of the number of times the consumer used any sorting tool divided by her total usage number of all possible search actions shown in Table W7. The baseline is the control condition ("All"). $^*p < 0.05$; $^\dagger p < 0.1$

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