

# Shuffling as a Sales Tactic: An Experimental Study of Selling Expert Advice\*

Qichao Shi<sup>†</sup>      James A. Dearden<sup>‡</sup>      Ernest K. Lai<sup>§</sup>

September 20, 2022

## Abstract

We investigate the strategic interaction between a product expert and a consumer. The expert publicly chooses a ranking methodology to rank two products with uncertain relative merits; the consumer decides whether to acquire the ranking report to guide her product choice. The expert cares only about selling the report; the consumer derives utility from the product itself and an extra ranking attribute controlled by the expert. Strategic shuffling, in which the expert induces demand for his report by manipulating the uncertainty in product rankings, using a methodology that sometimes ranks the inferior product first, emerges as an equilibrium phenomenon. When the consumer places high value on the top-ranked product, the unique expert-optimal equilibrium, which features shuffling, diverges from the consumer-optimal equilibrium. Laboratory evidence supports the predictions of the expert-optimal equilibrium. With limited field data due to proprietary ranking methodologies, our study provides useful alternative evidence on how ranking publishers may adopt methodologies that are not in consumers' best interests.

*Keywords:* Expert Advice; Product Ranking; Product Guidance; Ranking Uncertainty; Laboratory Experiment

*JEL classification:* C72; C92; D82; D83; L15

---

\*We are grateful to Weijia (Daisy) Dai, David Goldbaum, Oliver Yao, the associate editor, and two anonymous referees for their valuable comments and suggestions. We also thank seminar and conference participants at Lehigh University, Southwestern University of Finance and Economics, the 2018 China Meeting of the Economic Society, and the 30th International Conference on Game Theory for helpful comments and discussions. We acknowledge financial support from the Office of the Vice President and Associate Provost for Research and Graduate Studies at Lehigh University (Faculty Research Grant Account No.: 606975).

<sup>†</sup>School of Economics and China Center for Behavioral Economics and Finance, Southwestern University of Finance and Economics, Chengdu, Sichuan, China. Email: [shiqc@swufe.edu.cn](mailto:shiqc@swufe.edu.cn).

<sup>‡</sup>Lehigh University, Department of Economics, Bethlehem, PA 18015, USA. Email: [jad8@lehigh.edu](mailto:jad8@lehigh.edu).

<sup>§</sup>Lehigh University, Department of Economics, Bethlehem, PA 18015, USA. Email: [kw1409@lehigh.edu](mailto:kw1409@lehigh.edu).

# 1 Introduction

Consumers often seek expert advice prior to making purchases. In many cases, the advice takes the form of product rankings. Students and parents consulting university ranking publications (e.g., *U.S. News & World Report Best Colleges Ranking*), car buyers viewing auto rankings (e.g., *Kelley Blue Book Best Cars*), and home cooks accessing kitchen product rankings (e.g., *Cook's Illustrated*) are but few of the familiar examples. In each of these cases, a ranking publisher collects information about product attributes, chooses a ranking methodology that maps the attributes into a ranking of products, and offers the ranking reports to consumers.

Product rankings provide informational guidance to consumers about product attributes. The rankings may also influence consumer choices for reasons unrelated to product information. Analogous to how the consumption of an advertised product may be complementary to the advertisement itself due to image concerns (Becker and Murphy, 1993), owning a highly ranked product may confer sought-after social prestige. Consequently, product rankings have the effect of transforming a product with  $n$  intrinsic attributes into one with  $n + 1$  attributes, where the extra attribute is the prestige associated with the product's ranking. Not unlike fashion magazine editors who often have the magic wand to dictate an otherwise unremarkable (or bizarre) outfit as the season's stylish standard, ranking publishers may influence the values of the ranked products in a way that is extraneous to the intrinsic product attributes. The implication for consumers is that their willingness to pay or otherwise incur cost to access a ranking publication is derived not only from the informational guidance about existing attributes but also from the valuable opportunity to learn about the contrived ranking attribute.<sup>1</sup>

The popularity of a ranking publication among consumers benefits the publisher either directly through the subscription fee or indirectly through the incidental income from advertising and consulting services provided to sellers of the products being ranked. In choosing a ranking methodology to enhance the readership of its publication, the profit-driven management of a ranking publisher may not necessarily have consumers' best interests in mind. An adopted ranking methodology may not rank products in a manner that genuinely reflects the value of the intrinsic product attributes to consumers, and there are reasons to believe that publishers have incentives to leverage the extra attribute their ranking creates to generate sales and traffic. This divergence of interests has indeed been observed by popular press writers. In an article about university rankings, e.g., Tierney (2013) wrote in *The Atlantic*:

---

<sup>1</sup>Pope (2009) and Luca and Smith (2013) find evidence in, respectively, university and hospital rankings that the rankings themselves, after controlling for product qualities, influence consumer choices. More generally, product reviews, including those submitted by consumers, have been documented to influence consumer decisions ranging from purchases (Chevalier and Mayzlin, 2006; Sun, 2012; Zhu and Zhang, 2010) to returns (Sahoo et al., 2018).

*U.S. News* is always tinkering with the metrics they use, so meaningful comparisons from one year to the next are hard to make. Critics also allege that this is as much a marketing move as an attempt to improve the quality of the rankings: changes in the metrics yield slight changes in the rank orders, which induces people to buy the latest rankings to see what's changed.

The impartiality of a product ranking, if distorted by the publisher's profit motives, would have ramifications not only for consumers but also for other stakeholders, such as university management in the case of university rankings and car dealers in auto rankings. Criticisms like the one above are, however, based on indirect evidence that ranking publishers appear to frequently tweak their rankings. There is an inherent difficulty in obtaining direct empirical evidence given that ranking methodologies are often proprietary and complicated, not completely transparent to outsiders; by the very nature of the problem, relevant field data are hard to come by. To better understand the incentives and behavior of ranking publishers, who profit from the influences they possess and contrive on consumers, some form of evidence that goes beyond casual observations is needed. In this paper, we provide experimental evidence that a product expert, who benefits from a consumer's acquisition of his ranking advice amid his influence on product values via his ranking, may adopt a ranking methodology that is not in the best interests of the consumer.

We begin by analyzing a ranking-report game, which forms the basis of our experimental design and helps make precise some of the ideas expressed above. An expert (he), who cares only about whether a consumer (she) acquires his ranking report, chooses and commits to a ranking method to generate the report. There are two products, and a ranking method is modeled as a probability distribution that the products are ranked first conditional on the values of their intrinsic attributes. The consumer, who is imperfectly informed about the intrinsic values, observes the ranking method chosen by the expert, decides whether to acquire at a cost the generated report to view the ranking outcome, and then chooses a product.

The consumer experiences the intrinsic value of the chosen product and an additional ranking value if the product turns out to be ranked first. This ranking value accrues to the consumer even if she stumbles on the top-ranked product without the report, and this represents a key feature of our environment: in offering ranking advice to a consumer with this preference structure, the expert is in effect selling *product guidance* regarding intrinsic values as well as *resolution of ranking uncertainty* over which product carries the ranking value.

We characterize the subgame-perfect equilibria of this game and employ formal refinements to single out a robust equilibrium, which is expert-optimal, and an efficient equilibrium, which is consumer-optimal. A crucial insight of our analysis centers on an equilibrium phenomenon that we term "shuffling as a sales tactic." Leveraging the capability of his ranking report to resolve

the ranking uncertainty, the expert engages in *strategic shuffling*—endogenously manipulates the ranking uncertainty by choosing a method that sometimes ranks the intrinsically less valuable product first—to induce demand for his report, even when doing so misguides the consumer on the front of intrinsic values. While the consumer is worse off with the misguidance, she is willing to endure it and acquire the report because the accompanying shuffling, a spiteful move of the expert to the non-acquiring consumer, makes it even worse to do without the report.

This apparently paradoxical situation is most palpable to the consumer when the ranking value is relatively high, in which the expert-optimal equilibrium diverges from the consumer-optimal equilibrium. In the former, the consumer’s willingness to acquire the report is maximal among all equilibria under the shuffling, which operates as if the expert created a problem and then peddled a solution. In the latter, the consumer’s expected payoff from acquiring the report is instead maximal among all equilibria. When, on the other hand, the ranking value is relatively low so that the resolution of ranking uncertainty is not valuable enough to compensate for the misguidance, even though shuffling can still occur in equilibrium, the expert-optimal and the consumer-optimal equilibria coincide in which the expert does not shuffle.

We simplify the game for experimental implementation, drastically reducing the cardinality of the expert’s choice set while retaining all the major equilibrium features including the refined equilibria. We conduct four treatments with treatment variations in the ranking value and the cost for the consumer to acquire the report. The parameters are chosen so that two treatments belong to the case where the expert-optimal and the consumer-optimal equilibria coincide and the other two the case where they diverge. We formulate our experimental hypotheses based on the predictions of the broad subgame-perfect equilibria as well as the refined equilibria. Since the expert-optimal and the consumer-optimal equilibria predict differently for two out of the four treatments, they provide not only competing hypotheses but also a control to empirically differentiate the two refinements and the associated phenomenon of shuffling.

Our experimental findings support the qualitative predictions of the subgame-perfect equilibria. For experts, the ranking methods under which consumers are predicted to acquire the ranking report are on average chosen more often than those under which consumers do not acquire. For consumers, their aggregate report-acquisition decisions are overall in lockstep with experts’ choices. While the subgame-perfect predictions are least restrictive, a more demanding and interesting test of the theory lies in the competition between the expert-optimal and the consumer-optimal equilibria, both of which offer unique predictions.

Our data favor the former. In the treatments with high ranking value where the predictions of the two refined equilibria diverge, the equilibrium ranking method that is expert-optimal, which is also the shuffling method that induces the most ranking uncertainty, is most frequently chosen by a considerable margin. Our individual panel data analysis further reveals a

richer picture regarding the treatment effects: when a ranking method that is both consumer-optimal and expert-optimal becomes not expert-optimal in another treatment, the method is significantly less likely to be chosen; on the other hand, an expert-optimal ranking method is significantly more likely to be chosen than other methods even when it is not consumer-optimal.

Our theoretical and empirical findings contribute to shed light on the sentiment about ranking publishers that motivates our study. Repeated rankings by a shuffling expert would generate ranking outcomes that vary beyond what would be expected given the prior of the uncertain intrinsic values, reminiscent of a ranking publisher frequently tweaking its rankings and establishing a “shuffling reputation” that draws consumers to check its publication every year. The case of a high ranking value in which the expert-optimal and the consumer-optimal equilibria diverge further provides a theoretical basis to argue that the shuffling, which benefits the expert but hurts the consumer, is excessive from the vantage point of consumer welfare.

While the expert-optimal equilibrium involves a strategic sales motive that is spiteful in nature, a plausible reason to expect the consumer-optimal equilibrium to be played in the laboratory would be an altruistic motive on the part of experts. In the treatments with high ranking value, these two motives present a tradeoff to experts, either benefiting the acquiring consumers with minimal misguidance or shuffling to render the report indispensable yet hurting the non-acquiring consumers. The prevalence of the expert-optimal equilibrium in the laboratory suggests that experts are driven more by the sales motive than any altruistic motive. In light of this finding obtained in a relatively low-stake setting, it stands to reason that in the real world with substantially higher stakes, ranking publishers operating under comparative incentive structures might indeed be putting profits in front of consumer welfare.

***Related Literature.*** Our study is related to two separate strands of literature. In terms of the subject matter, we contribute to the literature on product rankings and more generally non-seller-provided product information. In terms of the theory and experiment, our study is broadly related to the literature on strategic information transmission.

In respect of product rankings, our game shares common features with the university-ranking model of [Dearden et al. \(2019\)](#). In their dynamic model, a finite number of universities with a finite number of attributes are ranked in each period by a ranking publisher, whose per-period payoff depends on the number of students who access the ranking. As in our environment, students derive prestige utilities from attending the top-ranked universities regardless of whether they access the ranking or not. This motivates the publisher to inject uncertainty into its ranking methodology. They consider an “attribute-and-aggregate” type of methodologies, where the publisher chooses the weight of each attribute in the aggregation. Our static model with a different kind of methodology captures their key result about the incentives of the expert to leverage the prestige effect to manipulate the ranking uncertainty.

As alluded to above, fashion magazine editors often determine a season’s “it” products. Furthermore, they appear to do it in a random manner. [Kuksov and Wang \(2013\)](#) analyze a model of fashion that shares a common theme with ours. Stylish consumers, who prefer to be identified, have exclusive access to a coordinator interpreted as a fashion magazine that makes product recommendations. By following the recommendations, which are random in nature, these high-type stylish consumers separate themselves from the low types, thus maximizing their utility under the prestige effect. The seeming randomness in product rankings in our case and fashion hits in theirs are commonly rationalized as outcomes of maximizing behavior.

Product rankings or recommendations by product magazines are not the only non-seller sources of product information—online product reviews are another. While these reviews submitted by consumers, e.g., physician ratings ([Lu and Rui, 2018](#)), have been shown to provide useful product information, the ubiquity of fake reviews, either submitted by sellers themselves or competitors ([Mayzlin et al., 2014](#)), dilutes the value of information provided by customer review platforms ([Anderson and Simester, 2014](#)), to the extent that some platforms have resorted to algorithms to filter out suspicious reviews ([Luca and Zervas, 2016](#)). Our research contributes to the picture of non-seller-based product information by illustrating that ranking publishers who take no interests in consumer choices may also have incentives to provide misleading product information under their own profit motives.

Our ranking-report game is a game of information transmission. Information transmission games encompass environments in which private information is transmitted via payoff-dependent (costly) messages ([Spence, 1973](#)), payoff-independent (cheap-talk) messages ([Crawford and Sobel, 1982](#)), and state-dependent (verifiable) messages ([Grossman, 1981](#); [Milgrom, 1981](#)). Similar to these environments, our game features a sender of information who influences the action of a receiver via the message sent; our ranking report can be viewed as a message.

There are nevertheless a number of critical differences. While it is costless for the expert in our game to generate the ranking report, the report directly influences the consumer’s payoff by means of the ranking value. Furthermore, the expert in our game provides comparative information regarding the ordinal rankings of some private information, and he takes no direct interest in the action (product choice) of the consumer. These features make our environment not readily fit into the three canonical environments of information transmission.<sup>2</sup> Another important distinction is that in our game information is not transmitted as a direct execution of the expert’s strategy; rather, it is transmitted under a committed signaling rule (ranking method), a mapping from states to messages. In this light, our setting is more closely related

---

<sup>2</sup>There are extensions of the canonical cheap-talk games that share some of our features. [Chakraborty and Harbaugh \(2007\)](#) consider a sender who provides comparative information to a receiver that takes the form of rankings of multidimensional issues. [Ottaviani and Sørensen \(2006\)](#) consider a sender who takes interest only in being perceived as informed in front of a receiver, not in any explicit action that the receiver may take.

to the recent literature on Bayesian persuasion (Kamenica and Gentzkow, 2011), in which a sender commits to a signaling rule, effectively choosing the receiver’s posteriors. In our game, the choice of a ranking method is also equivalent to choosing the consumer’s posteriors. Unlike our game, however, there is no element of selling information in Bayesian persuasion.<sup>3</sup>

On the experimental front, given our theoretical connection to strategic information transmission, naturally our experiment is related to the experimental strand of this literature. Early experimental work includes, e.g., Brandts and Holt (1992) and Banks et al. (1994) for costly signaling, Dickhaut et al. (1995) and Gneezy (2005) for cheap talk, and Forsythe et al. (1989) and King and Wallin (1991) for verifiable disclosures.<sup>4</sup> Experimental attempts on Bayesian persuasion include Nguyen (2016), Au and Li (2018), and Fréchette et al. (forthcoming).

The remainder of the paper proceeds as follows. Section 2 presents and analyzes our experimental ranking-report game. Section 3 describes our experimental design and hypotheses. We report our laboratory findings in Section 4. Section 5 concludes.

## 2 The Ranking-Report Game

### 2.1 The Setup

There are two players, a product expert (he) and a consumer (she), and two products,  $A$  and  $B$ . The expert chooses a ranking *method* to rank the products and benefits if the consumer acquires the resulting ranking *report*. The imperfectly informed consumer makes two decisions, whether to acquire the ranking report and which product to choose.

**Consumer Utility.** The consumer derives utility from the intrinsic attributes and the ranking attribute of the chosen product. The intrinsic attributes, which may include quality, features, price, etc., are determined exogenously by the product seller not being modeled. The ranking attribute, which concerns how the product is ranked, is determined through the expert’s endogenous choice of ranking method.

Intrinsic attributes give rise to *intrinsic values*. The intrinsic value of Product  $A$ ,  $\bar{v}_A > 0$ , is fixed and commonly known. The intrinsic value of Product  $B$ ,  $v_B$ , is uncertain; it can be

---

<sup>3</sup>It is worth comparing the role played by randomness in our game and that in cheap-talk games. Theory (Krishna and Morgan, 2004; Blume et al., 2007; Goltsman et al., 2009) and experiment (Blume et al., 2022) have shown that random transmissions of messages could improve cheap-talk communication, resulting in Pareto improvements. In our game, randomness has a different welfare effect, in which it benefits one party but hurts the other. Another contrast is that those randomly transmitted messages in cheap-talk games are an exogenous property of the communication process, while in our case the random ranking reports are partly endogenous.

<sup>4</sup>More recent experimental attempts include, e.g., Schmidt and Buell (2017) and Fudenberg and Vespa (2019) for costly signaling, de Groot Ruiz et al. (2015) and Lai and Lim (2018) for cheap talk, and Hagenbach and Perez-Richet (2018) and Jin et al. (2021) for verifiable disclosures.

either 0 or  $\bar{v}_B > 0$ . The common prior is that  $v_B = \bar{v}_B$  with probability  $0 < p < 1$ . The ranking attribute of a product yields to the consumer  $r > 0$  if the product is ranked first and 0 otherwise, independent of its intrinsic value. We call  $r$  the *ranking value* of the top-ranked product. To simplify the cases, we make the following assumption:

**Assumption 1** (Parameters). *The value parameters satisfy  $\bar{v}_B > \bar{v}_A \neq r$ .*

Product rankings serve comparable functions as advertising. The way we model the influence of the expert’s ranking on consumer utility is consistent with two economic views on why consumers respond to advertising (see, e.g., Bagwell, 2007). The first view considers advertising as information, through which consumers learn about product attributes. In our game, the ranking report may provide information about  $v_B$ . The second view considers advertising as a complement to the advertised product, where an increase in advertising raises the marginal utility yielded by the product. Analogously, in our game an increase in the ranking of a product, from second to first, raises the utility provided by the product by  $r$ .<sup>5</sup>

**Ranking Methods.** The expert chooses and commits to a ranking method, learns the realized intrinsic value of Product  $B$ , and then issues a ranking report,  $A$  or  $B$ , according to the committed method. Report  $A$  ( $B$ ) indicates that Product  $A$  ( $B$ ) is ranked first.

A ranking method is a mapping,  $\beta : \{0, \bar{v}_B\} \rightarrow [0, 1]$ , specifying for each possible intrinsic value of Product  $B$  a probability that Report  $B$  is issued. To design a simple experimental game, we restrict attention to the class of ranking methods where  $\beta(\bar{v}_B) = 1$ . The expert’s choice of a ranking method thus reduces to choosing  $\beta(0) = \beta_0 \in [0, 1]$ .<sup>6</sup> The consumer observes  $\beta_0$  but can access the ranking report if and only if she pays an exogenously given fee  $f > 0$ .<sup>7</sup> With or without viewing the report, the consumer then chooses between Products  $A$  and  $B$ , where product prices are assumed to be constituents of the intrinsic values so that the consumer does not explicitly pay for the product.

Our experiment explores the interplay of two properties of ranking methods. The first is about *product guidance*. By acquiring the ranking report, the consumer may be getting both guidance and misguidance. Product guidance is provided if the more intrinsically valuable product is ranked first.<sup>8</sup> For the class of ranking methods considered, this is always the case

<sup>5</sup>This complementary view of advertising (Becker and Murphy, 1993) suggests that consumers have imagine concerns and consuming an advertised product can give rise to valuable “social prestige.” In the case of product rankings, a similar prestige may be associated with consuming a highly ranked product.

<sup>6</sup>In online Appendix C, we analyze more general ranking methods by relaxing the restriction that  $\beta(\bar{v}_B) = 1$ .

<sup>7</sup>This fee can be interpreted as a report subscription fee or more generally any cost that the consumer incurs to access the report, not necessarily a payment to the expert (e.g., information search cost or the opportunity cost of her scarce attention).

<sup>8</sup>Product guidance so defined is a form of product information, one that is about the ordinal rankings of intrinsic values with no references to the cardinal values. To allow information about cardinal values in a product-ranking model, one can imagine a setting with a richer space of intrinsic values coupled with ranking



when  $v_B = \bar{v}_B$ . When  $v_B = 0$ , however, Report  $A$  guides the consumer while Report  $B$  misguides. Given that  $\beta_0$  is the probability that Report  $B$  is issued conditional on  $v_B = 0$ ,  $\beta_0$  measures a ranking method’s likelihood of misguidance. We highlight this property:

**Fact 1** (Product Guidance). *Ranking method  $\beta_0 = 0$  is the misguidance-proof method, whereas  $\beta_0 = 1$  is the most misguiding method.*

The second property concerns *ranking uncertainty*. While a ranking report provides information about the ranking, a ranking method may induce uncertainty about it. Without viewing the report, the consumer is almost always unsure about which product carries the ranking value  $r$ . The prior  $p$  represents the “natural level” of this uncertainty. It equals the probability that Product  $B$  is ranked first under the misguidance-proof  $\beta_0 = 0$ . By engaging in *strategic shuffling*—choosing  $\beta_0 > 0$  so that the less intrinsically valuable product is ranked first with positive probability—the expert can endogenously manipulate the uncertainty to deviate from its exogenous natural level. When the probabilities of the two products being ranked top become more uniform, ranking uncertainty rises as measured by entropy (Shannon, 1948). We summarize this second property in the following fact:

**Fact 2** (Ranking Uncertainty). *Ranking method  $\beta_0 = 0$  is uncertainty-neutral in that it does not alter the natural uncertainty, whereas  $\beta_0 = 1$  is uncertainty-eliminating. For  $p < \frac{1}{2}$ , a ranking method  $\beta_0 \in (0, \frac{1-2p}{1-p})$  adds on to the natural uncertainty, whereas any  $\beta_0 \in (\frac{1-2p}{1-p}, 1)$  dampens the uncertainty from its natural level.<sup>9</sup>*

For  $p \geq \frac{1}{2}$ , any  $\beta_0 > 0$  suppresses the ranking uncertainty. As will be discussed below, our experimental design adopts a  $p < \frac{1}{2}$ . Since viewing the report resolves the uncertainty for the consumer, the ability to control the ranking uncertainty acts as a strategic instrument of the expert to induce demand for his ranking report.

**Strategies and Payoffs.** We focus on pure strategies. The restriction is not essential to our analysis but significantly simplifies the exposition. For the expert, it can also be justified by the fact that he is choosing a probability, and thus a mixed strategy is analogously nothing more than a compound lottery reducible to a simple lottery. For the consumer, we remove her need to randomize by assuming the following tie-breaking rule:<sup>10</sup>

**Assumption 2** (Tie Breaking). *The consumer’s indifference is resolved in favor of, for report acquisition, acquiring the ranking report, and, for product choice, choosing Product  $A$ .*

---

methods that generate finer ranking categories such as “Product  $X$  is hands down better than Product  $Y$ ” and “Product  $X$  is slightly better than Product  $Y$ .”

<sup>9</sup>Shuffling is deemed to exist when the ranking uncertainty deviates from its natural level measured by  $p$ . This includes the case where the expert shuffles in a degenerate manner to eliminate the ranking uncertainty.

<sup>10</sup>We introduce randomization back into the consumer’s report-acquisition decision in Section 2.4 when we select equilibria using a perturbation-based refinement.

A pure strategy of the expert is a choice of ranking method  $\beta_0 \in [0, 1]$ . A pure strategy of the consumer consists of two mappings: (a) a report-acquisition decision rule,  $s : [0, 1] \rightarrow \{0, 1\}$ , specifying for each  $\beta_0$  whether she acquires the ranking report ( $s = 1$ ) or not ( $s = 0$ ), and (b) a product choice rule,  $a : \{A, B, \emptyset\} \rightarrow \{0, 1\}$ , specifying for given  $\beta_0$  and  $s$  whether she chooses Product  $A$  ( $a = 1$ ) or  $B$  ( $a = 0$ ) after viewing each report,  $A$ ,  $B$ , or none ( $\emptyset$ ). We call  $a(\emptyset)$  the consumer's *default product choice*.<sup>11</sup>

The expert's payoff equals the revenue  $\pi > 0$  derived from the consumer's acquisition of the ranking report, and he takes no interest in the consumer's product choice. He earns zero if the report is not acquired, and his choice of ranking method does not affect his payoff. Note that the expert's revenue is not necessarily the same as the fee the consumer pays. This captures that in practice ranking publishers derive benefits from consumers' costly attention to their rankings, even if consumers do not directly pay for the publications. For expositional convenience, however, hereafter we refer to the expert selling the report to the consumer.<sup>12</sup>

The consumer's payoff equals her utility from consuming the product of her choice, which consists of the intrinsic value and any ranking value, less the ranking report fee should she acquire the report. Given ranking outcome  $\mathbb{I}_A \in \{0, 1\}$ , where  $\mathbb{I}_A = 1$  indicates that Product  $A$  is ranked first, a consumer whose report-acquisition decision is  $s \in \{0, 1\}$  and product choice is  $a \in \{0, 1\}$  with resulting intrinsic value  $v(a)$  receives a payoff of

$$u(s, a, v(a), \mathbb{I}_A) = \begin{cases} v_B + r(1 - \mathbb{I}_A) - fs & \text{if } a = 0, \\ \bar{v}_A + r\mathbb{I}_A - fs & \text{if } a = 1, \end{cases}$$

where  $v_B \in \{0, \bar{v}_B\}$ . Note that the consumer receives  $r$  for choosing the top-ranked product irrespective of her report-acquisition decision. Under this payoff structure, the expert's choice of  $\beta_0$  influences how much the resolution of ranking uncertainty effected by viewing the ranking report is worth to the consumer, and this is a key feature of our game.<sup>13</sup>

---

<sup>11</sup>A complete contingency plan for the consumer's product choice specifies the choice in every subgame associated with a  $\beta_0$  and  $s$ . For notational brevity, unless otherwise needed, we omit  $\beta_0$  as an argument of the mapping  $a$ , while  $s$  is captured by  $A$ ,  $B$ , and  $\emptyset$ .

<sup>12</sup>In practice, ranking publishers typically have more lucrative income sources that are incidental to their ranking publications. In a two-sided market, even if they offer their product rankings to consumers for free, they derive revenues from advertising or consulting services provided to product sellers.

<sup>13</sup>Other than serving the function in our game, this payoff structure is also in line with the effects of product rankings in practice. For instance, a student attending the top-ranked university may eventually learn the university's ranking and enjoy the prestige even though the student did not see the ranking publication when making the attending decision. The ranking value may also take the form of future economic value. If employers recruit university graduates based on the rankings of their programs, then the job market values of attending top-ranked programs accrue independent of whether a student views the ranking. Likewise, a car model that is ranked top by an authoritative auto ranking is likely to have a higher resale value, and a consumer purchasing the vehicle benefits from it even without viewing the ranking publication.

## 2.2 Equilibrium Characterization

We begin by analyzing the consumer's product choice. A ranking method is said to be *influential* if the consumer always chooses the top-ranked product after viewing the ranking report. Since Report  $A$  is generated exclusively for  $v_B = 0$ , the consumer must be choosing Product  $A$  after viewing Report  $A$ . Consequently, whether a ranking method is influential hinges on the product choice made after Report  $B$ .

The probability of misguidance as measured by  $\beta_0$  and the ranking value  $r$  counteract to determine the influence of a ranking method. Let  $\mu_B(\beta_0) \in [p, 1]$  be the consumer's posterior belief that  $v_B = \bar{v}_B$  upon viewing Report  $B$  generated by ranking method  $\beta_0$ , where it can be shown that  $\mu'_B(\beta_0) < 0$ . The consumer follows Report  $B$ —and thus  $\beta_0$  is influential—if and only if, under our tie-breaking rule,  $\mu_B(\beta_0)\bar{v}_B + r > \bar{v}_A$ . If there is a  $\tilde{\beta}_0 \in (0, 1)$  where  $\mu_B(\tilde{\beta}_0)\bar{v}_B + r = \bar{v}_A$ , then any ranking method with a higher likelihood of misguidance  $\hat{\beta}_0 > \tilde{\beta}_0$  would not be influential. However,  $\hat{\beta}_0$  can become influential for a higher  $r$ . The following lemma provides the condition under which all ranking methods are influential:<sup>14</sup>

**Lemma 1.** *All ranking methods are influential, i.e.,  $a(A) = 1$  and  $a(B) = 0$  are optimal under all  $\beta_0 \in [0, 1]$ , if and only if  $p\bar{v}_B + r - \bar{v}_A > 0$ .*

If the most misguiding ranking method  $\beta_0 = 1$  is influential, then all others will be as well. Upon viewing Report  $B$  generated by  $\beta_0 = 1$ , the consumer's posterior is no different from the prior; her expected utility from Product  $B$  is  $p\bar{v}_B + r$ , while that from Product  $A$  is  $\bar{v}_A$ . The condition  $p\bar{v}_B + r - \bar{v}_A > 0$  then guarantees that the consumer chooses the top-ranked product under any ranking method.

For a non-influential ranking method, the consumer's report-acquisition decision is trivial: there is no reason for her to pay for something that will not influence her product choice. A ranking method being influential is not, however, sufficient for the consumer to be willing to pay. In addition to the report fee  $f$ , the consumer's default product choice—her alternative to acquiring the report—also plays a role. Let  $\beta_{AB} = \frac{\bar{v}_A - p\bar{v}_B + (1-2p)r}{2(1-p)r}$ . The following lemma characterizes the consumer's optimal default product choice in terms of  $\beta_{AB}$ :

**Lemma 2.** *Product  $A$  is the optimal default product, i.e.,  $a(\emptyset) = 1$ , if and only if  $\beta_0 \leq \beta_{AB}$ .*

The consumer's payoff equals her utility from the product less the report fee. Her expected utility evaluated after she observes  $\beta_0$  but before she views any report depends on and in turn shapes her default product choice and report-acquisition decision. If she eventually does not acquire the report, this expected utility equals that from choosing a default product, which is

<sup>14</sup>All proofs are relegated to Appendix A.

given by (1) for default Product  $A$  and (2) for default Product  $B$ :

$$p(\bar{v}_A + 0) + (1 - p)\beta_0(\bar{v}_A + 0) + (1 - p)(1 - \beta_0)(\bar{v}_A + r). \quad (1)$$

$$p(\bar{v}_B + r) + (1 - p)\beta_0(0 + r) + (1 - p)(1 - \beta_0)(0 + 0). \quad (2)$$

If she eventually acquires the report, her expected utility before viewing the report will be:

$$p(\bar{v}_B + r) + (1 - p)\beta_0(0 + r) + (1 - p)(1 - \beta_0)(\bar{v}_A + r). \quad (3)$$

These expected utilities expressed in fully expanded form make clear that they comprise three components, corresponding to the cases where (a)  $v_B = \bar{v}_B$  and Report  $B$  is generated, (b)  $v_B = 0$  and Report  $B$  is generated, and (c)  $v_B = 0$  and Report  $A$  is generated. The threshold  $\beta_{AB}$  in Lemma 2 is the value of  $\beta_0$  that equates (1) with (2).

We proceed to analyze the subgame-perfect equilibria of the game, restricting attention to the interesting cases where all ranking methods are influential and both products have the potential to be the optimal default ( $0 \leq \beta_{AB} < 1$ ). Of particular interest are the equilibria in which the consumer acquires the ranking report, which we term *acquisition equilibria*. The expert's choice of  $\beta_0$  initiates a subgame, where the consumer's optimal behavior down in the subgame at the product-choice stage (the two smaller subgames) is characterized in Lemmas 1 and 2. The excess of the expected utility in (3) over that in either (1) or (2), depending on the default product, represents the consumer's *expected gain from viewing* the report and measures her *willingness to pay*. In the acquisition equilibria, the expert chooses a  $\beta_0$  that renders the consumer's willingness to pay greater than the report fee  $f$ .

To organize the cases, we compartmentalize the possible parameters into six categories based on (a) the relative sizes of the ranking value  $r$  and Product  $A$ 's intrinsic value  $\bar{v}_A$ , and (b) the size of the report fee  $f$  relative to  $f_1 = p(\bar{v}_B + r - \bar{v}_A)$  and  $f_2 = \frac{(p\bar{v}_B + r - \bar{v}_A)(\bar{v}_A + r)}{2r}$ . Let  $\beta_A = \frac{f - f_1}{(1 - p)(r - \bar{v}_A)}$  and  $\beta_B = 1 - \frac{f}{(1 - p)(\bar{v}_A + r)}$ . The following proposition characterizes the expert's equilibrium choices of  $\beta_0$  in the six parameter cases:

**Proposition 1.** *In any pure-strategy subgame-perfect equilibrium of the game in which all ranking methods  $\beta_0 \in [0, 1]$  are influential and both products may be the optimal default,*

(a) *for  $r < \bar{v}_A$  so that  $f_2 \leq f_1$ ,*

(i) *if  $f \in (0, f_2]$ , then the expert chooses a  $\beta_0 \in [0, \beta_B]$  to sell the ranking report,*

(ii) *if  $f \in (f_2, f_1]$ , then the expert chooses a  $\beta_0 \in [0, \beta_A]$  to sell the ranking report, and*

(iii) *if  $f \in (f_1, \infty)$ , then the expert chooses a  $\beta_0 \in [0, 1]$  without selling the ranking report;*

(b) *for  $r > \bar{v}_A$  so that  $f_1 \leq f_2$ ,*

- (i) if  $f \in (0, f_1]$ , then the expert chooses a  $\beta_0 \in [0, \beta_B]$  to sell the ranking report,
- (ii) if  $f \in (f_1, f_2]$ , then the expert chooses a  $\beta_0 \in [\beta_A, \beta_B]$  to sell the ranking report, and
- (iii) if  $f \in (f_2, \infty)$ , then the expert chooses a  $\beta_0 \in [0, 1]$  without selling the ranking report.

As will be discussed in detail in Section 3.1, the four cases of acquisition equilibria in Proposition 1 form the basis for our experimental design. The two thresholds,  $\beta_A$  and  $\beta_B$ , impose restrictions on  $\beta_0$  for acquisitions to take place in equilibrium. The threshold  $\beta_B$  is associated Product  $B$  serving as the default alternative to support the consumer's decision to acquire the report. When the consumer would go for Product  $B$  without viewing any report, viewing Report  $B$  does not yield any benefit, which can be seen from the identical last terms in (1) and (3). When acquiring the report in this case, the consumer pays  $f$  for the expected gain from viewing Report  $A$ , which equals  $(1 - \beta_0)(1 - p)(\bar{v}_A + r)$ . The requirement that her willingness to pay be no less than  $f$  imposes an upper bound,  $\beta_B = 1 - \frac{f}{(1-p)(\bar{v}_A+r)}$ , on  $\beta_0$ .

The other threshold  $\beta_A$  is associated with Product  $A$  as the default alternative, under which viewing Report  $A$  is superfluous, which can be seen from the identical first two terms in (2) and (3). The consumer in this case pays  $f$  for the expected gain from viewing Report  $B$ , which amounts to  $f_1 + \beta_0(1 - p)(r - \bar{v}_A)$ . There are two incarnations of Report  $B$ . First, it is always generated when  $v_B = \bar{v}_B$ , and  $f_1$  is a positive component of the expected gain derived from this incarnation. Report  $B$  is also generated with probability  $\beta_0$  when  $v_B = 0$ , and the associated term  $\beta_0(1 - p)(r - \bar{v}_A)$  can be either positive or negative. Proposition 1(a) concerns the scenario where, with  $r < \bar{v}_A$ , the term represents a loss. The requirement that the consumer's willingness to pay be no less than  $f$  imposes an upper bound,  $\beta_A = \frac{f-f_1}{(1-p)(r-\bar{v}_A)}$ , on  $\beta_0$ .

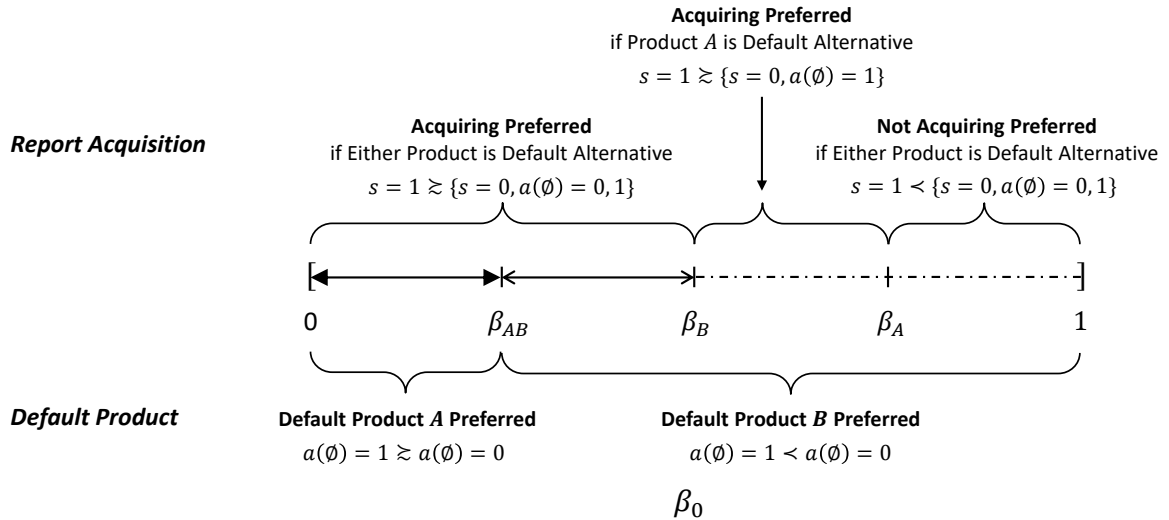


Figure 1: Consumer's Report Acquisition and Default Product for  $r < \bar{v}_A$  and  $f \in (0, f_2]$

Though not appearing in the proposition statement, the threshold in Lemma 2 regarding optimal default products,  $\beta_{AB}$ , also plays a role in the characterization. Figure 1 illustrates the

relative magnitudes of the three thresholds for the case in Proposition 1(a)(i), in which they satisfy  $\beta_{AB} \leq \beta_B \leq \beta_A$ .<sup>15</sup> Sequential rationality off equilibrium paths requires the supporting default product be optimal. Since  $\beta_{AB} \leq \beta_A$ , for Product A to be the optimal supporting default,  $\beta_{AB}$  supersedes  $\beta_A$  as the relevant upper bound. The restriction on  $\beta_0$  in Proposition 1(a)(i),  $[0, \beta_B]$ , is therefore made up of two segments,  $[0, \beta_{AB}]$  (“ $\longleftrightarrow$ ” in Figure 1), under which the consumer acquires the report supported by the sequentially rational alternative of Product A, and  $(\beta_{AB}, \beta_B]$  (“ $\longleftrightarrow$ ” in Figure 1), under which the consumer acquires the report supported by Product B as the sequentially rational alternative. For the case in Proposition 1(a)(ii), the three thresholds instead satisfy  $\beta_A < \beta_B < \beta_{AB}$ , and the consumer acquires the report only for  $\beta_0 \in [0, \beta_A]$  supported by Product A as the optimal alternative.

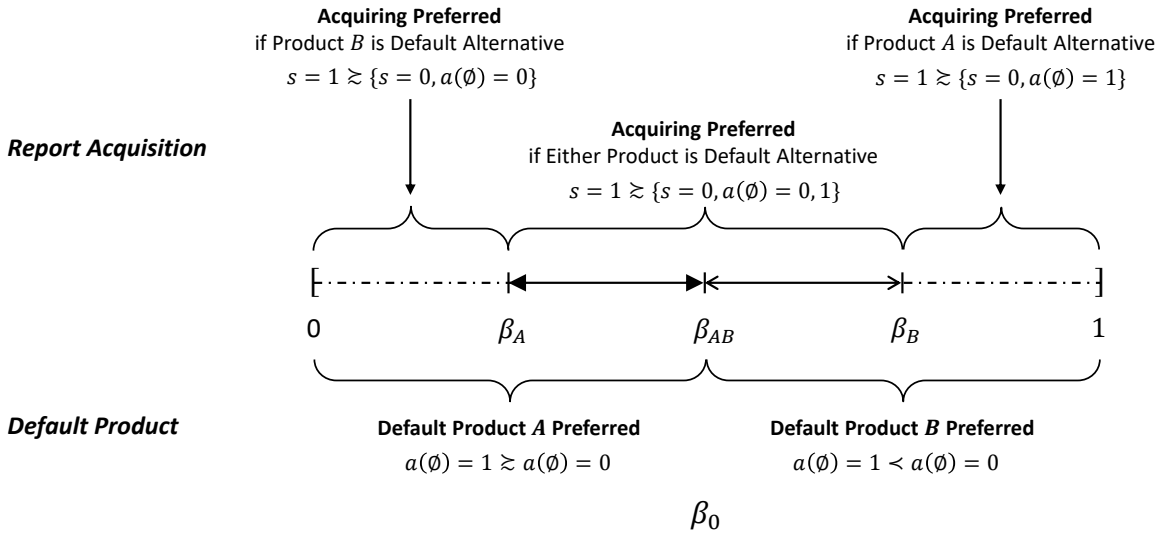


Figure 2: Consumer’s Report Acquisition and Default Product with  $r > \bar{v}_A$  and  $f \in (f_1, f_2]$

Proposition 1(b) concerns the scenario where, with  $(1 - p)(r - \bar{v}_A)$  now being positive, the threshold  $\beta_A$  becomes a lower bound. Figure 2 illustrates Proposition 1(b)(ii) in which the three thresholds satisfy  $\beta_A \leq \beta_{AB} \leq \beta_B$ . The restriction on  $\beta_0$  in this case,  $[\beta_A, \beta_B]$ , is made up of  $[\beta_A, \beta_{AB}]$  (“ $\longleftrightarrow$ ” in Figure 2) and  $(\beta_{AB}, \beta_B]$  (“ $\longleftrightarrow$ ” in Figure 2), under which the consumer’s decision to acquire the report is supported by optimal Products A and B respectively. For the case in Proposition 1(b)(i),  $\beta_A$  is non-positive, and the restriction reduces to  $[0, \beta_B]$ . Finally, for the non-acquisition equilibria in Propositions 1(a)(iii) and 1(b)(iii), there exists no  $\beta_0$  under which report acquisition can be supported by sequentially rational default product choice.

<sup>15</sup>Figure 1 (as well as Figure 2 below) should not be construed as indicating that the thresholds are equally distanced. Furthermore,  $\beta_A$  can be greater than one for sufficiently small  $f$ .

## 2.3 Comparative Statics, Product Guidance, and Ranking Uncertainty

How the expert’s choice of ranking method varies with the ranking value in the acquisition equilibria underscores the tension between product guidance and ranking uncertainty, one of the main issues that we explore in the experiment. We present the comparative statics of the two threshold restrictions, now denoted as  $\beta_A(r)$  and  $\beta_B(r)$ , with respect to  $r$ . Along the way, we discuss the expert’s incentives in (mis)guiding the consumer and in manipulating the ranking uncertainty to influence the consumer’s willingness to pay.

The incentive consideration varies depending on which product is the default alternative. We begin with  $\beta_A(r)$ , which concerns the case where Product  $A$  is the alternative.<sup>16</sup>

**Corollary 1.** *For  $r < \bar{v}_A$  ( $r > \bar{v}_A$ ), the upper (lower) bound  $\beta_A(r) \in [0, 1]$  on  $\beta_0$  is increasing (decreasing) in  $r$ .*

When Product  $A$  is the alternative, the consumer’s willingness to pay,  $f_1 + \beta_0(1-p)(r - \bar{v}_A)$ , is induced by two “goods” and one “bad”: product guidance as a good, resolution of ranking uncertainty as another good, and misguidance as a bad. The last two “commodities” form a bundle, the value of which can be manipulated by the expert through his choice of  $\beta_0$ . A higher  $\beta_0$  results in not only a higher probability of misguidance but also a wider differential in the probabilities of earning  $r$  with and without the report.<sup>17</sup> How well the good in the bundle compensates the bad restricts the expert’s choice of  $\beta_0$ . For the case where  $r < \bar{v}_A$ , the resolution of ranking uncertainty falls short of compensating for the misguidance, and the consumer’s willingness to pay is decreasing in  $\beta_0$ . To induce the consumer to acquire the report, the expert cannot misguide too often, and with  $\beta_A(r)$  increasing in  $r$  a less valuable resolution of ranking uncertainty calls for a weakly lower probability of misguidance.

There is a qualitative difference when  $r > \bar{v}_A$ . The consumer’s willingness to pay is increasing in  $\beta_0$ . If the expert cannot sell the report under a low  $\beta_0$ , such as the misguidance-proof  $\beta_0 = 0$ , then he will be able to sell by choosing some ranking method with a higher probability of misguidance because the misguidance is now bundled with a compensating resolution of ranking uncertainty. The comparative statics is also opposite: as the uncertainty resolution becomes less valuable the expert needs to misguide weakly more often. Note that a larger increase in the probability of earning  $r$  due to accessing the ranking report means a larger

<sup>16</sup>We examine the comparative statics when  $\beta_A(r)$  is binding upper or lower bound, which corresponds to cases (a)(ii) and (b)(ii) in Proposition 1. For brevity, we do not state the cases in the following corollary.

<sup>17</sup>With Product  $A$  being the alternative, without the report the consumer always obtains  $\bar{v}_A$  and earns  $r$  with probability  $(1-p)(1-\beta_0)$ . Viewing the report results in exchanging  $\bar{v}_A$  for the higher  $\bar{v}_B$  with probability  $p$  (product guidance), raising the probability of earning  $r$  from  $(1-p)(1-\beta_0)$  to one (eliminating uncertainty in  $r$ ), and exchanging  $\bar{v}_A$  for 0 with probability  $(1-p)\beta_0$  (misguidance).

probability of losing  $r$  without the report; by shuffling with a sufficiently high  $\beta_0$  so as to sell the report, it is as if the expert peddled a solution for a problem he created.

We turn to the comparative statics of  $\beta_B(r)$ , which concerns the case where Product  $B$  is the default alternative:

**Corollary 2.** *The upper bound  $\beta_B(r) \in [0, 1]$  on  $\beta_0$  is increasing in  $r$ .*

When Product  $B$  is the alternative, the consumer’s willingness to pay,  $(1 - \beta_0)(1 - p)(\bar{v}_A + r)$ , is induced only by product guidance and resolution of ranking uncertainty.<sup>18</sup> As in the case of  $r < \bar{v}_A$  in Corollary 1, to induce the consumer to acquire the report, the expert cannot choose too high a  $\beta_0$ , and a lower  $r$  calls for a weakly lower  $\beta_0$ . With the expert manipulating the value of a bundle made up of product guidance and uncertainty resolution only, however, the interpretation here is not so much that the expert cannot misguide too often; rather, it is that he cannot guide too rarely. The misguiding Report  $B$  generated with probability  $\beta_0$  when  $v_B = 0$  does not impact the consumer’s willingness to pay—Product  $B$  would be chosen anyway without the report. Yet a higher  $\beta_0$  also means that Report  $A$  is generated less often, and the guiding report is what the expert counts on in luring the consumer to pay.

## 2.4 Equilibrium Refinements

Under the equilibrium multiplicity, there is a wide range of ranking methods that survive the restrictions of the comparative statics. To enrich the basis for our experimental hypotheses, we further restrict behavior by refining the set of subgame-perfect acquisition equilibria.

The expert’s choice of  $\beta_0$  can be seen as an effort to make the ranking report alluring to the consumer. From this perspective, selecting the equilibrium with the most alluring report has a natural appeal. There can, however, be two different ways to think of what constitutes “most alluring”: a report that renders the acquiring consumer the highest expected payoff or a report that imposes the highest expected loss on the deviating consumer who does not acquire. Since  $\beta_0$  affects the consumer’s payoff on and off equilibrium paths, the two interpretations do not necessarily point to the same equilibrium.

We employ formal criteria to refine equilibria under the two interpretations of most alluring reports. Efficiency refines for the first interpretation. Given that the expert receives  $\pi$  in any subgame-perfect acquisition equilibrium, the equilibria can be Pareto ranked by the consumer’s expected payoff. There are two cases depending on whether  $r < \bar{v}_A$  or  $r > \bar{v}_A$ :

---

<sup>18</sup>With Product  $B$  being the alternative, without the report the consumer earns  $r$  with probability  $p + (1 - p)\beta_0$  and obtains  $\bar{v}_B$  and 0 with complementary probabilities  $p$  and  $1 - p$ . Viewing the report results in exchanging 0 for  $\bar{v}_A$  with probability  $(1 - p)(1 - \beta_0)$  (product guidance) and raising the probability of earning  $r$  by the same  $(1 - p)(1 - \beta_0)$  to probability one (eliminating uncertainty in  $r$ ). There is no misguidance involved.



**Proposition 2.** For  $r < \bar{v}_A$ , the unique efficient acquisition equilibrium admits  $\beta_0 = 0$ . For  $r > \bar{v}_A$ , the unique efficient acquisition equilibrium admits  $\beta_0 = 0$  if  $f \in (0, f_1]$  and  $\beta_0 = \beta_A$  if  $f \in (f_1, f_2]$ .

As a behavioral hypothesis, efficiency may not be appealing; there is no reason to expect that in the laboratory subjects would have concern about efficiency and play the efficient equilibrium. Nonetheless, since the Pareto-ranking is conducted solely in terms of one party’s payoff, social preferences can operationalize an efficient outcome as an outcome of maximizing behavior. Specifically, any “ $\epsilon$ -altruism” of the expert toward the consumer, including the limit as  $\epsilon \rightarrow 0$ , would select the efficient equilibrium.<sup>19</sup> This altruistic perspective circles back to the first interpretation of most alluring reports, where, within the confine that the report will be acquired, the expert provides a report that benefits the consumer the most. It is also in this sense that the efficient equilibrium can be regarded as the *consumer-optimal equilibrium*.

The second interpretation of most alluring reports coincides with maximizing the consumer’s willingness to pay. While the first interpretation has an altruistic angle, this has a spiteful spin; it echoes the idea that the expert peddles a solution for a self-created problem, profiting from shuffling the ranking to make not acquiring the report a worse choice.

We develop a perturbation-based refinement to select the equilibrium under this interpretation. Our objective is not so much achieving theoretical generality as furnishing a formal basis for developing experimental hypotheses. Accordingly, we consider the simplest type of perturbation, introducing trembles *only* to the consumer’s report acquisition. We term the resulting refinement *robust acquisition equilibrium*. Though *ad hoc*, designed specifically for our game, robust acquisition equilibrium shares the spirit of Myerson’s (1978) proper equilibrium, in which more costly mistakes are less likely to be made.

We denote by  $s(\beta_0)$  the consumer’s optimal report-acquisition decision when the expert chooses  $\beta_0$  and by  $a(\beta_0, s)$  the consumer’s optimal product choice when the expert chooses  $\beta_0$  and her report-acquisition decision is  $s$ . We define  $G(\beta_0, s) = V(\beta_0, s(\beta_0), a(\beta_0, s(\beta_0))) - V(\beta_0, s, a(\beta_0, s))$ , which is the consumer’s expected gain from choosing the optimal  $s(\beta_0)$  instead of the non-optimal  $s \neq s(\beta_0)$ , where  $V$  equals the expected utility in either (1), (2), or (3) less  $f$ . The gain from doing the right thing relative to doing the wrong equals (the magnitude of) the loss from the wrong relative to the right; we specify  $s \neq s(\beta_0)$  as an argument of  $G$  and use it to measure the size of the consumer’s expected loss from choosing  $s \neq s(\beta_0)$  instead of  $s(\beta_0)$ . The consumer’s trembles are captured by a mixed report-acquisition rule  $\sigma : [0, 1] \times \{0, 1\} \rightarrow [0, 1]$ , where  $\sigma(\beta_0, s)$  is the probability that she chooses  $s \in \{0, 1\}$  given  $\beta_0$ .

A robust acquisition equilibrium is the limit of a sequence of  $\epsilon$ -constrained acquisition

---

<sup>19</sup>In an experimental study of equilibrium selection in coordination games, Chen and Chen (2011) use group-identity based altruistic preferences to select the more efficient equilibria for the minimum-effort game.

equilibria, in which totally mixed  $\sigma$  is constrained in a way that reflects the relative sizes of  $G$ —the consumer’s loss from making acquisition mistakes—across different values of  $\beta_0$ . For  $\epsilon > 0$ , we define a “mistake function”  $e_\epsilon : [0, 1] \times \{0, 1\} \rightarrow (0, \epsilon)$ , where  $e_\epsilon(\beta_0, s)$  is the minimum weight the consumer’s mixed report-acquisition rule puts on  $s$  in the subgame set off by  $\beta_0$ . A mistake function satisfies *strict loss monotonicity* if for all  $\tilde{\beta}_0, \hat{\beta}_0 \in [0, 1]$  and all  $s', s'' \in \{0, 1\}$ ,  $G(\tilde{\beta}_0, s') > G(\hat{\beta}_0, s'')$  implies that  $e_\epsilon(\tilde{\beta}_0, s') < e_\epsilon(\hat{\beta}_0, s'')$ .<sup>20</sup>

**Definition 1** (Robust Acquisition Equilibrium). *For  $\epsilon > 0$ , a strategy profile  $(\beta_0, (\sigma_\epsilon, a))$  with totally mixed  $\sigma_\epsilon$  is an  $\epsilon$ -constrained acquisition equilibrium if*

- (a)  $\beta_0$  is the expert’s optimal choice of ranking method given  $(\sigma_\epsilon, a)$ ,
- (b)  $\sigma_\epsilon$  is the consumer’s constrained optimal report-acquisition rule subject to  $\sigma_\epsilon(\beta_0, s) \geq e_\epsilon(\beta_0, s)$  for all  $\beta_0 \in [0, 1]$ , all  $s \in \{0, 1\}$ , and any  $e_\epsilon : [0, 1] \times \{0, 1\} \rightarrow (0, \epsilon)$  that satisfies *strict loss monotonicity*, and
- (c)  $a = a(\beta_0, s)$  is the consumer’s optimal product choice rule.

A robust acquisition equilibrium is any limit of  $\epsilon$ -constrained acquisition equilibria as  $\epsilon \rightarrow 0$ .

Applying Definition 1, we obtain the following characterization of robust acquisition equilibria, again with two cases depending on whether  $r < \bar{v}_A$  or  $r > \bar{v}_A$ :

**Proposition 3.** *For  $r < \bar{v}_A$ , the unique robust acquisition equilibrium admits  $\beta_0 = 0$ . For  $r > \bar{v}_A$ , the unique robust acquisition equilibrium admits  $\beta_0 = \beta_{AB}$ .*

The consumer’s willingness to pay for the ranking report is maximized under  $\beta_0 = 0$  and  $\beta_0 = \beta_{AB}$  in the respective cases. If acquiring the ranking report is the optimal decision, then the function  $G$  leveraged in our refinement equals the willingness to pay less the report fee; behind our formal perturbation argument lies the intuitive fact that  $\beta_0 = 0$  or  $\beta_0 = \beta_{AB}$  is selected because, as the consumer’s willingness to pay increases, the probability of acquisition mistakes vanishes. Furthermore, since this vanishing probability of acquisition mistakes is equivalent to the probability of the report being acquired approaching one, the robust equilibrium can be regarded as the *expert-optimal equilibrium* in the presence of the consumer’s trembles.<sup>21</sup>

<sup>20</sup>Myerson’s (1978) proper equilibrium is devised for finite games and cannot be directly extended to infinite games as there may be uncountably many successively costlier mistakes creating cardinality issues in assigning mistake weights. Simon and Stinchcombe (1995) introduce various approaches (e.g., using limits of finite approximations) to adapt the concept to infinite games. While we can adopt their approaches, we introduce instead the monotone mistake function for its simplicity and intuitive construction. Note also that our tremble restrictions can be viewed as being imposed across different agents of the consumer each playing a subgame. See Milgrom and Mollner (2021) for a refinement of proper equilibrium by adding across-player tremble restrictions.

<sup>21</sup>Given that the consumer’s willingness to pay is maximized, the robust acquisition equilibrium is the unique subgame-perfect acquisition equilibrium if  $f$  is endogenously set by the expert and his  $\pi$  is increasing in  $f$ . We establish this formally in our analysis of the game with more general ranking methods in online Appendix C.

We conclude the theory section by tying together the equilibrium refinements and the idea of product guidance and ranking uncertainty. Contrasting Proposition 2 with Proposition 3 reveals that the predictions of efficient and robust equilibria coincide for  $r < \bar{v}_A$  but differ for  $r > \bar{v}_A$ . These coincidence and difference can be understood through the lens of misguidance and the resolution of ranking uncertainty.

The consumer’s expected payoff from viewing the ranking report increases as the ranking method misguides less often, i.e., as  $\beta_0$  decreases. When  $r < \bar{v}_A$ , the misguidance-proof and uncertainty-neutral  $\beta_0 = 0$  maximizes both this expected payoff, which corresponds to the efficient equilibrium, and the consumer’s expected willingness to pay for the report, which corresponds to the robust equilibrium. As discussed in Section 2.3, this is the case where the resolution of ranking uncertainty is not quite valuable relative to the loss from misguidance, and the consumer’s willingness to pay is maximized with as little misguidance as possible.

When instead  $r > \bar{v}_A$ , the resolution of ranking uncertainty is more valuable, and the  $\beta_0 = \beta_{AB}$  that maximizes the consumer’s willingness to pay involves misguidance and shuffling. This differs from the ranking method that maximizes the consumer’s expected payoff in the acquisition equilibria, either  $\beta_0 = 0$  or  $\beta_0 = \beta_A$  depending on  $f$ . As the methods that maximize payoff and willingness to pay differ, the two criteria select different equilibria, with efficiency selecting a method that involves less misguidance and manipulation of ranking uncertainty.

## 3 Experimental Implementation

### 3.1 Treatment Parameters

We assign experimental values to the six parameters of the game,  $\bar{v}_A$ ,  $\bar{v}_B$ ,  $p$ ,  $r$ ,  $f$ , and  $\pi$ , in accordance with the four cases of acquisition equilibria in Proposition 1.<sup>22</sup> This yields us four experimental treatments (Table 1). We induce treatment variations in  $r$  and  $f$ , while adopting the same values of  $\bar{v}_A = 100$ ,  $\bar{v}_B = 250$ ,  $p = 0.2$ , and  $\pi = 300$  for all four treatments. The ranking value varies between  $r = 55$  and  $r = 250$ , and the report fee among  $f = 5$ ,  $f = 30$ , and  $f = 110$ . Only four combinations in the  $2 \times 3$  factorial are relevant in light of the equilibrium cases. Apart from satisfying the parameter conditions for acquisition equilibria, we choose these experimental values to induce salient incentives with large payoff differentials. We label the four treatments by *LL*, *LM*, *HL*, and *HH*, where the first letter refers to *Low* or *High* for the ranking value and the second letter refers to *Low*, *Medium*, or *High* for the report fee.

Table 1 lists the corresponding case in Proposition 1 for each of the four treatments. It also summarizes the theoretical predictions of subgame-perfect, efficient, and robust equilibria

---

<sup>22</sup>For brevity, we omit “acquisition” from now on when referring to acquisition equilibria.

Table 1: Treatment Parameters and Theoretical Predictions

	Low Report Fee ( $f = 5$ )	Medium Report Fee ( $f = 30$ )
Low Ranking Value ( $r = 55$ )	<p style="text-align: center;"><i>LL</i></p> <p style="text-align: center;">Proposition 1(a)(i)</p> <p style="text-align: center;">Subgame-Perfect: <math>\beta_0 \in [0, \frac{119}{124}]</math></p> <p style="text-align: center;">Efficient: <math>\beta_0 = 0</math></p> <p style="text-align: center;">Robust: <math>\beta_0 = 0</math></p> <p style="text-align: center;">Default: <math>\beta_{AB} = \frac{83}{88}</math></p>	<p style="text-align: center;"><i>LM</i></p> <p style="text-align: center;">Proposition 1(a)(ii)</p> <p style="text-align: center;">Subgame-Perfect: <math>\beta_0 \in [0, \frac{11}{36}]</math></p> <p style="text-align: center;">Efficient: <math>\beta_0 = 0</math></p> <p style="text-align: center;">Robust: <math>\beta_0 = 0</math></p> <p style="text-align: center;">Default: <math>\beta_{AB} = \frac{83}{88}</math></p>
	Low Report Fee ( $f = 5$ )	High Report Fee ( $f = 110$ )
High Ranking Value ( $r = 250$ )	<p style="text-align: center;"><i>HL</i></p> <p style="text-align: center;">Proposition 1(b)(i)</p> <p style="text-align: center;">Subgame-Perfect: <math>\beta_0 \in [0, \frac{55}{56}]</math></p> <p style="text-align: center;">Efficient: <math>\beta_0 = 0</math></p> <p style="text-align: center;">Robust: <math>\beta_0 = \frac{1}{2}</math></p> <p style="text-align: center;">Default: <math>\beta_{AB} = \frac{1}{2}</math></p>	<p style="text-align: center;"><i>HH</i></p> <p style="text-align: center;">Proposition 1(b)(ii)</p> <p style="text-align: center;">Subgame-Perfect: <math>\beta_0 \in [\frac{1}{4}, \frac{17}{28}]</math></p> <p style="text-align: center;">Efficient: <math>\beta_0 = \frac{1}{4}</math></p> <p style="text-align: center;">Robust: <math>\beta_0 = \frac{1}{2}</math></p> <p style="text-align: center;">Default: <math>\beta_{AB} = \frac{1}{2}</math></p>

Note: All treatments share the parameter values  $\bar{v}_A = 100$ ,  $\bar{v}_B = 250$ ,  $p = 0.2$ , and  $\pi = 300$ . The case in Proposition 1 and the key predictions of the three equilibrium concepts are listed for each treatment.

given the treatment parameters. Three observations are apparent: (a) increasing the report fee narrows the subgame-perfect equilibrium range of  $\beta_0$ ; (b) for the three treatments with either low ranking value or low report fee, efficient equilibria admit  $\beta_0 = 0$ , leaving *HH* the only treatment with a positive efficient  $\beta_0$ ; and (c) robust equilibria admit  $\beta_0 = 0$  under the low ranking value and a positive  $\beta_0$  under the high ranking value. As we discuss in the next subsection, we considerably simplify the strategic environment in designing the laboratory counterpart of the game. Nevertheless, our experimental hypotheses build on these observations.

### 3.2 Design and Procedures

In rendering a laboratory counterpart of the game, we balance a faithful experimental implementation with a simple and user-friendly environment that is conducive to subjects' comprehension of the key tension of the problem. The second consideration is particularly important for our experiment given that the choice of a ranking method is essentially a choice of the consumer's posteriors, and subjects are notoriously non-Bayesian (e.g., [Camerer, 1995](#)). We settle with two design choices: (a) we discretize the set of ranking methods into five choices, and (b) we provide graphical aids based on joint probabilities to facilitate subjects' process-

ing of conditional probabilities. We illustrate these design features by way of explaining the experimental procedures.

Our experiment was conducted using oTree (Chen et al., 2016) at the Experimental Economics Laboratory of Southwestern University of Finance and Economics. A total of 316 undergraduate subjects with no prior experience in our experiment participated. Upon arrival, subjects were instructed to sit at individual computer terminals separated by partitions. Each received a copy of a summary of the experimental instructions, which were read aloud by the experimenter. Subjects were then given time to go through the more detailed on-screen version of the instructions before they completed a comprehension quiz and a practice round.<sup>23</sup> Subjects kept the hard-copy summary for references during the experiment.

Using a *between-subject* design, we conducted *four sessions* for each of the four treatments, with 18 to 24 subjects participated in a session. In each session, half of the subjects were randomly assigned to the role of an expert and the other half to the role of a consumer. Roles remained fixed throughout a session. Subjects played *40 rounds* of the game. In each round, one expert was *randomly matched* with one consumer to form a decision group.

All treatment parameters other than the prior probability were induced as monetary incentives. The amounts subjects received or paid during the experiment were denominated in Experimental Currency Unit (ECU), where 1 ECU was equivalent to 0.25 Chinese RMB. In the following, we use the parameter values in treatment *HH* to illustrate.

Subjects were told that there were two products, A and B. The fixed value of Product A was 100 ECU. Drawn by the computer in each round, the uncertain value of Product B was either 0 ECU with 80% chance or 250 ECU with 20% chance. Product A (B) was referred to as the better product if the value of Product B was drawn to be 0 (250) ECU.

The expert made one decision in each round, and that was to choose one of five ranking methods. The available choices—the  $\beta_0$  in the game—were 0%, 25%, 50%, 75%, and 100% referred to as Methods 1, 2, 3, 4, and 5 respectively. These choices *cover the efficient and robust equilibrium methods* in all four treatments. The five methods always ranked Product B first when it was the better product. When instead Product A was the better product, the five methods ranked Product B first with the percentages listed above.

The probabilities of the values of Product B and the ranking probabilities were first separately presented to subjects. Their joint probabilities, framed as the probabilities concerning which product would be better and which could be ranked first under the five ranking methods,

---

<sup>23</sup>The experiment was conducted in Chinese. We first composed the experimental instructions in English, and the authors who read and write Chinese then translated the instructions into Chinese. Appendix B contains as a sample the translated English instructions from treatment *HH*. The Chinese version including screenshots of the oTree decision interfaces is in online Appendix ??.

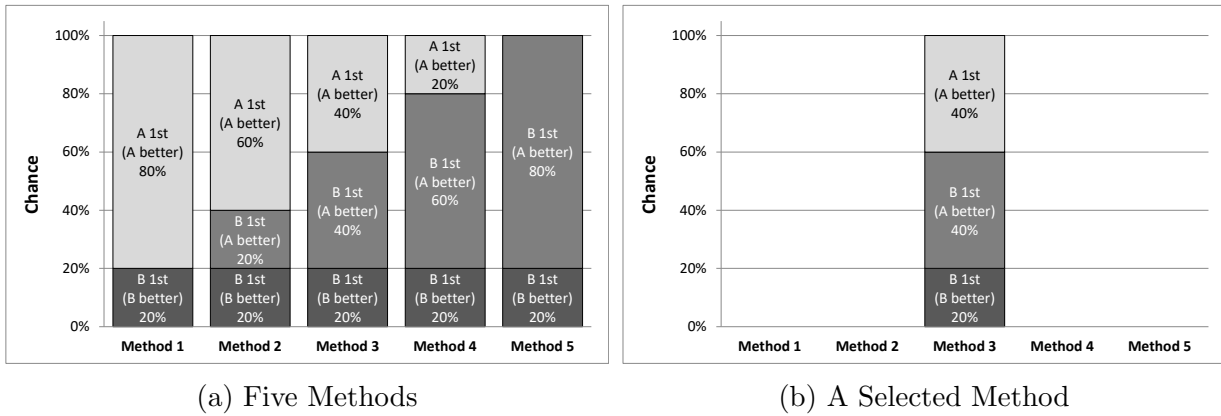


Figure 3: Ranking Methods Presented to Subjects

were further depicted using a bar chart. The chart, which is reproduced in Figure 3(a), was shown on the expert’s decision screen.

After the expert selected a ranking method, the consumer made the first of two decisions in the round. It was emphasized to subjects that the expert did not know which product was better when choosing a ranking method. The selected ranking method was revealed to the consumer using a similar bar chart. Figure 3(b) shows an example where Method 3 was selected. With the chart depicted on the decision screen, the consumer then decided whether to pay 110 ECU to view the ranking report and learn which product was ranked first.

The round then advanced to the product-choice stage, where the consumer made the second and last decision in the round. If in the previous stage the consumer decided not to pay for the ranking report, then the bar chart in Figure 3(b) would remain on the consumer’s screen. If the consumer instead decided to pay, then, depending on the draw of the value of Product B and thus which product was ranked first, one of the two charts in Figure 4 would be shown to the consumer. Whether paying for the report or not, the consumer proceeded to choose a product, after which all decisions in the round would be completed.

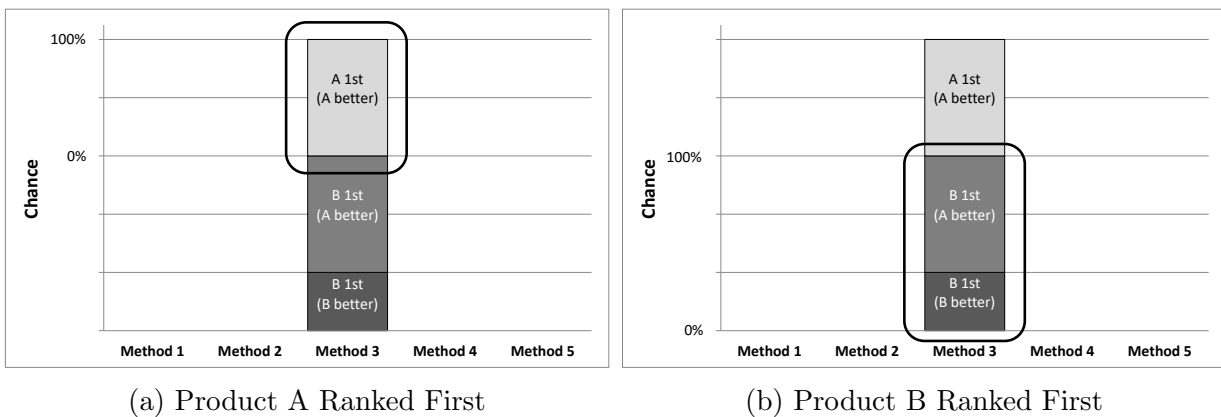


Figure 4: Ranking Reports Presented to Subjects

The expert would earn 300 ECU if the consumer acquired the ranking report; otherwise, the expert would earn nothing for the round. The consumer earned the value of the chosen product, which would be 100 ECU if Product A was chosen and either 0 or 250 ECU if Product B was chosen. Irrespective of whether the consumer paid to view the report, the first ranked product was worth an extra 250 ECU to the consumer. The consumer’s earning from the product would be deducted by the report fee 110 ECU if the consumer paid for the report.

Each round was concluded with an information feedback, which summarized the events in the round including the expert’s choice of ranking method, the randomly selected value of Product B, the top-ranked product, the consumer’s report-acquisition decision, the consumer’s product choice, and the subject’s earning for the round.

We randomly selected three out of the 40 rounds for calculating subject payments. The average ECU earned in the three selected rounds was converted into Chinese RMB at a fixed and known exchange rate of 4 ECU for 1 RMB. A show-up fee of 20 RMB was also paid. A session lasted about an hour, and subjects on average earned 62.02 RMB.<sup>24</sup>

### 3.3 Experimental Hypotheses

From the theoretical perspective, the discretization of the choices of ranking methods amounts to reducing the continuum of subgames down to five. The truncation entails no change in the logic of the equilibria, and the characterizations including the refinements can be readily applied to the discretized game. Table 2 adapts the equilibrium predictions listed in Table 1 to the five experimental ranking methods, namely, Method 1 (0%), Method 2 (25%), Method 3 (50%), Method 4 (75%), and Method 5 (100%).

Table 2: Basis for Experimental Hypotheses

Treatment	(1) Subgame- Perfect	(2) Efficient (Consumer-Optimal)	(3) Robust (Expert-Optimal)	(4) Default Product <i>B</i>
<i>LL</i>	Methods 1, 2, 3, 4	Method 1	Method 1	Method 5
<i>LM</i>	Methods 1, 2	Method 1	Method 1	Method 5
<i>HL</i>	Methods 1, 2, 3, 4	Method 1	Method 3	Methods 4, 5
<i>HH</i>	Methods 2, 3	Method 2	Method 3	Methods 4, 5

Note: Columns (1), (2), and (3) contain the equilibrium ranking method(s) predicted by the three equilibrium concepts. Column (4) contains the ranking method(s) under which Product *B* is the optimal default (for *HL* and *HH*, the consumer is indifferent between the two products under Method 3, which is resolved in favor of Product *A* by Assumption 2).

The equilibrium predictions form the *sole* basis for our experimental hypotheses. As a

<sup>24</sup>As a point of reference, the hourly minimum wage in Beijing, which was the highest among all regions in China, was RMB 25.3 in 2021.

matter of interpretation, however, we also refer to the properties of product guidance and ranking uncertainty. Adapting Facts 1 and 2 to the experimental ranking methods, it is readily seen that Method 1 is misguidance-proof and uncertainty-neutral. Method 5 at the other end is most misguiding and uncertainty-eliminating. While the degree of misguidance is monotone across the five methods, the level of ranking uncertainty is “hump-shaped”; Method 3 in the middle is the most uncertainty-inducing method.<sup>25</sup>

Experts’ choices of ranking methods represent our primary interest. We develop separate hypotheses, some of them mutually exclusive, for each of the three equilibrium concepts. As experimental data are often noisy, the hypotheses are formulated in terms of qualitative comparisons of frequencies of choices that are implied by the equilibrium predictions. We conduct two sets of comparisons for each equilibrium concept, one within treatments and one between treatments. For within-treatment comparisons, the general hypothesis is that equilibrium behavior occurs more often than non-equilibrium behavior. The between-treatment comparisons evaluate the treatment effects in light of the equilibrium predictions. While the equilibrium predictions provide a basis for any pairwise comparison of treatments, our hypotheses compare only between treatments that differ by one treatment variation to avoid confounds.<sup>26</sup>

We begin with the predictions of subgame-perfect equilibria, which impose the least restriction on behavior:

**Hypothesis 1A** (Subgame-Perfect: Within Treatments). *For each treatment, the average relative frequency of subgame perfect equilibrium ranking methods is higher than that of non-equilibrium methods.*

**Hypothesis 1B** (Subgame-Perfect: Between Treatments). *For the treatment effects,*

- (a) *increasing the ranking value given the low report fee has no effect on the choices of ranking methods: the relative frequency distribution of the five methods in LL is not different from that in HL;*
- (b) *increasing the report fee narrows the choices of ranking methods:*
  - (i) *the average relative frequency of Methods 3 and 4 is lower in LM than in LL; and*
  - (ii) *the average relative frequency of Methods 1 and 4 is lower in HH than in HL.*

---

<sup>25</sup>In our design, the natural level of ranking uncertainty corresponds to  $p = 0.2$ , which equals the *ex-ante* probability that Product *B* is ranked first under Method 1. The *ex-ante* probabilities that Products *A* and *B* are ranked first under Method 3, respectively 0.4 and 0.6, are the most uniform among the five methods. Product *B* is always ranked first under Method 5. Note also that Method 4, under which Products *A* and *B* are ranked first with respective probabilities 0.2 and 0.8, shares the same ranking uncertainty with Method 1.

<sup>26</sup>For example, we compare between *LL* and *HL* but not between *LM* and *HH*.



To elaborate on Hypothesis 1A, for each treatment we sort the ranking methods into equilibrium and non-equilibrium groups based on the subgame-perfect prediction in column (1) of Table 2. With an odd number of methods, the sizes of the dichotomous groups are bound to be uneven. To control for the size effects, we compare the average relative frequency of the methods in the equilibrium group with that in the non-equilibrium group.<sup>27</sup> Hypothesis 1B is based on relevant pairwise comparisons of the entries in column (1). Factors that determine how subjects choose among multiple equilibria are outside the realm of the equilibrium concept. Part (a) of the hypothesis, which concerns two treatments with identical predictions, proceeds on the assumption that these factors, whatever they are, do not systematically change between *LL* and *HL*. Part (b) directs attention to the ranking methods that are equilibrium in the lower-fee treatment but not in the higher-fee treatment.

The efficient (consumer-optimal) equilibrium ranking methods listed in column (2) of Table 2 provide the basis for our next set of hypotheses:

**Hypothesis 2A** (Efficient: Within Treatments). *Method 1 is most frequently chosen in each of LL, LM, and HL, whereas Method 2 is most frequently chosen in HH.*

**Hypothesis 2B** (Efficient: Between Treatments). *For the treatment effects,*

- (a) *increasing the ranking value given the low report fee has no effect on the choices of Method 1: the relative frequency of Method 1 in LL is not different from that in HL;*
- (b) *increasing the report fee has no effect on the choices of Method 1 for the low ranking value and shifts choices from Method 1 to Method 2 for the high ranking value:*
  - (i) *the relative frequency of Method 1 in LL is not different from that in LM; and*
  - (ii) *the relative frequencies of Methods 1 and 2 in HL are respectively higher and lower than those in HH.*

The robust (expert-optimal) equilibrium ranking methods listed in column (3) of Table 2 provide the basis for our last set of hypotheses for experts:

**Hypothesis 3A** (Robust: Within Treatments). *Method 1 is most frequently chosen in each of LL and LM, whereas Method 3 is most frequently chosen in each of HL and HH.*

**Hypothesis 3B** (Robust: Between Treatments). *For the treatment effects,*

- (a) *increasing the ranking value given the low report fee shifts choices from Method 1 to Method 3: the relative frequencies of Methods 1 and 3 in LL are respectively higher and lower than those in HL;*

---

<sup>27</sup>Comparing instead the combined frequency of the methods in each group may unfoundedly favor or disfavor the hypotheses even when choices are haphazard (e.g., experts pick a ranking method at random).

(b) *increasing the report fee has no effect on the choices of Method 1 for the low ranking value and the choices of Method 3 for the high ranking value:*

(i) *the relative frequency of Method 1 in LL is not different from that in LM; and*

(ii) *the relative frequency of Method 3 in HL is not different from that in HH.*

Some of these hypotheses are competing. The contrast between Propositions 2 and 3, for instance, translates into the contrast between Hypotheses 2A and 3A. For the low ranking value, efficient and robust equilibria both predict the uncertainty-neutral Method 1 to be the modal method. For the high ranking value, however, the two refined equilibria offer different predictions: robust equilibria predict the modal method to be the most uncertainty-inducing Method 3, while efficient equilibria predict either Method 1 or Method 2. The contrast provides a basis to empirically differentiate the two refinements. Furthermore, while “shuffling as a sales tactic” is a theme of our study, by allowing hypothesized behavior to go the other way with the uncertainty-neutral Method 1, our treatment design has in place a control to see if shuffling is pursued for its own sake or for the incentives that it presents.

For brevity, we do not hypothesize about consumers, although their report acquisitions and product choices still form an integral part of our data analysis. In the theory, the expert never chooses in an acquisition equilibrium a ranking method under which the consumer does not acquire the report; the consumer’s rationality off the equilibrium path is never subject to test. In the experiment, we expect all methods to be chosen as part of noisy laboratory behavior, and that allows us to evaluate whether consumers behave as predicted by sequential rationality even in cases where theoretically it is off the equilibrium path.

## 4 Experimental Findings

In Section 4.1, we analyze aggregate behavior and evaluate the experimental hypotheses using session-level independent observations. In Section 4.2, we estimate regressions to further examine the treatment effects at the individual level and to shed light on the drives of subject behavior that might not be apparent in aggregation.

### 4.1 Aggregate Analysis

***Aggregate Behavior of Experts.*** Our aggregate analysis uses session-level data from the last 20 rounds.<sup>28</sup> For experts, we are interested in how their choices of ranking methods bear out

---

<sup>28</sup>There is moderate learning observed over rounds. We use data from the last 20 rounds to capture reasonably converged aggregate behavior. Using data from, e.g., all 40 rounds or last 10 rounds do not change the

the at times conflicting predictions of the three equilibrium concepts and reflect the properties of product guidance and ranking uncertainty. Figure 5 presents the relative frequencies of the five ranking methods. The subgame-perfect equilibrium methods are labeled in bold, and the efficient and robust methods are marked accordingly.

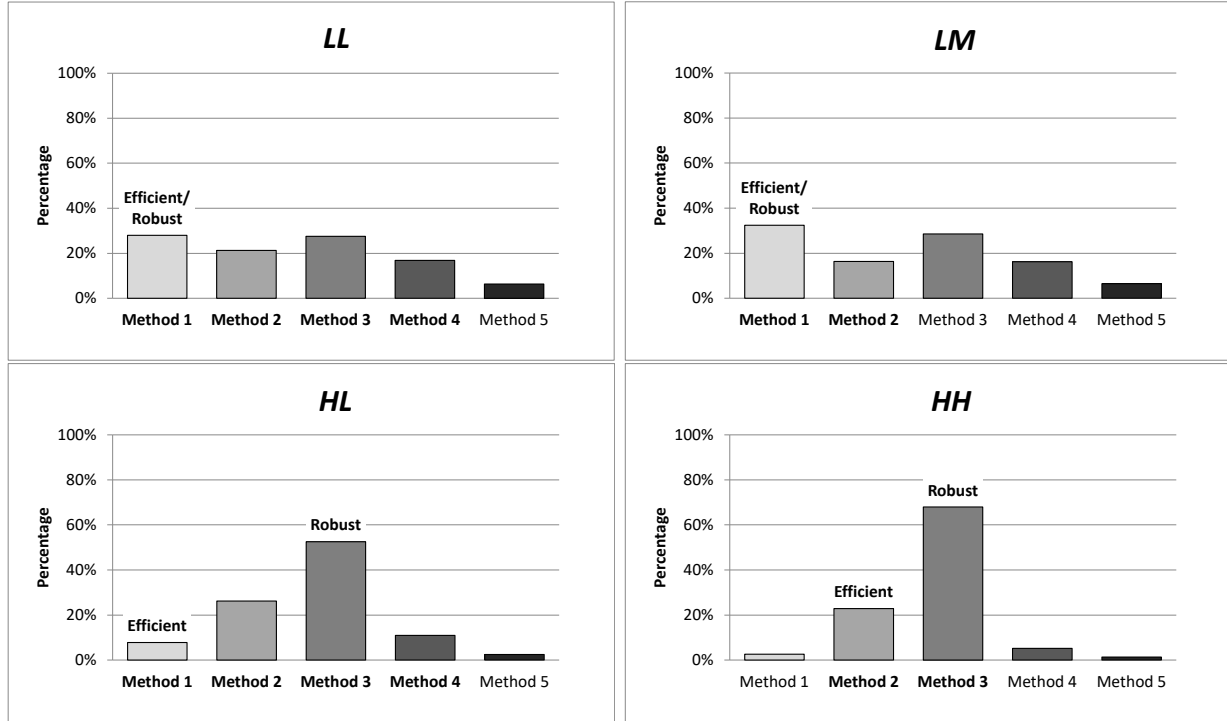


Figure 5: Relative Frequencies of Choices of Ranking Methods

We begin by using the subgame-perfect equilibria as a gauge to see if experts' behavior is broadly governed by equilibrium incentives. Table 3 consolidates for each treatment the data depicted in Figure 5 into average relative frequencies of equilibrium and non-equilibrium methods. All four within-treatment comparisons between the equilibrium and non-equilibrium groups support Hypothesis 1A. The equilibrium ranking methods are on average chosen significantly more often than the non-equilibrium methods ( $p = 0.06$ , Wilcoxon signed rank tests).<sup>29</sup> The finding from *HH* is most remarkable, where the two equilibrium methods together account for 90.8% of the observations. On the other hand, the difference between the equilibrium and non-equilibrium groups, though statistically significant, is smallest in *LM*, where the two equilibrium methods together account for 48.8% of the observations.

Turning to the between-treatment comparisons, part (a) of Hypothesis 1B presents the most stringent test of the absence of an effect of ranking value. A visual inspection of the qualitative findings.

<sup>29</sup>Unless otherwise indicated, our non-parametric statistical tests are performed using session-level observations, and reported  $p$ -values are from one-sided tests. Note that with four independent observations,  $p = 0.0625$ , which we round up to 0.06, is the lowest possible  $p$ -value for the Wilcoxon signed rank test.

Table 3: Relative Frequencies of Subgame-Perfect Equilibrium and Non-Equilibrium Methods

Treatment	Equilibrium Methods	Non-Equilibrium Methods	Wilcoxon Signed Rank Test
<i>LL</i>	23.4% (4)	6.4% (1)	$p = 0.06$
<i>LM</i>	24.4% (2)	17.1% (3)	$p = 0.06$
<i>HL</i>	24.4% (4)	2.5% (1)	$p = 0.06$
<i>HH</i>	45.4% (2)	3.1% (3)	$p = 0.06$

Note: The percentage represents the average relative frequency of the ranking method(s) in the equilibrium or non-equilibrium group. The parenthesis contains the number of methods in the group. The  $p$ -values are from one-sided tests. With four independent observations,  $p = 0.0625$  is the lowest possible  $p$ -value for the Wilcoxon signed rank test.

left two panels in Figure 5 suggests that the distributions of the relative frequencies in *LL* and *HL* differ, and the hypothesized invariance is formally rejected by a chi-square test of homogeneity ( $p < 0.01$ ).<sup>30</sup> Nonetheless, if we turn to a coarser measure using the dichotomous equilibrium and non-equilibrium groups to gauge the invariance, then the difference between the two treatments becomes insignificant. The average relative frequencies of the equilibrium Methods 1–4 and the non-equilibrium Method 5 are 23.4% and 6.4% in *LL*, compared with 24.4% and 2.5% in *HL* (two-sided  $p = 0.34$ , Mann-Whitney test). While this broad comparison may merely be a manifestation of Method 5 being less focal and rarely chosen, the observation is not at odd with the subgame-perfect predictions.

For the narrowing effects of the report fee, part (b) of Hypothesis 1B is supported for the high ranking value. The average relative frequency of Methods 1 and 4 is 3.9% in *HH*, significantly lower than the 9.4% in *HL* ( $p = 0.03$ , Mann-Whitney test), supporting (b)(ii). For the low ranking value, however, the average relative frequencies of Methods 3 and 4 are virtually the same in *LL* and *LM* (22.4% vs. 22.2%, two-sided  $p = 1$ , Mann-Whitney test), rejecting (b)(i). We summarize the above findings about the subgame-perfect equilibrium predictions:

**Finding 1.** *Evaluating experts’ aggregate behavior in light of the predictions of subgame-perfect equilibria yields the following findings:*

- (a) *the equilibrium ranking methods are chosen more often than the non-equilibrium methods;*
- (b) *for the low report fee, increasing the ranking value has no effect on the relative frequency distribution over the dichotomous equilibrium and non-equilibrium methods; and*

<sup>30</sup>The chi-square test compares between the two treatments the distributions of the frequency counts of the five methods, rather than the relative frequencies in percentage terms that are reported.

(c) increasing the report fee narrows the choices of ranking methods for the high ranking value but not for the low ranking value.

Finding 1 provides a starting point to suggest that the observed choices of ranking methods are qualitatively consistent with the broad predictions of subgame-perfect equilibria. We embark on the more demanding test of the theory, further evaluating the observations in light of the refined equilibria. Theoretically, the concepts of efficient and robust equilibria each uniquely select an equilibrium among the multiple subgame-perfect equilibria, a consumer-optimal one in the former and an expert-optimal one in the latter. We perform a parallel empirical analysis with our within-treatment comparisons: for each treatment we single out the modal choice of ranking method and juxtapose it with the unique theoretical predictions.

For the treatments with low ranking value, the predictions of efficient and robust equilibria coincide. Both predict Method 1, which is chosen 28.0% and 32.4% of the time in *LL* and *LM* respectively. Method 1 is indeed the modal choice in both cases, although it is not significantly more frequent than the second-place Method 3 ( $p \geq 0.31$ , Wilcoxon signed rank tests).

The empirical appraisal of the refined equilibria culminates with the high-ranking-value treatments, in which the two equilibrium concepts offer different predictions. The data favor robust equilibria. Neither the efficient Method 1 in *HL* nor the efficient Method 2 in *HH* is modal. Method 2 is chosen 22.9% of the time in *HH*, while the relative frequency of Method 1 is only 7.8% in *HL*. By contrast, the robust Method 3 is chosen 52.6% and 68% of the time in *HL* and *HH* respectively, and in both cases it is significantly more frequent than the second-place Method 2 ( $p = 0.06$ , Wilcoxon signed rank tests). For the high ranking value, the observations thus favor Hypothesis 3A over the competing Hypothesis 2A, while for the low-ranking-value treatments both hypotheses are qualitatively supported but not with statistical significance.

Robust equilibria also stand out in the between-treatment comparisons. Hypothesis 2B regarding efficient equilibria and Hypothesis 3B regarding robust equilibria are identical with respect to their parts (b)(i); both equilibria predict no effect of report fee under the low ranking value, and this is supported by the insignificant difference between the 28.0% in *LL* and the 32.4% in *LM* of Method 1 (two-sided  $p = 0.69$ , Mann-Whitney test). For the other parts in which the two hypotheses differ, the observations do not support Hypothesis 2B, while all parts of Hypothesis 3B are supported.

The relative frequency of Method 1 is 7.8% in *HL*, significantly lower than the 28.0% of Method 1 in *LL* ( $p = 0.01$ , Mann-Whitney test), rejecting the invariance in part (a) of Hypothesis 2B regarding the absence of an effect of the ranking value. While this 7.8% is significantly higher than the 2.6% of Method 1 in *HH* ( $p = 0.01$ , Mann-Whitney test), the relative frequencies of Method 2 in *HL* and *HH*, 26.2% and 22.9%, are not significantly different (two-sided  $p = 0.69$ , Mann-Whitney test), overall not supporting part (b)(ii) of Hypothesis 2B

regarding the effect of the report fee under the high ranking value. For part (a) of Hypothesis 3B regarding the effect of the ranking value, in addition to the aforementioned significantly less frequent Method 1 in *HL* than in *LL*, the relative frequency of Method 3 in *HL* at 52.6% is significantly higher than the 27.5% in *LL* ( $p = 0.01$ , Mann-Whitney test). For part (b) regarding the absence of an effect of the report fee, (b)(i) has already been established above, and the relative frequencies of the robust Method 3 are not significantly different between *HL* and *LL* (52.6% vs. 68%, two-sided  $p = 0.49$ , Mann-Whitney test), further supporting (b)(ii). We summarize the above findings comparing the predictive powers of the two refined equilibria:

**Finding 2.** *Aggregate choices of ranking methods are more consistent with robust equilibria than efficient equilibria. In particular, in the treatments with high ranking value where the predictions of the two refined equilibria diverge, equilibrium methods that are robust and thus expert-optimal are most frequently chosen by a considerable margin.*

As aforementioned, the efficient equilibrium can be motivated by an altruistic motive of the expert toward the acquiring consumer, and the robust equilibrium by a strategic sales motive that is spiteful in nature to the non-acquiring consumer. In the treatments with high ranking value, the two motives present a tradeoff to experts: either benefit the acquiring consumers with product guidance but render the ranking report more dispensable, or hurt the non-acquiring consumers by shuffling but make doing without the report less tolerable. Interpreting Finding 2 from this perspective, the prevalence of robust equilibria in *HL* and *HH* suggests that experts are, on average, driven more by the strategic sales motive than any altruistic motive.

The distinctive behavior of experts observed across treatments reflect the different ranking values and report fees. In addition to the significant effects of the ranking value, the fact that the observed distribution of ranking methods in *HH* is noticeably more concentrated than that in *HL* suggests that experts also respond to the report fees—as the ranking report becomes more expensive, they shuffle more often with more frequent choices of Method 3. Note, however, that selling the reports earns experts the same rewards in all treatments; unlike consumers, experts are not directly impacted by the exogenous parameters of ranking value and report fee, and their responses to the treatment variations are presumably via the endogenous choices of consumers. We turn next to this linkage, examining the aggregate behavior of consumers.

**Aggregate Behavior of Consumers.** Figure 6 presents the relative frequencies of report acquisitions under each ranking method. The subgame-perfect equilibrium methods are listed in bold. Sequential rationality predicts the consumer to acquire the report only under these equilibrium methods. The three equilibrium concepts do not differ in their predictions.

Table 4 consolidates the relative frequencies by whether the ranking methods are equilibrium or non-equilibrium. In each treatment, consumers on average acquire the reports more often when theory predicts that they should than when theory predicts that they should not,

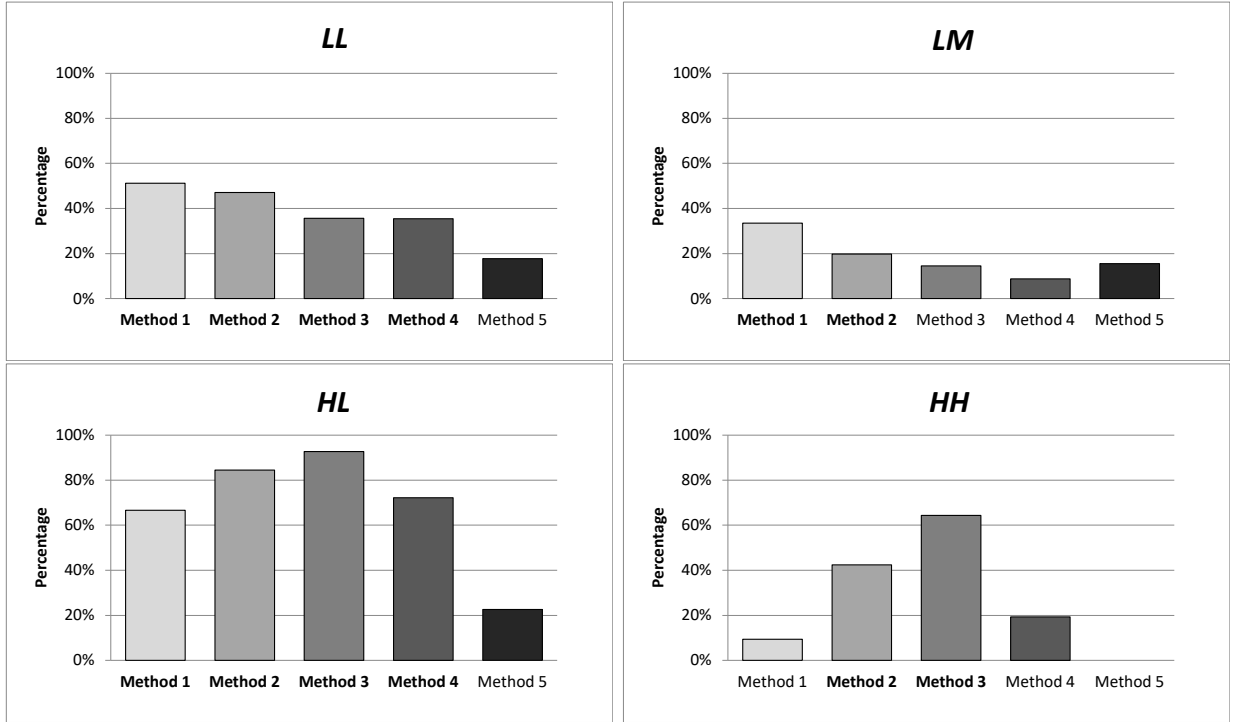


Figure 6: Relative Frequencies of Report Acquisitions

and the directional differences are significant in all but one treatment ( $p = 0.13$  in *LL* and  $p = 0.06$  in *LM*, *HL*, and *HH*, Wilcoxon signed rank tests).

To show the treatment effects, Table 4 also includes the total relative frequencies of report acquisitions without conditional on ranking methods. Consumers acquire the ranking reports most often when, considering only the exogenous treatment parameters, the reports have the highest “benefit-cost ratio”; in *HL* where the ranking value is high and the report fee is low, consumers acquire the reports 85.2% of the time. This stands in contrast to *LM* with the lowest ranking-value to report-fee ratio, in which the reports are acquired only 27.7% of the time.<sup>31</sup> Although these are not part of the equilibrium predictions, the treatment effects provide clear evidence that consumers respond to the induced incentives.

We further examine consumers’ product choices, which provide yet another gauge to see if consumers appreciate the tension of the problem. Table 5 presents the relative frequencies of Product *B* being chosen as the default under two groups of ranking methods. For within-treatment comparisons, the relative frequency of default Product *B* is significantly lower under Methods 1 – 3 than under Methods 4 – 5 in all four treatments ( $p = 0.06$ , Wilcoxon signed rank tests). The magnitudes of the differences are greater in the treatments with high ranking value, and the largest difference is recorded in *HL* with 11.8% vs. 96.9%.

<sup>31</sup>Statistically using the Mann-Whitney tests, we find that, relative to *LL* as the baseline, the relative frequencies are marginally significantly lower in *LM* ( $p = 0.06$ ), significantly higher in *HL* ( $p = 0.01$ ), and not significantly different in *HH* (two-sided  $p = 0.34$ ).

Table 4: Relative Frequencies of Report Acquisitions By Equilibrium and Non-Equilibrium Ranking Methods

Treatment	Equilibrium Methods	Non-Equilibrium Methods	Wilcoxon Signed Rank Test	Total
<i>LL</i>	42.4%	17.7%	$p = 0.13$	42.0%
<i>LM</i>	26.6%	12.9%	$p = 0.06$	21.7%
<i>HL</i>	79.0%	22.6%	$p = 0.06$	85.2%
<i>HH</i>	53.4%	10.6%	$p = 0.06$	55.6%

Note: The  $p$ -values are from one-sided tests. With four independent observations,  $p = 0.0625$  is the lowest and  $p = 0.125$  the second lowest possible  $p$ -values for the Wilcoxon signed rank test.

For between-treatment comparisons, we leverage the prediction in column (4) of Table 2 that Product  $B$  is the optimal default under Method 4 in *HL* and *HH* but not in *LL* and *LM*. In any pairwise comparison between a treatment with high ranking value and a treatment with low ranking value (e.g., between the 96.9% in *HL* and the 40.0% in *LL*), the relative frequency of default Product  $B$  under Methods 4–5 is significantly higher in the former than in the latter ( $p = 0.01$ , Mann-Whitney tests).

Table 5: Relative Frequencies of Product Choices

Treatment	Without Acquiring Report: Default Product $B$		Wilcoxon Signed Rank Test	Acquiring Report: Top-Ranked Product
	Methods 1 – 3	Methods 4 – 5		All Methods
<i>LL</i>	6.5%	40.0%	$p = 0.06$	91.9%
<i>LM</i>	8.7%	44.0%	$p = 0.06$	95.2%
<i>HL</i>	11.8%	96.9%	$p = 0.06$	98.1%
<i>HH</i>	20.0%	100.0%	$p = 0.06$	99.3%

Note: The  $p$ -values are from one-sided tests. With four independent observations,  $p = 0.0625$  is the lowest possible  $p$ -values for the Wilcoxon signed rank test.

Table 5 also provides the relative frequencies of the top-ranked products conditional on the acquisitions of reports. The top-ranked products are chosen more than 90% of the time in all treatments. Predictably, the ranking reports influence consumers’ product choices. We summarize the findings about consumers:

**Finding 3.** *Evaluating consumers’ aggregate behavior in light of the predictions of sequential rationality yields the following findings:*

- (a) *ranking reports are acquired more often under equilibrium ranking methods than under non-equilibrium methods;*



(b) regarding product choices,

(i) when ranking reports are not acquired, a given product is chosen more often under the ranking methods where it is the optimal default than under the methods where it is not optimal; and

(ii) when ranking reports are acquired, the top-ranked products are nearly always chosen.

Our findings in this subsection reveal that subjects' behavior, when evaluated in aggregate, is overall well predicted by equilibria. This is especially the case when incentives are more salient in the treatments with high ranking value. In the next subsection, we examine the constituents of these aggregate observations by analyzing subject-level data using regressions.

## 4.2 Individual Analysis

The objectives of our regression analysis are twofold. First, we attempt to confirm the treatment effects using the richer panel data of 158 experts/consumers making decisions in 40 rounds. Second, we further explore other behavioral impetuses that cannot be readily investigated with aggregate behavior. We estimate binary outcome panel data models using random-effects logit, which take the following generic form:

$$\Pr(Y_{it} = 1 | \mathbf{X}_{it}, \alpha_i) = \Lambda(\mathbf{X}_{it}\boldsymbol{\theta} + \alpha_i), \quad (4)$$

where  $\alpha_i$  is the subject-specific effect and  $\Lambda(z) = \frac{e^z}{1+e^z}$  is the logistic cumulative distribution.

We examine the behavior of experts and consumers with separate regressions. For experts, we construct the dependent outcome variable  $Y_{it}$  by partitioning the five ranking methods into binary sets. We consider four alternative specifications of  $Y_{it}$  that correspond broadly to the four key concepts in our study: product guidance, ranking uncertainty, efficient equilibria, and robust equilibria; the corresponding specifications are (a)  $Y_{it} = MD_{it}^{\text{mmg}}$ , (b)  $Y_{it} = MD_{it}^{\text{shf}}$ , (c)  $Y_{it} = MD_{it}^1$ , and (d)  $Y_{it} = MD_{it}^3$ , where  $MD_{it}^{\text{mmg}}$  takes the value of one (zero otherwise) if expert  $i$  chooses in round  $t$  one of the two most misleading methods, Method 4 or 5, and  $MD_{it}^{\text{shf}}$  takes the value of one (zero otherwise) if expert  $i$  chooses in round  $t$  one of the two shuffling methods that generate the most uncertain ranking, Method 2 or 3.  $MD_{it}^1$  is analogously defined for Method 1, which is efficient in three treatments and robust in two treatments, and  $MD_{it}^3$  for Method 3, which is robust in two treatments.

For dependent variable  $Y_{it} \in \{MD_{it}^{\text{mmg}}, MD_{it}^{\text{shf}}, MD_{it}^1, MD_{it}^3\}$ , the specification of  $\mathbf{X}_{it}\boldsymbol{\theta}$  on the right-hand side of (4) is given by

$$\mathbf{X}_{it}\boldsymbol{\theta} = \theta_0 + \theta_1 LM_i + \theta_2 HL_i + \theta_3 HH_i + \theta_4 Y_{i,t-1} + \theta_5 SL_{i,t-1} + \theta_6 (Y_{i,t-1} \times SL_{i,t-1}),$$

where the independent variables are defined and motivated as follows:

(a) Treatment effects:  $LM_i$ ,  $HL_i$ , and  $HH_i$

- $LM_i$ ,  $HL_i$ , and  $HH_i$  each take the value of one (zero otherwise) if expert  $i$  is in the respective treatment.
- The coefficients  $\theta_1$ ,  $\theta_2$ , and  $\theta_3$  measure how, relative to the baseline  $LL$ , the experts in the respective treatments are more or less likely (in log odds) to choose the ranking method(s). For instance, for outcome  $MD_{it}^3$ , robust equilibria and consistency with the aggregate findings would predict that  $\theta_1 = 0$ ,  $\theta_2 > 0$ , and  $\theta_3 > 0$ .

(b) Choice persistence and experience:  $Y_{i,t-1}$ ,  $SL_{i,t-1}$ , and  $Y_{i,t-1} \times SL_{i,t-1}$

- $Y_{i,t-1}$  takes the value of one (zero otherwise) if expert  $i$  chooses in round  $t - 1$  the ranking method(s) in the corresponding case of the dependent variable.
- $SL_{i,t-1}$  takes the value of one (zero otherwise) if expert  $i$  sells the ranking report in round  $t - 1$ .
- Besides the treatment effects predicted by equilibria, it is conceivable that persistence and experience may play a role as behavioral determinants in the laboratory. If experts exhibit persistence in their choices of ranking methods irrespective of whether the choices lead to sales, then we will expect that  $\theta_4 > 0$ . If experience matters, then—using outcome  $MD_{it}^3$  as an example—a previous successful experience of selling the report without Method 3 may decrease the odds that the method would be chosen again ( $\theta_5 < 0$ ), and a previous successful selling experience with Method 3 may increase the odds that it would be chosen again ( $\theta_6 > 0$ ).

Columns (1) and (2) of Table 6 report the estimation results for outcomes  $MD_{it}^1$  and  $MD_{it}^3$  respectively. The coefficients of the treatment dummies  $HL_i$  and  $HH_i$  indicate that, relative to the baseline  $LL$ , experts in  $HL$  and  $HH$  are significantly less likely to choose Method 1 and more likely to choose Method 3. Recall that Method 1 is both efficient and robust in  $LL$  and is only efficient in  $HL$ , whereas Method 3 is robust in  $HL$  and  $HH$ . As with the aggregate findings, the regression results lend support to the expert-optimal, robust equilibria: when an efficient and robust method becomes not robust, it is less likely to be chosen, and when a ranking method is robust, it is more likely to be chosen even if it is not efficient. Also in line with the aggregate findings, the regressions reveal that experts' behavior in  $LM$  is least different among the three treatments from that in  $LL$ .

With Method 3 inducing the most uncertain ranking, the findings above also suggest that experts in the high-ranking-value treatments are more inclined to shuffle. The regression result

Table 6: Choices of Ranking Methods: Treatment Effects and Behavioral Determinants

	$Y_{it} = MD_{it}^1$	$Y_{it} = MD_{it}^3$	$Y_{it} = MD_{it}^{\text{mmg}}$	$Y_{it} = MD_{it}^{\text{shf}}$
	(1)	(2)	(3)	(4)
$LM_i$	0.438* (0.201)	-0.066 (0.265)	-0.122 (0.434)	-0.234 (0.187)
$HL_i$	-0.958*** (0.213)	0.692* (0.289)	-0.329 (0.369)	0.960*** (0.226)
$HH_i$	-1.206*** (0.371)	1.243*** (0.254)	-0.628* (0.303)	1.362*** (0.151)
$Y_{i,t-1}$	1.243*** (0.207)	0.464** (0.166)	0.657*** (0.163)	0.693*** (0.181)
$SL_{i,t-1}$	-0.582** (0.189)	-0.877*** (0.161)	-0.883*** (0.164)	-1.031*** (0.218)
$Y_{i,t-1} \times SL_{i,t-1}$	1.934*** (0.479)	1.855*** (0.286)	1.576*** (0.343)	1.932*** (0.340)
Constant	-2.280*** (0.133)	-1.230*** (0.205)	-1.606*** (0.323)	-0.274 (0.156)
Observations	6162	6162	6162	6162

Note: Columns (1)–(4) report estimates from four different specifications of dependent variables. The independent variable  $Y_{i,t-1}$  is the one-round lagged value of the dependent variable of the column. Standard errors clustered at the session level are in parentheses. \*\*\* indicates significance level at 0.1%, \*\* at 1%, and \* at 5%.

reported in column (4) using the broader measure of shuffling further substantiates this. On the other hand, while experts in  $HL$  and  $HH$  are less inclined to choose the misguidance-proof Method 1, the estimates in column (3) show that they are not more likely to go to the other end offering maximal misguidance. Note also that for all four outcomes the coefficients of  $HH_i$  are greater in magnitudes than those of  $HL_i$ , suggesting that the treatment effects are stronger when incentives are more salient under the higher report fee.

The coefficients of the three variables capturing the effects of choice persistence and experience are all significant with predicted signs. For all four outcome variables, experts are prone to repeat their choices, less likely to choose a ranking method when they are able to sell the ranking report in the previous round with another method, and more likely to choose a ranking method that enables them to sell the report in the previous round.

Turning to consumers, we use report-acquisition decisions as the outcome variable, where  $Y_{it} = AQ_{it}$  takes the value of one (zero otherwise) if consumer  $i$  acquires the ranking report in round  $t$ . For parsimonious regression equations, we examine the treatment effects and behavioral determinants separately with different sets of specifications of independent variables.

Slightly abusing notation by recycling the use of  $\boldsymbol{\theta}$ , the first specification is

$$\mathbf{X}_{it}\boldsymbol{\theta} = \theta_0 + \theta_1 LM_i + \theta_2 HL_i + \theta_3 HH_i + \theta_4 MD_{it}^1 + \theta_5 MD_{it}^2 + \theta_6 MD_{it}^3 + \theta_7 MD_{it}^4. \quad (5)$$

Besides leveraging the panel data to further substantiate the treatment effects for consumers, we control for ranking methods in the regression, where  $MD_{it}^j$  takes the value of one (zero otherwise) if consumer  $i$  encounters Method  $j$  in round  $t$ . Using  $LL$  as the baseline, consistency with the aggregate findings would predict that  $\theta_1 < 0$ ,  $\theta_2 > 0$ , and  $\theta_3 = 0$ .

In light of the observation in Section 4.1 that the aggregate report acquisitions reflect the benefit-cost ratio of the ranking reports, we also estimate an alternative specification to evaluate the treatment effects:

$$\mathbf{X}_{it}\boldsymbol{\theta} = \theta_0 + \theta_1 (R/F)_i + \theta_2 MD_{it}^1 + \theta_3 MD_{it}^2 + \theta_4 MD_{it}^3 + \theta_5 MD_{it}^4, \quad (6)$$

where  $(R/F)_i$ , which measures the ratio of ranking value to report fee of the treatment in which consumer  $i$  makes decisions, supersedes the three treatment dummies in (5).

Table 7 reports the estimation results. Column (1) contains the estimates of specification (5). The coefficients of the treatment dummies are all in line with the predicted effects extrapolated from the aggregate findings. Column (2) contains the estimates of specification (6). The positive and significant coefficient of  $(R/F)_i$  further corroborates the aggregate finding that the higher the benefit-cost ratio of the ranking reports, the more likely they are acquired.<sup>32</sup>

The use of  $(R/F)_i$  as a proxy for the treatment dummies with significant and meaningful estimates suggests that we may pierce the veil of the treatment labels and view consumers as simply responding to the incentives of the induced ranking values and report fees. This perspective serves as our starting point to further investigate the behavioral determinants of their report-acquisition decisions, and our next regression extends on (6) by adding independent variables that capture persistence and experience as we have done for experts. To better understand how the incentive parameters may interact with the ranking methods encountered by consumers, we also include interaction terms between  $(R/F)_i$  and  $MD_{it}^j$ .

The variables on decision persistence and experience are  $AQ_{i,t-1}$ ,  $TP_{i,t-1}$ , and their interaction, where  $TP_{i,t-1}$ , not hitherto defined, takes the value of one (zero otherwise) if consumer  $i$  chooses the top-ranked product in round  $t - 1$ .<sup>33</sup> Persistence would predict the coefficient of

---

<sup>32</sup>We reiterate that for the results reported in Table 7 the ranking-method dummies serve as control variables to demonstrate the differences between treatments, and we postpone discussing their coefficients until our analysis of behavioral determinants below.

<sup>33</sup>The variable  $AQ_{i,t-1}$  captures the same behavior as  $SL_{i,t-1}$  that is used for regressions for experts. The two variables, however, differ by the meaning of the index  $i$ , where  $AQ_{i,t-1}$  captures the previous-round report acquisition of consumer  $i$  and  $SL_{i,t-1}$  captures the report acquisition of the consumer matched with expert  $i$  in the previous round.

Table 7: Report Acquisitions: Treatment Effects

	$AQ_{it}$	
	(1)	(2)
$LM_i$	-1.775** (0.591)	- -
$HL_i$	2.403*** (0.542)	- -
$HH_i$	-0.097 (0.376)	- -
$(R/F)_i$	- -	0.068*** (0.012)
$MD_{it}^1$	2.865*** (0.492)	2.862*** (0.494)
$MD_{it}^2$	2.668*** (0.604)	2.682*** (0.606)
$MD_{it}^3$	3.145*** (0.679)	3.166*** (0.682)
$MD_{it}^4$	1.778*** (0.532)	1.785*** (0.534)
Constant	-2.923*** (0.544)	-3.881*** (0.610)
Observations	6320	6320

Note: Standard errors clustered at the session level are in parentheses. \*\*\* indicates significance level at 0.1%, \*\* at 1%, and \* at 5%.

$AQ_{i,t-1}$  to be positive, and previous experience of choosing the top-ranked product, if matters, would predict the coefficient of  $TP_{i,t-1}$  to be negative and that of  $AQ_{i,t-1} \times TP_{i,t-1}$  to be positive.

Column (1) of Table 8 reports the estimation result. Unlike experts, consumers are not persistent in their report-acquisition decisions. Neither does stumbling on the top-ranked products without acquiring the ranking reports have any significant impact. Their decisions to acquire are nevertheless moderately reinforced by previous experience of securing the top-ranked products via viewing the reports.

The stand-alone effect of  $(R/F)_i$  becomes insignificant in the richer specification, but its interactions with the ranking-method dummies paint an informative picture. Recall that it is never sequentially rational to acquire the report under Method 5, and the aggregate data reveal that it is indeed rarely chosen. This has motivated us to use the most misleading method as the baseline for evaluating the within-treatment effects of ranking methods. Consumers are, relative to this baseline, significantly more likely to acquire the reports under Methods 1, 2, and 3, but not under the second most misleading Method 4.

The interaction between  $(R/F)_i$  and  $MD_{it}^4$ , however, is positive and highly significant. This is in tandem with the fact that acquiring the ranking report under Method 4 is sequentially rational only in  $HL$  and  $LL$ , and, among the four treatments,  $HL$  has the highest  $(R/F)_i$  followed by  $LL$ . By contrast, the interaction effect is not significant at all for Method 1, under which acquiring the report is sequentially rational even in  $LM$  with the lowest  $(R/F)_i$ .

Table 8: Report Acquisitions: Behavioral Determinants

	$AQ_{it}$			
	(1)	(2)	(3)	(4)
$(R/F)_i$	0.009 (0.018)	– –	– –	– –
$G_{it}$	– –	0.043*** (0.005)	– –	0.047*** (0.007)
$AQ_{i,t-1}$	–0.059 (0.260)	–0.043 (0.279)	–0.112 (0.267)	–0.025 (0.263)
$TP_{i,t-1}$	–0.093 (0.113)	–0.075 (0.124)	–0.097 (0.114)	–0.077 (0.122)
$AQ_{i,t-1} \times TP_{i,t-1}$	0.628* (0.274)	0.557 (0.297)	0.668* (0.284)	0.554 (0.284)
$MD_{it}^1$	2.165*** (0.461)	– –	2.945*** (0.533)	–0.045 (0.388)
$MD_{it}^2$	1.467** (0.489)	– –	2.729*** (0.649)	–0.071 (0.316)
$MD_{it}^3$	1.958** (0.705)	– –	3.180*** (0.733)	–0.239 (0.282)
$MD_{it}^4$	0.519 (0.362)	– –	1.847*** (0.580)	–0.209 (0.215)
$(R/F)_i \times MD_{it}^1$	0.023 (0.015)	– –	– –	– –
$(R/F)_i \times MD_{it}^2$	0.066* (0.027)	– –	– –	– –
$(R/F)_i \times MD_{it}^3$	0.065* (0.026)	– –	– –	– –
$(R/F)_i \times MD_{it}^4$	0.068*** (0.014)	– –	– –	– –
$LM_i$	– –	– –	–1.674** (0.554)	–0.575 (0.578)
$HL_i$	– –	– –	2.212*** (0.507)	–1.174 (0.734)
$HH_i$	– –	– –	–0.105 (0.335)	0.706 (0.386)
Constant	–2.921*** (0.430)	–1.615*** (0.225)	–3.126*** (0.549)	–1.451*** (0.370)
Observations	6162	6162	6162	6162

Note: Standard errors clustered at the session level are in parentheses. \*\*\* indicates significance level at 0.1%, \*\* at 1%, and \* at 5%.

The above finding motivates us to go one step further to subsume also the ranking methods into incentive values. For our last regression specification, we construct a summary incentive

variable measuring the expected gain from acquiring the ranking report,  $G_{it}$ , which amounts to the theoretical willingness to pay less the report fee (the same  $G$  used in the definition of robust equilibria if acquiring the report is the optimal decision), given the ranking method consumer  $i$  encounters in round  $t$ . Since  $G_{it}$  contains information about not only the ranking value and report fee but also the ranking method, it supersedes  $(R/F)_i$  and  $MD_{it}^j$ . The persistence and experience variables are preserved in the specification.

Column (2) of Table 8 reports the estimation result. We first note that there are no dramatic differences in the effects of persistence and experience in this specification. Regarding the effect of  $G_{it}$ , consumers are significantly more likely to acquire the reports when the expected gains are higher. To underscore the significance of this finding, we estimate two additional regressions, in one replacing  $G_{it}$  back with the treatment and ranking-method dummies and in the other adding these dummies without omitting  $G_{it}$ . The juxtaposition of the estimates in columns (3) and (4) shows that the significant treatment and ranking-method effects seen in column (3) vanish once we control for  $G_{it}$ .

Even though consumers acquire the reports substantially less often than the point predictions of sequential rationality, the series of regression findings, culminated in the distillation of the between- and within-treatment effects into the effects of a summary incentive variable, provides strong evidence that consumers respond to the induced incentives. This in turn rationalizes choices of ranking methods by experts, who are not directly impacted by the variations in ranking values and report fees, as responses to consumers who respond to the incentive parameters. We conclude our data analysis by summarizing the regression findings:

**Finding 4.** *The analysis of subject-level panel data corroborates the aggregate findings. For experts' choices of ranking methods, the regressions further bolster the predictions of robust equilibria. For report acquisitions, the regressions reveal that consumers respond to the bare incentives behind the ranking methods they encounter. The effects of lagged variables indicate that experts are persistent in their choices and influenced by experience, more so than consumers.*

## 5 Concluding Remarks

Motivated by the lack of structured evidence on the sentiment expressed by some commentators that ranking publishers excessively alter their product rankings for marketing purposes, this study resorts to laboratory evidence. Guided by the formal analysis of a ranking-report game, which helps make precise the layman view, we use monetary payments to induce in the laboratory plausible incentives faced by ranking publishers.

In our game, “altering the product rankings” manifests as the expert engaging in strategic shuffling, sometimes ranking the less intrinsically valuable product at the top, even when

doing so means not offering product guidance to the consumer. This strategic move engenders consumer’s willingness to pay for the ranking report to resolve the uncertainty over which product carries a ranking value interpreted as prestige. Our equilibrium analysis provides a sense that this shuffling, while benefiting the expert, may be done excessively from the vantage point of consumer welfare. When the ranking value is relatively high, the robust equilibrium that is also expert-optimal diverges from the efficient equilibrium that is consumer-optimal.

Our experimental findings show that this excessive shuffling is not only an equilibrium phenomenon but also a laboratory one. As a starting point, we find that subjects’ behavior is overall consistent with the board predictions of subgame-perfect equilibria. Further evaluating the predictive powers of the refined equilibria, we find that equilibrium ranking methods that are expert-optimal and consumer-optimal, when the two coincide, are chosen more often than other equilibrium methods. More importantly, when they diverge, the expert-optimal equilibrium ranking method, which is also the shuffling method that induces the most ranking uncertainty, is most frequently chosen by a considerable margin. Our experiment provides evidence supporting the view that a profit-driven ranking publisher may adopt a ranking methodology to promote subscriptions and popularity of its ranking publication at the expense of consumers.

We discuss two directions for future research. The sellers of the products being ranked are not part of our environment. In practice, ranking publishers may derive profits directly from these sellers by, e.g., providing consulting services to them, and the shuffling might serve to also induce sellers to sign up these services to keep up-to-date about the ranking criteria. Furthermore, sellers may play a strategic role in the impacts of product rankings on consumers. [Luca and Smith \(2015\)](#), e.g., provide empirical evidence that business schools selectively promote the publications in which their MBA programs are favorably ranked. How in a two-sided market sellers and consumers respond when ranking publishers engage in strategic shuffling represents an important question of interest that could be addressed theoretically and experimentally.

For a simple experimental environment, we have considered a game without competition, whereas the markets for product rankings are typically characterized by multiple publishers ranking the same class of products; other than *Kelley Blue Book*, e.g., *Car and Driver* also offers their editor’s choices of cars. Competition may drive methodology specialization. In the rankings of undergraduate programs, e.g., one publisher may emphasize student qualities, while another may focus on the value-added of the educational experiences. The options for consumers to access multiple rankings might dilute the effect of the ranking value from any given ranking. If competition lowers the effective ranking value, then it may have the effect of, as our existing analysis suggests, aligning the expert-optimal and the consumer-optimal equilibria, echoing the familiar theme that competition benefits consumers. It is a natural next step to explore the effects of competition on experts selling ranking advice, whether it enhances or, as we conjecture, attenuates the shuffling that prevails in the absence of competition.



## References

- Anderson, Eric T. and Duncan I. Simester (2014), “Reviews without a purchase: Low ratings, loyal customers, and deception.” *Journal of Marketing Research*, 51, 249–269.
- Au, Pak Hung and King King Li (2018), “Bayesian persuasion and reciprocity: Theory and experiment.” Working Paper.
- Bagwell, Kyle (2007), “The economic analysis of advertising.” In *Handbook of Industrial Organization* (Mark Armstrong and Robert Porter, eds.), volume 3, 1701–1844, North Holland.
- Banks, Jeffrey C., Colin F. Camerer, and David Porter (1994), “Experimental tests of nash refinements in signaling games.” *Games and Economic Behavior*, 6, 1–31.
- Becker, Gary S. and Kevin M. Murphy (1993), “A simple theory of advertising as a good or bad.” *The Quarterly Journal of Economics*, 108, 941–964.
- Blume, Andreas, Oliver J. Board, and Kohei Kawamura (2007), “Noisy talk.” *Theoretical Economics*, 2, 395–440.
- Blume, Andreas, Ernest K. Lai, and Wooyoung Lim (2022), “Mediated talk: An experiment.” Working Paper.
- Brandts, Jordi and Charles A. Holt (1992), “An experimental test of equilibrium dominance in signaling games.” *American Economic Review*, 82, 1350–1365.
- Camerer, Colin (1995), “Individual decision making.” In *Handbook of Experimental Economics* (John H. Kagel and Alvin E. Roth, eds.), 587–683, Princeton University Press.
- Chakraborty, Archishman and Rick Harbaugh (2007), “Comparative cheap talk.” *Journal of Economic Theory*, 132, 70–94.
- Chen, Daniel L., Martin Schonger, and Chris Wickens (2016), “oTree—An open-source platform for laboratory, online, and field experiments.” *Journal of Behavioral and Experimental Finance*, 9, 88–97.
- Chen, Roy and Yan Chen (2011), “The potential of social identity for equilibrium selection.” *American Economic Review*, 101, 2562–2589.
- Chevalier, Judith A and Dina Mayzlin (2006), “The effect of word of mouth on sales: Online book reviews.” *Journal of Marketing Research*, 43, 345–354.
- Crawford, Vincent P. and Joel Sobel (1982), “Strategic information transmission.” *Econometrica*, 50, 1431–1451.

- de Groot Ruiz, Adrian, Theo Offerman, and Sander Onderstal (2015), “Equilibrium selection in experimental cheap talk games.” *Games and Economic Behavior*, 91, 14–25.
- Dearden, James A., Rajdeep Grewal, and Gary L. Lilien (2019), “Strategic manipulation of university rankings, the prestige effect, and student university choice.” *Journal of Marketing Research*, 56, 691–707.
- Dickhaut, John W., Kevin A. McCabe, and Arijit Mukherji (1995), “An experimental study of strategic information transmission.” *Economic Theory*, 6, 389–403.
- Forsythe, Robert R., Mark Isaac, and Thomas R. Palfrey (1989), “Theories and tests of ‘blind bidding’ in sealed-bid auctions.” *RAND Journal of Economics*, 20, 214–238.
- Fréchette, Guillaume, Alessandro Lizzeri, and Jacopo Perego (forthcoming), “Rules and commitment in communication: An experimental analysis.” *Econometrica*.
- Fudenberg, Drew and Emanuel Vespa (2019), “Learning theory and heterogeneous play in a signaling-game experiment.” *American Economic Journal: Microeconomics*, 11, 186–215.
- Gneezy, Uri (2005), “Deception: The role of consequences.” *American Economic Review*, 95, 384–394.
- Goltsman, Maria, Johannes Hörner, Gregory Pavlov, and Francesco Squintani (2009), “Mediation, arbitration, and negotiation.” *Journal of Economic Theory*, 144, 1397–1420.
- Grossman, Sanford J. (1981), “The informational role of warranties and private disclosure about product quality.” *Journal of Law & Economics*, 24, 461–483.
- Hagenbach, Jeanne and Eduardo Perez-Richet (2018), “Communication with evidence in the lab.” *Games and Economic Behavior*, 112, 139–165.
- Jin, Ginger Zhe, Michael Luca, and Danel Martin (2021), “Is no news (perceived as) bad news? An experimental investigation of information disclosure.” *American Economic Journal: Microeconomics*, 13, 141–73.
- Kamenica, Emir and Matthew Gentzkow (2011), “Bayesian persuasion.” *American Economic Review*, 101, 2590–2615.
- King, Ronald R. and David E. Wallin (1991), “Voluntary disclosures when seller’s level of information is unknown.” *Journal of Accounting Research*, 29, 96–108.
- Krishna, Vijay and John Morgan (2004), “The art of conversation: Eliciting information from experts through multi-stage communication.” *Journal of Economic Theory*, 1417, 147–179.

- Kuksov, Dmitri and Kangkang Wang (2013), “A model of the “it” products in fashion.” *Marketing Science*, 32, 51–69.
- Lai, Ernest K. and Wooyoung Lim (2018), “Meaning and credibility in experimental cheap-talk games.” *Quantitative Economics*, 9, 1453–1487.
- Lu, Susan F. and Huaxia Rui (2018), “Can we trust online physician ratings? Evidence from cardiac surgeons in Florida.” *Management Science*, 64, 2557–2573.
- Luca, Michael and Jonathan Smith (2013), “Salience in quality disclosure: Evidence from the US News college rankings.” *Journal of Economics & Management Strategy*, 22, 58–77.
- Luca, Michael and Jonathan Smith (2015), “Strategic disclosure: The case of business school rankings.” *Journal of Economic Behavior & Organization*, 112, 17–25.
- Luca, Michael and Georgios Zervas (2016), “Fake it till you make it: Reputation, competition, and Yelp review fraud.” *Management Science*, 62, 3412–3427.
- Mayzlin, Dina, Yaniv Dover, and Judith Chevalier (2014), “Promotional reviews: An empirical investigation of online review manipulation.” *American Economic Review*, 104, 2421–55.
- Milgrom, Paul and Joshua Mollner (2021), “Extended proper equilibrium.” *Journal of Economic Theory*, 194, 105258.
- Milgrom, Paul R. (1981), “Good news and bad news: Representation theorems and applications.” *Bell Journal of Economics*, 12, 380–391.
- Myerson, Roger (1978), “Refinements of the nash equilibrium concept.” *International Journal of Game Theory*, 7, 73–80.
- Nguyen, Quyen (2016), “Bayesian persuasion: Evidence from the laboratory.” Working Paper.
- Ottaviani, Marco and Peter Norman Sørensen (2006), “Reputational cheap talk.” *Rand Journal of Economics*, 37, 155–175.
- Pope, Devin G. (2009), “Reacting to rankings: Evidence from ‘America’s best hospitals.’” *Journal of Health Economics*, 28, 1154–1165.
- Sahoo, Nachiketa, Chrysanthos Dellarocas, and Shuba Srinivasan (2018), “The impact of online product reviews on product returns.” *Information Systems Research*, 29, 723–738.
- Schmidt, William and Ryan W. Buell (2017), “Experimental evidence of pooling outcomes under information asymmetry.” *Management Science*, 63, 1271–1656.

- Shannon, Claude (1948), “A mathematical theory of communication.” *Bell System Technical Journal*, 27, 379–423, 623–656.
- Simon, Leo K. and Maxwell B. Stinchcombe (1995), “Equilibrium refinement for infinite normal-form games.” *Econometrica*, 63, 1421–1443.
- Spence, Michael (1973), “Job market signaling.” *Quarterly Journal of Economics*, 87, 355–374.
- Sun, Monic (2012), “How does the variance of product ratings matter?” *Management Science*, 58, 696–707.
- Tierney, John (2013), “Your annual reminder to ignore the US News & World Report college rankings.” *The Atlantic*, URL <https://www.theatlantic.com/education/archive/2013/09/your-annual-reminder-to-ignore-the-em-us-news-world-report-em-college-rankings/279103/>. Last accessed January 5, 2021.
- Zhu, Feng and Xiaoquan Zhang (2010), “Impact of online consumer reviews on sales: The moderating role of product and consumer characteristics.” *Journal of Marketing*, 74, 133–148.

## Appendix A Proofs

We use the following notation and definitions throughout the appendix beginning with the proof of Lemma 2:

- $a_K^K$ : The product choice rule with the property that Product  $K \in \{A, B, TP\}$  is chosen upon viewing the ranking report, where  $TP$  denotes the top-ranked product, and Product  $K' \in \{A, B\}$  is the default product.

For example,  $a_A^{TP}$  refers to the rule where  $a(A) = 1$ ,  $a(B) = 0$ , and  $a(\emptyset) = 1$ . We omit the superscript or the subscript when either the product choice after viewing the report or the default product is not relevant.

- $U(\beta_0, s, a)$ : The consumer's expected utility from product choice rule  $a$  given  $\beta_0$  and her report-acquisition decision  $s$ , evaluated before she views the ranking report, if any.

Given  $\beta_0$  and  $s \in \{0, 1\}$ , the expected utilities, which are equivalent to the expressions in (1), (2), and (3), are

$$\begin{aligned} U(\beta_0, 0, a_A) &= U(\beta_0, 1, a^A) = \bar{v}_A + (1-p)(1-\beta_0)r, \\ U(\beta_0, 0, a_B) &= U(\beta_0, 1, a^B) = p\bar{v}_B + [p + (1-p)\beta_0]r, \text{ and} \\ U(\beta_0, 1, a^{TP}) &= p\bar{v}_B + (1-p)(1-\beta_0)\bar{v}_A + r. \end{aligned}$$

**Proof of Lemma 1.** Upon viewing Reports  $A$  and  $B$ , the consumer's posterior beliefs that  $v_B = \bar{v}_B$  are  $\mu_A(\beta_0) = 0$  and  $\mu_B(\beta_0) = \frac{p}{p+(1-p)\beta_0}$  respectively. (If  $\beta_0 = 1$ , then viewing Report  $A$  is a zero-probability event, and we assign belief that the probability of  $\bar{v}_B$  is zero.) The consumer's expected utilities from choosing Products  $A$  and  $B$  after viewing Report  $A$  are  $\bar{v}_A + r$  and 0 respectively, and those after viewing Report  $B$  are  $\bar{v}_A$  and  $\mu_B(\beta_0)\bar{v}_B + r$  respectively. In the former case, since  $\bar{v}_A + r > 0$ ,  $a(A) = 1$  is the optimal choice for any  $\beta_0 \in [0, 1]$ . In the latter case,  $\mu_B(\beta_0)$  achieves the minimum at  $\beta_0 = 1$ , and thus  $a(B) = 0$  is the optimal choice for any  $\beta_0 \in [0, 1]$  given the tie-breaking rule in Assumption 2 if and only if  $p\bar{v}_B + r - \bar{v}_A > 0$ . □

**Proof of Lemma 2.** Given  $\beta_0$  and the tie-breaking rule in Assumption 2, Product  $A$  is the optimal default product if and only if  $U(\beta_0, 0, a_A) \geq U(\beta_0, 0, a_B)$ . Since  $\frac{\partial[U(\beta_0, 0, a_A) - U(\beta_0, 0, a_B)]}{\partial\beta_0} = -(1-p)r < 0$ ,  $U(\beta_0, 0, a_A) - U(\beta_0, 0, a_B)$  is strictly decreasing in  $\beta_0$ . It follows that the consumer optimally chooses Product  $A$  as the default if and only if  $\beta_0 \leq \beta_{AB} = \frac{\bar{v}_A - p\bar{v}_B + (1-2p)r}{2(1-p)r}$ . □

**Proof of Proposition 1.** In equilibrium, the expert chooses a  $\beta_0$ , if one exists, so that the consumer acquires the ranking report. We prove the proposition by characterizing the consumer's equilibrium (sequentially rational) strategies under all influential ranking methods ( $p\bar{v}_B + r - \bar{v}_A > 0$  per Lemma 1).

The consumer prefers acquiring the report over not acquiring with Product  $A$  as the default if and only if  $U(\beta_0, 1, a^{TP}) - U(\beta_0, 0, a_A) - f \geq 0$ , which is equivalent to

$$\beta_0 \leq \beta_A = \frac{f - f_1}{(1-p)(r - \bar{v}_A)} \text{ and } r < \bar{v}_A, \text{ or} \quad (7)$$

$$\beta_0 \geq \beta_A = \frac{f - f_1}{(1-p)(r - \bar{v}_A)} \text{ and } r > \bar{v}_A, \quad (8)$$

where  $f_1 = p(\bar{v}_B + r - \bar{v}_A)$ . She prefers acquiring the report over not acquiring with Product  $B$  as the default if and only if  $U(\beta_0, 1, a^{TP}) - U(\beta_0, 0, a_B) - f \geq 0$ , which is equivalent to

$$\beta_0 \leq \beta^B = 1 - \frac{f}{(1-p)(\bar{v}_A + r)} < 1. \quad (9)$$

The preference conditions (7), (8), and (9) are established by fixing a default product as alternative to acquiring the report. Sequential rationality requires the default alternative to be optimal, and the condition from Lemma 2 for Product  $A$  to be the optimal default is

$$\beta_0 \leq \beta_{AB} = \frac{\bar{v}_A - p\bar{v}_B + (1-2p)r}{2(1-p)r}, \quad (10)$$

where the equilibria are characterized for parameters that satisfy  $0 \leq \beta_{AB} < 1$ . We let  $f_2 = \frac{(p\bar{v}_B - \bar{v}_A + r)(\bar{v}_A + r)}{2r}$  and use conditions (7)–(10) and the tie-breaking rule in Assumption 2 to complete the proof.

For part (a) of the proposition where  $r < \bar{v}_A$  so that  $f_2 \leq f_1$ , (i) if  $f \in (0, f_2]$ , then the three thresholds in (7), (9), and (10) satisfy  $0 \leq \beta_{AB} \leq \beta_B \leq \beta_A$ , (ii) if  $f \in (f_2, f_1]$ , then the thresholds satisfy  $0 \leq \beta_A < \beta_B < \beta_{AB} < 1$ , and (iii) if  $f \in (f_1, \infty)$ , then the thresholds satisfy  $\beta_A < \beta_B < \beta_{AB} < 1$  and  $\beta_A < 0$ . The following thus constitute the sequentially rational strategies of the consumer: for case (i),  $s(\beta_0) = 1$  with  $a_A^{TP}$  for  $\beta_0 \in [0, \beta_{AB}]$ ,  $s(\beta_0) = 1$  with  $a_B^{TP}$  for  $\beta_0 \in (\beta_{AB}, \beta_B]$ , and  $s(\beta_0) = 0$  with  $a_B^{TP}$  for  $\beta_0 \in (\beta_B, 1]$ ; for case (ii),  $s(\beta_0) = 1$  with  $a_A^{TP}$  for  $\beta_0 \in [0, \beta_A]$ ,  $s(\beta_0) = 0$  with  $a_A^{TP}$  for  $\beta_0 \in (\beta_A, \beta_{AB}]$ , and  $s(\beta_0) = 0$  with  $a_B^{TP}$  for  $\beta_0 \in (\beta_{AB}, 1]$ ; and for case (iii),  $s(\beta_0) = 0$  with  $a_A^{TP}$  for  $\beta_0 \in [0, \beta_{AB}]$ , and  $s(\beta_0) = 0$  with  $a_B^{TP}$  for  $\beta_0 \in (\beta_{AB}, 1]$ .

For part (b) of the proposition where  $r > \bar{v}_A$  so that  $f_1 \leq f_2$ , (i) if  $f \in (0, f_1]$ , then the three thresholds in (8), (9), and (10) satisfy  $\beta_A \leq 0 \leq \beta_{AB} \leq \beta_B < 1$ , (ii) if  $f \in (f_1, f_2]$ , then the thresholds satisfy  $0 < \beta_A \leq \beta_{AB} \leq \beta_B < 1$ , and (iii) if  $f \in (f_2, \infty)$ , then the thresholds satisfy  $\beta_B < \beta_{AB} < \beta_A$ . The following thus constitute the sequentially rational strategies of

the consumer: for case (i),  $s(\beta_0) = 1$  with  $a_A^{TP}$  for  $\beta_0 \in [0, \beta_{AB}]$ ,  $s(\beta_0) = 1$  with  $a_B^{TP}$  for  $\beta_0 \in (\beta_{AB}, \beta_B]$ , and  $s(\beta_0) = 0$  with  $a_B^{TP}$  for  $\beta_0 \in (\beta_B, 1]$ ; for case (ii),  $s(\beta_0) = 0$  with  $a_A^{TP}$  for  $\beta_0 \in (0, \beta_A)$ ,  $s(\beta_0) = 1$  with  $a_A^{TP}$  for  $\beta_0 \in [\beta_A, \beta_{AB}]$ ,  $s(\beta_0) = 1$  with  $a_B^{TP}$  for  $\beta_0 \in (\beta_{AB}, \beta_B]$ , and  $s(\beta_0) = 0$  with  $a_B^{TP}$  for  $\beta_0 \in (\beta_B, 1]$ ; and for case (iii),  $s(\beta_0) = 0$  with  $a_A^{TP}$  for  $\beta_0 \in [0, \beta_{AB}]$  and  $s(\beta_0) = 0$  with  $a_B^{TP}$  for  $\beta_0 \in (\beta_{AB}, 1]$ . □

**Proof of Corollary 1.** The derivative of  $\beta_A(r)$  with respect to  $r$  is  $\frac{\partial \beta_A(r)}{\partial r} = \frac{f_1 - f}{(1-p)(r - \bar{v}_A)^2}$ . According to Proposition 1 and its proof, for  $r < \bar{v}_A$ ,  $\beta_A(r) \in [0, 1]$  is the upper bound on  $\beta_0$  only if  $f \leq f_1$ , and thus  $\frac{\partial \beta_A(r)}{\partial r} \geq 0$  with strict inequality if  $f < f_1$ ; for  $r > \bar{v}_A$ ,  $\beta_A(r) \in [0, 1]$  is the lower bound on  $\beta_0$  only if  $f \geq f_1$ , and thus  $\frac{\partial \beta_A(r)}{\partial r} \leq 0$  with strict inequality if  $f > f_1$ . □

**Proof of Corollary 2.** The corollary follows from the fact that  $\frac{\partial \beta_B(r)}{\partial r} = \frac{f}{(1-p)(\bar{v}_A + r)^2} > 0$ . □

**Proof of Proposition 2.** Let  $\mathcal{B}_0^{\text{SPE}}$  be the set of all subgame-perfect acquisition equilibrium ranking methods. Since  $\frac{\partial U(\beta_0, 1, a^{TP})}{\partial \beta_0} = -(1-p)\bar{v}_A < 0$ , the unique efficient acquisition equilibrium admits  $\beta_0 = \min\{\mathcal{B}_0^{\text{SPE}}\}$ . The proposition follows from the characterization of  $\min\{\mathcal{B}_0^{\text{SPE}}\}$  in the different cases in Proposition 1. □

**Proof of Proposition 3.** Let  $\mathcal{B}_0^{\text{SPE}}$  be the set of all subgame-perfect acquisition equilibrium ranking methods. We prove the proposition by first verifying the following claim:

**Claim.** *If  $\beta_0$  is a robust acquisition equilibrium ranking method, then  $\beta_0 \in \operatorname{argmax}_{\hat{\beta}_0 \in \mathcal{B}_0^{\text{SPE}}} G(\hat{\beta}_0, 0)$ .*

In any  $\epsilon$ -constrained acquisition equilibrium, the consumer's totally mixed  $\sigma_\epsilon$  satisfies: for any  $\beta_0 \in [0, 1]$ , if  $V(\beta_0, 1, a(\beta_0, 1)) \geq V(\beta_0, 0, a(\beta_0, 0))$ , then  $\sigma_\epsilon(\beta_0, 0) = e_\epsilon(\beta_0, 0)$ , and if  $V(\beta_0, 1, a(\beta_0, 1)) < V(\beta_0, 0, a(\beta_0, 0))$ , then  $\sigma_\epsilon(\beta_0, 1) = e_\epsilon(\beta_0, 1)$ , where  $V(\beta_0, 1, a(\beta_0, 1)) = U(\beta_0, 1, a^{TP}) - f$ ,  $V(\beta_0, 0, a(\beta_0, 0)) = \max\{U(\beta_0, 0, a_A), U(\beta_0, 0, a_B)\}$ , and  $e_\epsilon \in (0, \epsilon)$ . Note that the use of weak inequality in the first case follows from the tie-breaking rule in Assumption 2.

It follows from the definition of  $G$  that for  $\beta_0 \in [0, 1]$  where  $G(\beta_0, 0) = V(\beta_0, 1, a(\beta_0, 1)) - V(\beta_0, 0, a(\beta_0, 0)) \geq 0$ ,  $\sigma_\epsilon(\beta_0, 0) = e_\epsilon(\beta_0, 0)$ , and for  $\beta_0 \in [0, 1]$  where  $G(\beta_0, 1) = V(\beta_0, 0, a(\beta_0, 0)) - V(\beta_0, 1, a(\beta_0, 1)) > 0$ ,  $\sigma_\epsilon(\beta_0, 1) = e_\epsilon(\beta_0, 1)$ . This totally mixed report-acquisition rule induces the following expected payoff for the expert from choosing  $\beta_0 \in [0, 1]$ :

$$\pi\{[1 - e_\epsilon(\beta_0, 0)]\mathbb{I}_G + e_\epsilon(\beta_0, 1)(1 - \mathbb{I}_G)\}, \quad (11)$$

where  $\mathbb{I}_G \in \{0, 1\}$  takes the value of one if  $G(\beta_0, 0) \geq 0$  and zero if  $G(\beta_0, 1) > 0$ . Since  $1 - e_\epsilon(\beta_0, 0) > e_\epsilon(\beta_0, 1)$  for  $e_\epsilon(\beta_0, 0) < \frac{1}{2}$  and  $e_\epsilon(\beta_0, 1) < \frac{1}{2}$ , in any  $\epsilon$ -constrained acquisition equilibrium with  $\epsilon < \frac{1}{2}$ , the expert must choose a  $\beta_0$  for which  $G(\beta_0, 0) \geq 0$ , and the expression of the expert's expected payoff in (11) reduces to  $\pi[1 - e_\epsilon(\beta_0, 0)]$ .

We next invoke the strict loss monotonicity of  $e_\epsilon$ , which implies that  $e_\epsilon(\beta_0, 0)$  is strictly decreasing in  $G(\beta_0, 0)$ . Therefore, in any  $\epsilon$ -constrained acquisition equilibrium with  $\epsilon < \frac{1}{2}$ , by best responding to the consumer's constrained optimal  $\sigma_\epsilon$ , choosing a  $\beta_0$  that maximizes  $\pi[1 - \sigma_\epsilon(\beta_0, 0)] = \pi[1 - e_\epsilon(\beta_0, 0)]$ , the expert also chooses a  $\beta_0$  that maximizes  $G(\beta_0, 0)$ . The claim follows by noting that a robust acquisition equilibrium is any limit of  $\epsilon$ -constrained acquisition equilibria as  $\epsilon \rightarrow 0$ , and thus  $\epsilon < \frac{1}{2}$  must hold approaching the limit.

The remainder of the proof solves  $\max_{\beta_0 \in \mathcal{D}_0^{\text{SPE}}} G(\beta_0, 0)$ . There are two instances for the derivative of  $G(\beta_0, 0)$ : (i)  $\frac{\partial G(\beta_0, 0)}{\partial \beta_0} = (1-p)(r - \bar{v}_A)$  for the case where  $U(\beta_0, 0, a_A) \geq U(\beta_0, 0, a_B)$ , and (ii)  $\frac{\partial G(\beta_0, 0)}{\partial \beta_0} = -(1-p)(\bar{v}_A + r)$  for the case where  $U(\beta_0, 0, a_A) < U(\beta_0, 0, a_B)$ . If  $r < \bar{v}_A$ , then  $\frac{\partial G(\beta_0, 0)}{\partial \beta_0} < 0$  in both cases (i) and (ii), and according to Proposition 1(a) the unique solution to the maximization problem is  $\beta_0 = 0$ . If  $r > \bar{v}_A$ , then  $\frac{\partial G(\beta_0, 0)}{\partial \beta_0} > 0$  in case (i) and  $\frac{\partial G(\beta_0, 0)}{\partial \beta_0} < 0$  in case (ii). From the proof of Proposition 1(b), the unique relevant solution to the maximization problem is  $\beta_0 = \beta_{AB}$  from case (i), where  $0 \leq \beta_{AB} < 1$ . Finally, we note that while the claim above states a necessary condition, the unique solution to the maximization problem implies that the robust acquisition equilibrium in each case of  $r < \bar{v}_A$  and  $r > \bar{v}_A$  exists and is unique. □



# Appendix B Translated Sample Experimental Instructions: Treatment *HH*

## Experimental Instructions

### Screen 1

Welcome to this economic experiment about decision making. The experiment will take approximately 1 hour. You and other participants will engage in 40 rounds of decision making.

Please read the instructions carefully. A correct understanding of the instructions is essential for making sound decisions and affects the payment you will receive at the end of the experiment.

Click “Next” below to learn about your roles in the experiment.

-----

### Screen 2

#### Roles in Experiment

There are 20 participants in today’s session. The computer will randomly assign 10 participants the role of **product expert** (hereafter “expert” for short) and the other 10 the role of **consumer**. The role of each participant remains fixed throughout the experiment.

At the beginning of each round, the computer will randomly match one expert with one consumer. The two participants form a decision group for the round (in total 10 groups).

After each round, the computer will randomly rematch to form the groups, and the matching in each round will be anonymous.

Click “Next” below for an overview of your experimental tasks.

-----

### Screen 3

#### Experimental Tasks: Overview

In the experiment, there are two products with different values for the consumer to choose. The products are **Product A** and **Product B**, which are illustrated in Figure A.1:

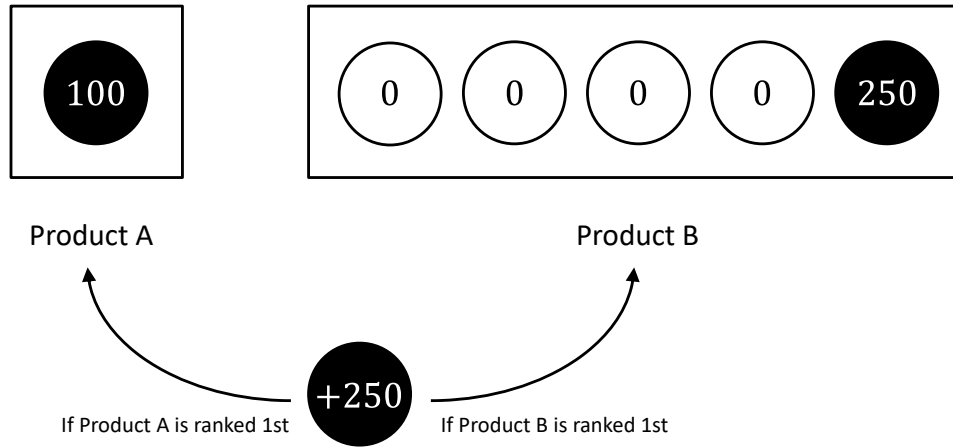


Figure A.1: Product Values

- The value of Product A is fixed at 100 Experimental Currency Unit (ECU).
- The value of Product B is either 0 or 250 ECU. In each round, the computer randomly draws a ball in the box representing Product B (Figure A.1), i.e., the chance of 0 is 80%, and that of 250 is 20%.

If the value of Product B is 0, then Product A is relatively better; if the value of Product B is 250, then Product B is relatively better. When choosing a product, the consumer does not know which product is better but may obtain certain useful product information from the expert.

The product information provided by the expert takes the form of product ranking and is costly for the consumer to obtain. In each round, the expert's task is to choose a **ranking method** to rank the two products. In addition to its value, the first ranked product would be worth an extra 250 ECU.

In each round, the consumer has two tasks: (1) decide whether to pay 110 ECU to see the ranking outcome (which product is ranked first), and (b) choose one of the two products.

Click “Next” below to learn more about the expert's task.

-----

## Screen 4

### Expert's Task: Choose Ranking Method

A “ranking method” is a relationship between the ranking of the products and the value of Product B. There are five ranking methods for the expert to choose.

When Product B is better (its value is randomly drawn to be 250), all five methods rank Product B first; the differences between the five methods lie in the chances that Product B is still ranked first when it is not better (its value is drawn to be 0, i.e., Product A is better). Table A.1 below provides the details:

Table A.1: Five Choices of Ranking Methods

	Chance that Product B is Ranked First	
	When Product A is better (Product B value = 0)	When Product B is better (Product B value = 250)
Method 1	0%	100%
Method 2	25%	100%
Method 3	50%	100%
Method 4	75%	100%
Method 5	100%	100%

According to Table A.1 and the fact that the chances of 0 and 250 as the value of Product B are 80% and 20% respectively, the five ranking methods and their corresponding chances of generating different ranking outcomes can be represented by the bars in Figure A.2 below:

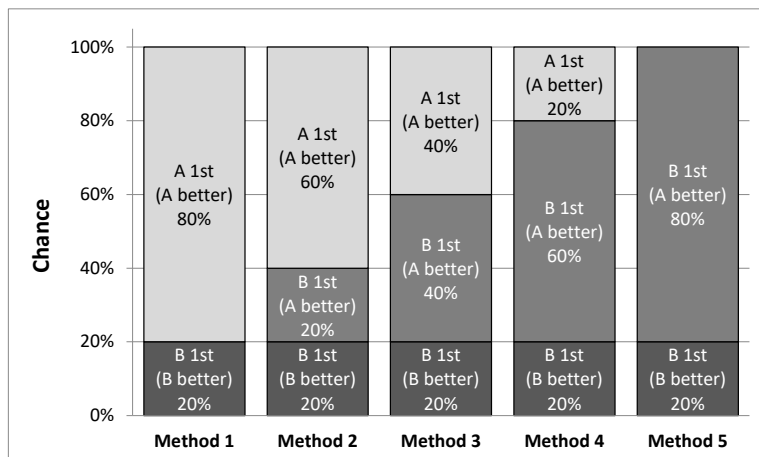


Figure A.2: Five Choices of Ranking Methods

Figure A.2 will be shown on the expert's choice interface. In each round before the computer draws the value of Product B, the expert chooses one of the ranking methods.

Reminder: When choosing a ranking method, the expert does not know which product will be better.

Click “Next” below to learn more about the first task of the consumer.

-----

### Screen 5

#### Consumer’s First Task: Decide Whether to Pay to See Product Ranking

After the expert chooses a ranking method, the chosen method will be revealed to the matched consumer. As an example, suppose that the expert has chosen “Method 3.” The consumer will be shown Figure A.3 below.

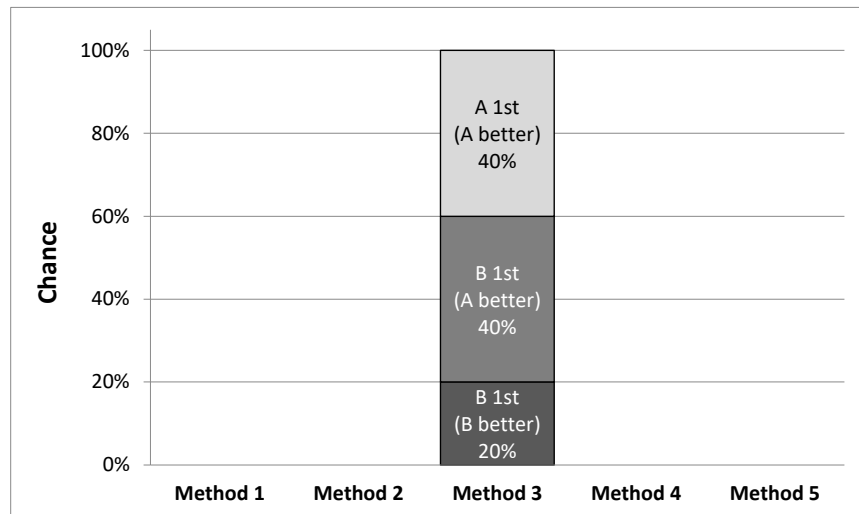


Figure A.3: Example of Ranking Method Chosen by Expert

The computer randomly draws the value of Product B and, based on this value, ranks the two products according to the ranking method chosen by the expert.

Reminder: The expert does not directly rank the products. The expert chooses a ranking method beforehand and then let the computer execute the method and automatically rank the products based on the value of Product B.

In each round, after seeing the ranking method chosen by the expert, the consumer decides whether to pay 110 ECU to see the ranking outcome. By paying 110 ECU, the consumer sees only which product is ranked first and will not be shown the randomly drawn value of Product B.

Click “Next” below to learn more about the second task of the consumer.

-----

## Screen 6

### Consumer's Second Task: Choose Product

Using the above example where the expert has chosen Method 3, if the consumer chooses to pay to see the ranking outcome, Figure A.3 above will be updated to one of the charts in Figure A.4 below to reveal to the consumer which product has been ranked first in that round.

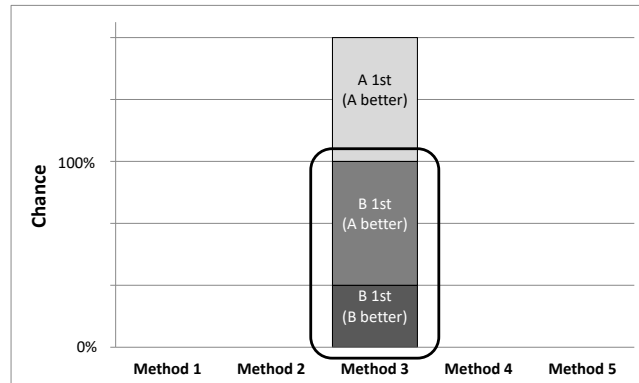


Figure A.4: Example of Product Rankings Revealed

Continuing with the example, if the consumer chooses not to pay, the whole bar in Figure A.3 above will remain without any update.

Irrespective of whether the consumer chooses to pay to see the ranking outcome, the consumer then chooses between Products A and B. After the consumer chooses a product, all the tasks in the round are completed.

Click “Next” below to learn about the expert’s reward in each round.

-----

## Screen 7

### Expert's Reward in Each Round

All participants, experts or consumers, earn their rewards in the experiment in terms of ECU. How the ECU is converted into cash payment will be explained momentarily.

In each round, the expert earns 300 ECU if the matched consumer pays to see the ranking outcome; if the consumer chooses not to pay, the expert will earn 0 ECU.

Click “Next” below to learn about the consumer’s reward in each round.

-----

## Screen 8

### Consumer's Reward in Each Round

The consumer's total reward in each round is made up of three parts:

- Earning: The value of the chosen product.

If Product A is chosen, then the consumer earns 100 ECU; if Product B is chosen, then depending on which value is drawn by the computer the consumer earns either 0 or 250 ECU.

- Earning: Extra 250 ECU if the first-ranked product is chosen.

Even if the consumer does not pay to see the ranking outcome, so long as the chosen product has been ranked first, the consumer will still earn 250 ECU.

- Paying: 110 ECU if deciding to see the ranking outcome.

Click "Next" to learn about the result feedback provided at the end of each round.

-----

## Screen 9

### Result Feedback

At the end of each round, the computer will summarize for you the results in that round, which include the following information:

- Expert's choice of ranking method
- Value of Product B drawn by computer
- First-ranked product
- Consumer's decision whether to see ranking outcome
- Consumer's product choice
- Your reward for the round

A history of the above result items in all previous rounds will also be provided.

Click "Next" below to learn about the payment from the experiment.

-----

## Screen 10

### Payment from Experiment

After completing all rounds, the computer will randomly select 3 rounds out of the 40 rounds of results and calculate the average of the ECU earned in these 3 rounds for your payment. So it is in your interest to take each round equally seriously as they are equally important.

The average of the ECU earned in these 3 rounds will be converted at an exchange rate of 4 ECU for 1 RMB as your cash payment. In addition, you will receive a fixed participation fee of 20 RMB.

The above are all of the experimental instructions. To ensure that you fully understand the instructions, please complete a short quiz. The quiz result will not count toward your payment.

Click “Next” below to start the quiz.

-----

## Screen 11

### Quiz

1. If the value of Product B is drawn to be 250, then Product A is better.
  - (a) True
  - (b) False
2. The expert chooses a ranking method after seeing whether 0 or 250 is drawn to be the value of Product B.
  - (a) True
  - (b) False
3. The expert has direct control over which product is ranked first.
  - (a) True
  - (b) False

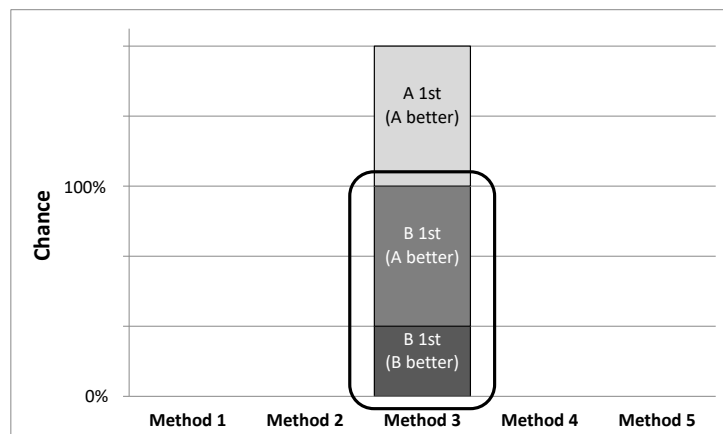
4. If the consumer does not pay to see which product is ranked first, the consumer will never earn the 250 ECU.

- (a) True
- (b) False

5. If the consumer pays to see which product is ranked first, the consumer will learn for sure which product is better (i.e., whether the value of Product B is 0 or 250).

- (a) True
- (b) False

6. Refer to the example in the following figure. The expert chooses Method 3, the consumer pays to see the ranking outcome, and the ranking outcome is that Product B is ranked first. Which of the following best describes the chance of which product is better?



- (a) Product A must be (100%) better.
- (b) Product B must be (100%) better.
- (c) Products A and B are equally likely (50–50%) to be better.
- (d) Product A has 40% chance to be better, and Product B has 20% chance to be better.
- (e) Product A has 66.67% ( $\frac{2}{3}$ ) chance to be better, and Product B has 33.33% ( $\frac{1}{3}$ ) chance to be better.

Click “Next” below to start a practice round. The practice-round result will not count toward your payment.



# Appendix C General Ranking Method (Online, Not Intended for Publication)

## C.1 The Two-Dimensional Ranking-Report Game

Recall that a ranking method is a mapping,  $\beta : \{0, \bar{v}_B\} \rightarrow [0, 1]$ , that specifies for each possible intrinsic value of Product  $B$  a probability that Report  $B$  is issued. For simplicity, in the game that forms the basis of our experiment we restrict attention to the class of ranking methods where  $\beta(\bar{v}_B) = 1$ . In this appendix, we analyze a general class of ranking methods.

Identifying a ranking method by a pair  $(\beta_0, \beta_{\bar{v}_B}) = (\beta(0), \beta(\bar{v}_B))$ , we consider  $\beta_0 \in [0, 1]$  and  $\beta_{\bar{v}_B} \in [0, 1]$  that satisfy, without loss of generality,  $\beta_{\bar{v}_B} \geq \beta_0$ .<sup>34</sup> We denote the set of these ranking methods by  $\mathcal{B} = \{(\beta_0, \beta_{\bar{v}_B}) \in [0, 1]^2 : \beta_{\bar{v}_B} \geq \beta_0\}$  and call the game the *two-dimensional ranking-report game*, referring to the version in the main text as one-dimensional. A pure strategy of the expert is now a choice  $(\beta_0, \beta_{\bar{v}_B}) \in \mathcal{B}$ , and a report-acquisition pure decision rule of the consumer is  $s : \mathcal{B} \rightarrow \{0, 1\}$ . Other elements of the game, including the parameter restriction in Assumption 1 and the tie-breaking rule in Assumption 2, remain the same.

Our main results are that the set of equilibrium ranking methods of the one-dimensional game is a subset of those of the two-dimensional game (Proposition C.1 and Corollary C.1), and more importantly the efficient and robust equilibrium ranking methods of the two games coincide (Proposition C.2 and Corollary C.2). The results suggest that our pursuit of a parsimonious experimental game achieves the purpose without sacrificing the key features of equilibria; the tradeoff between simplicity and generality, we contend, favors simplicity.

## C.2 Equilibrium Analysis

Adopting the notations introduced in Appendix A, we denote by  $a_K^K$ , the product choice rule where Product  $K \in \{A, B, TP\}$  is chosen upon viewing the ranking report and Product  $K' \in \{A, B\}$  is the default product, omitting the superscript or the subscript when the contingency is not relevant for the analysis in question. We denote by  $U((\beta_0, \beta_{\bar{v}_B}), s, a)$  the consumer's expected utility from product choice rule  $a$  given ranking method  $(\beta_0, \beta_{\bar{v}_B})$  and her report-acquisition decision  $s$ , evaluated before she views the ranking report, if any. The cases of the

---

<sup>34</sup>We have adopted the semantics to label the report generated with  $\beta_0$  and  $\beta_{\bar{v}_B}$  as Report  $B$  with meaning that Product  $B$  is ranked first. It is, however, the profile of these probabilities that determines the meaning of a report in equilibrium. Swapping “Report  $A$ ” and “Report  $B$ ” with everything else unchanged results in the same set of equilibria up to different labels of reports. Likewise, assuming  $\beta_{\bar{v}_B} \leq \beta_0$  only yields mirror cases.

expected utilities are

$$U((\beta_0, \beta_{\bar{v}_B}), 0, a_A) = U((\beta_0, \beta_{\bar{v}_B}), 1, a^A) = \bar{v}_A + [p(1 - \beta_{\bar{v}_B}) + (1 - p)(1 - \beta_0)]r, \quad (\text{C.1})$$

$$U((\beta_0, \beta_{\bar{v}_B}), 0, a_B) = U((\beta_0, \beta_{\bar{v}_B}), 1, a^B) = p\bar{v}_B + [p\beta_{\bar{v}_B} + (1 - p)\beta_0]r, \text{ and} \quad (\text{C.2})$$

$$U((\beta_0, \beta_{\bar{v}_B}), 1, a^{TP}) = p\beta_{\bar{v}_B}\bar{v}_B + [p(1 - \beta_{\bar{v}_B}) + (1 - p)(1 - \beta_0)]\bar{v}_A + r. \quad (\text{C.3})$$

Abusing notation somewhat by reusing  $G$  employed in the main text with a slightly different meaning here, we define:

$$G((\beta_0, \beta_{\bar{v}_B}), a^{TP}, a_A) = [U((\beta_0, \beta_{\bar{v}_B}), 1, a^{TP}) - f] - U((\beta_0, \beta_{\bar{v}_B}), 0, a_A), \quad (\text{C.4})$$

$$G((\beta_0, \beta_{\bar{v}_B}), a^{TP}, a_B) = [U((\beta_0, \beta_{\bar{v}_B}), 1, a^{TP}) - f] - U((\beta_0, \beta_{\bar{v}_B}), 0, a_B), \text{ and} \quad (\text{C.5})$$

$$G((\beta_0, \beta_{\bar{v}_B}), a_A, a_B) = U((\beta_0, \beta_{\bar{v}_B}), 0, a_A) - U((\beta_0, \beta_{\bar{v}_B}), 0, a_B). \quad (\text{C.6})$$

The following indifference conditions,  $G((\beta_0, \beta_{\bar{v}_B}), a^{TP}, a_A) = 0$ ,  $G((\beta_0, \beta_{\bar{v}_B}), a^{TP}, a_B) = 0$ , and  $G((\beta_0, \beta_{\bar{v}_B}), a_A, a_B) = 0$ , identify the set of ranking methods under which the consumer is indifferent, respectively, between acquiring the ranking report and not acquiring with default Product  $A$ , between acquiring the report and not acquiring with default Product  $B$ , and, in the case of not acquiring the report, between Products  $A$  and  $B$  as the default. Isolating  $\beta_0$  in the three conditions gives rise to the following three functions, each of which characterizes for given  $\beta_{\bar{v}_B}$  the value of  $\beta_0$  such that the consumer exhibits the respective indifference:

$$\beta_0 = \phi_A(\beta_{\bar{v}_B}) = \frac{f - p(\bar{v}_B + r - \bar{v}_A)\beta_{\bar{v}_B}}{(1 - p)(r - \bar{v}_A)}, \quad (\text{C.7})$$

$$\beta_0 = \phi_B(\beta_{\bar{v}_B}) = 1 - \frac{f - p(\bar{v}_A + r - \bar{v}_B)(1 - \beta_{\bar{v}_B})}{(1 - p)(\bar{v}_A + r)}, \text{ and} \quad (\text{C.8})$$

$$\beta_0 = \phi_{AB}(\beta_{\bar{v}_B}) = \frac{\bar{v}_A - p\bar{v}_B + (1 - 2p\beta_{\bar{v}_B})r}{2(1 - p)r}. \quad (\text{C.9})$$

For  $\beta_{\bar{v}_B} = 1$ , (C.7)–(C.9) reduce to the three thresholds in the one-dimensional game:  $\phi_A(1) = \beta_A$ ,  $\phi_B(1) = \beta_B$ , and  $\phi_{AB}(1) = \beta_{AB}$ . We further define  $(I_0, I_{\bar{v}_B})$  where  $I_0 = \phi_A(I_{\bar{v}_B}) = \phi_B(I_{\bar{v}_B}) = \phi_{AB}(I_{\bar{v}_B})$ , i.e.,  $(I_0, I_{\bar{v}_B})$  is the point where all three indifference conditions are satisfied.

We characterize the subgame-perfect equilibria using these functions and  $(I_0, I_{\bar{v}_B})$ . As for the one-dimensional game, we restrict attention to the cases where all ranking methods are influential and  $0 \leq \phi_{AB}(1) = \beta_{AB} < 1$ . The following lemma shows that in the two-dimensional game the condition for all influential ranking methods calls for an additional upper bound, and  $0 \leq \phi_{AB}(1) = \beta_{AB} < 1$ , which in the one-dimensional game ensures that both products have the potential to be the optimal default, now guarantees that for Product  $A$ :

**Lemma C.1.** *In the two-dimensional game,*

- (a) *all ranking methods are influential, i.e.,  $a(A) = 1$  and  $a(B) = 0$  are optimal under all  $(\beta_0, \beta_{\bar{v}_B}) \in \mathcal{B}$ , if and only if  $0 < p\bar{v}_B + r - \bar{v}_A \leq 2r$ , and*
- (b) *if  $0 \leq \phi_{AB}(1) = \beta_{AB} < 1$ , then there always exists  $(\beta_0, \beta_{\bar{v}_B}) \in \mathcal{B}$  such that  $a(\emptyset) = 1$  is optimal under  $(\beta_0, \beta_{\bar{v}_B})$ .*

As we have done for Proposition 1, we organize the equilibrium cases by compartmentalizing the possible parameters into six categories based on the relative sizes of  $r$  and  $\bar{v}_A$  and the size of  $f$  relative to  $f_1 = p(\bar{v}_B + r - \bar{v}_A)$  and  $f_2 = \frac{(p\bar{v}_B - \bar{v}_A + r)(\bar{v}_A + r)}{2r}$ . The following proposition characterizes the expert's equilibrium choices of ranking method in the six cases:

**Proposition C.1.** *In any pure-strategy subgame-perfect equilibrium of the two-dimensional game in which all ranking methods  $(\beta_0, \beta_{\bar{v}_B}) \in \mathcal{B}$  are influential and  $0 \leq \phi_{AB}(1) < 1$ ,*

- (a) *for  $r < \bar{v}_A$  so that  $f_2 \leq f_1$ ,*
  - (i) *if  $f \in (0, f_2]$ , then the expert chooses a  $(\beta_0, \beta_{\bar{v}_B}) \in \mathcal{B}_1 \cup \mathcal{B}_2$  to sell the ranking report, where*

$$\mathcal{B}_1 = \{(\beta_0, \beta_{\bar{v}_B}) \in \mathcal{B} : \beta_0 \in [0, \min\{\phi_A(\beta_{\bar{v}_B}), 1\}] \text{ and } \beta_{\bar{v}_B} \in [\phi_A^{-1}(0), I_{\bar{v}_B}]\} \text{ and}$$

$$\mathcal{B}_2 = \{(\beta_0, \beta_{\bar{v}_B}) \in \mathcal{B} : \beta_0 \in [0, \min\{\phi_B(\beta_{\bar{v}_B}), 1\}] \text{ and } \beta_{\bar{v}_B} \in [I_{\bar{v}_B}, 1]\},$$
  - (ii) *if  $f \in (f_2, f_1]$ , then the expert chooses a  $(\beta_0, \beta_{\bar{v}_B}) \in \mathcal{B}_3$  to sell the ranking report, where  $\mathcal{B}_3 = \{(\beta_0, \beta_{\bar{v}_B}) \in \mathcal{B} : \beta_0 \in [0, \phi_A(\beta_{\bar{v}_B})] \text{ and } \beta_{\bar{v}_B} \in [\phi_A^{-1}(0), 1]\}$ , and*
  - (iii) *if  $f \in (f_1, \infty)$ , then the expert chooses a  $(\beta_0, \beta_{\bar{v}_B}) \in \mathcal{B}$  without selling the ranking report;*
- (b) *for  $r > \bar{v}_A$  so that  $f_1 \leq f_2$ ,*
  - (i) *if  $f \in (0, f_1]$ , then the expert chooses a  $(\beta_0, \beta_{\bar{v}_B}) \in \mathcal{B}_4$  to sell the ranking report, where  $\mathcal{B}_4 = \{(\beta_0, \beta_{\bar{v}_B}) \in \mathcal{B} : \beta_0 \in [\max\{0, \phi_A(\beta_{\bar{v}_B})\}, \min\{\phi_B(\beta_{\bar{v}_B}), 1\}] \text{ and } \beta_{\bar{v}_B} \in [\max\{0, \phi_A^{-1}(1), I_{\bar{v}_B}\}, 1]\}$ ,*
  - (ii) *if  $f \in (f_1, f_2]$ , then the expert chooses a  $(\beta_0, \beta_{\bar{v}_B}) \in \mathcal{B}_5$  to sell the ranking report, where  $\mathcal{B}_5 = \{(\beta_0, \beta_{\bar{v}_B}) \in \mathcal{B} : \beta_0 \in [\phi_A(\beta_{\bar{v}_B}), \phi_B(\beta_{\bar{v}_B})] \text{ and } \beta_{\bar{v}_B} \in [\max\{0, I_{\bar{v}_B}\}, 1]\}$ , and*
  - (iii) *if  $f \in (f_2, \infty)$ , then the expert chooses a  $(\beta_0, \beta_{\bar{v}_B}) \in \mathcal{B}$  without selling the ranking report.*

With  $\beta_{\bar{v}_B}$  fixed at one in the one-dimensional game, we have referred to  $\beta_0$  as a ranking method there. It is obvious that all  $\beta_0 \in [0, 1]$  paired with  $\beta_{\bar{v}_B} = 1$ , the set of these one-dimensional ranking methods, is nested in  $\mathcal{B}$ . A key question of interest is whether this nested property extends to equilibria. In this regard, note that every case of the equilibrium sets of ranking methods characterized in Proposition C.1 includes  $\beta_{\bar{v}_B} = 1$ . Also recall that  $\phi_A(1) = \beta_A$  and  $\phi_B(1) = \beta_B$ . The following corollary, which is then immediate from comparing Proposition C.1 with Proposition 1, gives an affirmative answer to the question:

**Corollary C.1.** *For a given  $f$ , if  $\beta_0$  is a subgame-perfect equilibrium ranking method of the one-dimensional game, then  $(\beta_0, 1)$  is a subgame-perfect equilibrium ranking method of the two-dimensional game.*

This nested property of equilibria suggests that by streamlining the environment from two dimensional to one dimensional, we reduce the set of equilibrium ranking methods but do not come by cases that are not equilibria in the more general environment. We proceed to characterize the efficient and robust acquisition equilibria of the two-dimensional game, in which the refinements of equilibria also refine the nested property to an equivalence property.<sup>35</sup>

**Proposition C.2.** *For  $r < \bar{v}_A$ , both the unique efficient acquisition equilibrium and the unique robust acquisition equilibrium admit  $(\beta_0, \beta_{\bar{v}_B}) = (0, 1)$ . For  $r > \bar{v}_A$ , the unique efficient acquisition equilibrium admits  $(\beta_0, \beta_{\bar{v}_B}) = (0, 1)$  if  $f \in (0, f_1]$  and  $(\beta_0, \beta_{\bar{v}_B}) = (\beta_A, 1)$  if  $f \in (f_1, f_2]$ , while the unique robust acquisition equilibrium admits  $(\beta_0, \beta_{\bar{v}_B}) = (\beta_{AB}, 1)$ .*

Juxtaposing Proposition C.2 with Propositions 2 and 3 for the one-dimensional game makes apparent the following equivalence property:

**Corollary C.2.** *The unique efficient (robust) acquisition equilibrium of the two-dimensional game admits  $(\beta_0, 1)$  if and only if the unique efficient (robust) acquisition equilibrium of the one-dimensional game admits  $\beta_0$ .*

While the subgame-perfect acquisition equilibria of the two-dimensional game admit  $\beta_{\bar{v}_B} < 1$ , both the efficient and robust acquisition equilibria admit only  $\beta_{\bar{v}_B} = 1$ . The exogenously imposed restriction of the one-dimensional game where product guidance is always provided when  $v_B = \bar{v}_B$  arise endogenously as a property of the refined equilibria in the two-dimensional game. In the unique efficient and robust equilibria of the two-dimensional game, misguidance and shuffling may occur only under one dimension with  $\beta_0$  when  $v_B = 0$ .

Figure C.1 depicts the set of acquisition equilibrium ranking methods of the two-dimensional game under the parameters of our four experimental treatments. The top side of each unit

<sup>35</sup>Both refinements, which operate on the consumer's payoff, can be directly extended to the two-dimensional game where the change is with the expert's choice set.

square contains for the corresponding treatment the equilibria of the one-dimensional game. Echoing Corollary C.2, the efficient and robust acquisition equilibria of the two-dimensional game lie on these top sides of the squares. Although we lose some generality by focusing on the one-dimensional case for the experimental game, given that the two refined equilibria serve important roles in the interpretation of our data, our experimental design based on the one-dimensional game allow us to focus on the dimension of interest.

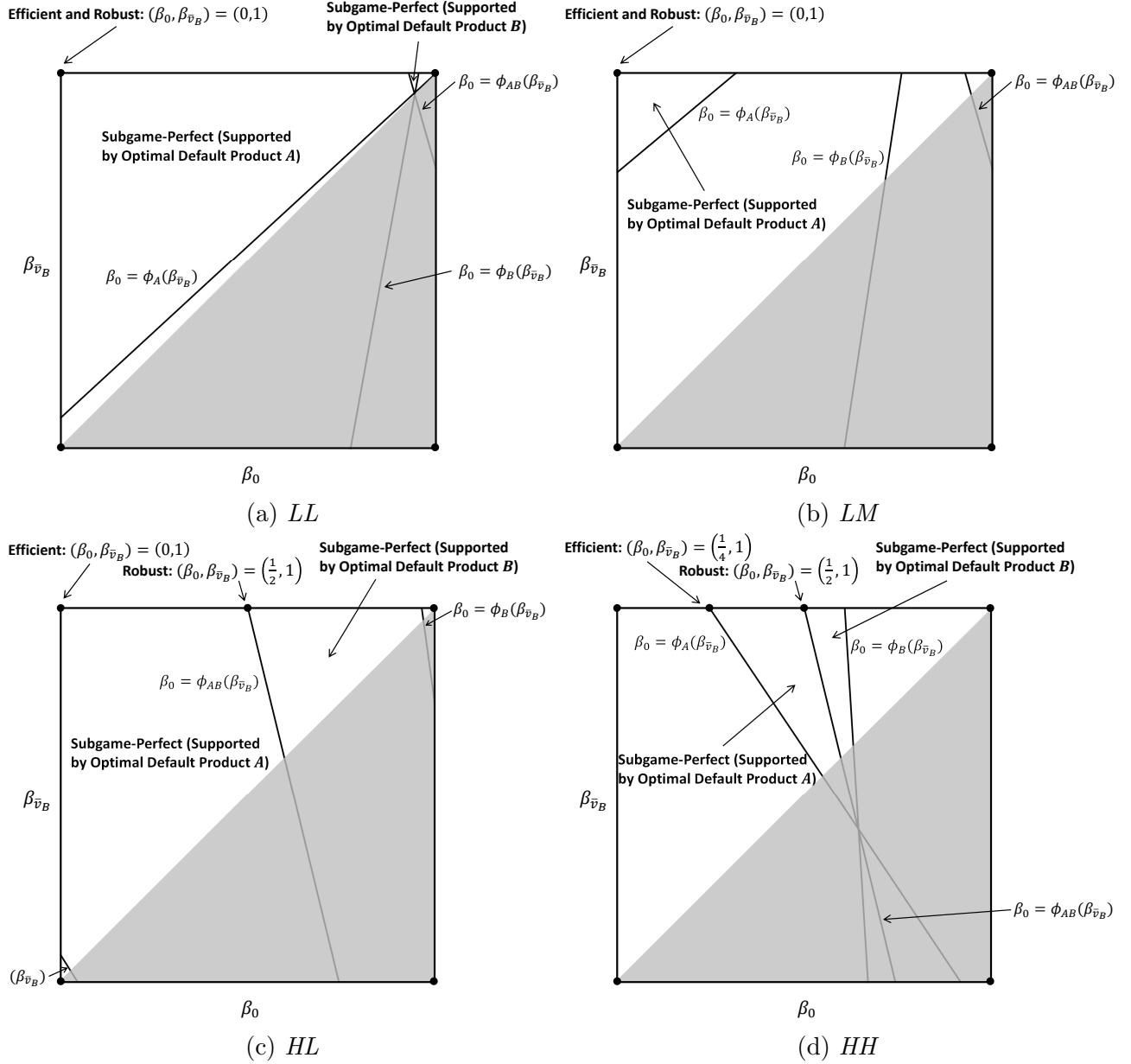


Figure C.1: Acquisition Equilibrium Ranking Methods of the Two-Dimensional Game Under the Parameters of Experimental Treatments

We conclude our analysis of the two-dimensional game by considering a variation where the report fee is endogenous. We modify the game by introducing a stage after the expert chooses a

ranking method, in which he makes a take-it-or-leave-it offer  $f_e \geq 0$  to the consumer to acquire the ranking report. The expert's payoff (revenue)  $\pi$  is increasing in this endogenous fee  $f_e$ . The rest of the game remains the same. The equilibrium characterization of this game follows immediately from the property of robust acquisition equilibrium of the game with exogenous fee, as the following corollary demonstrates:

**Corollary C.3.** *In the unique subgame-perfect equilibrium of the two-dimensional game with endogenous report fee, the expert chooses the ranking method of the robust acquisition equilibrium under exogenous fee,  $(\beta_0, \beta_{\bar{v}_B}) = (0, 1)$  if  $r < \bar{v}_A$  and  $(\beta_0, \beta_{\bar{v}_B}) = (\beta_{AB}, 1)$  if  $r > \bar{v}_A$ , and sets  $f_e$  to fully extract the consumer's willingness to pay for the ranking report.*

Endogenizing the report fee thus has the effect of “selecting” the same equilibrium ranking method as our perturbation-based refinement. Although we have not made the point in the main text in order to stay focused on the key characterizations, it is obvious that Corollary C.3 readily applies to the one-dimensional game with endogenous report fee.

### C.3 Proofs

In this section, we furnish the proofs for Lemma C.1, Proposition C.1, Proposition C.2, and Corollary C.3. Corollaries C.1 and C.2 are obvious, and their proofs are omitted.

**Proof of Lemma C.1.** For part (a), upon viewing Reports  $A$  and  $B$ , the consumer's posterior beliefs that  $v_B = \bar{v}_B$  are  $\mu_A(\beta_0, \beta_{\bar{v}_B}) = \frac{p(1-\beta_{\bar{v}_B})}{p(1-\beta_{\bar{v}_B})+(1-p)(1-\beta_0)}$  and  $\mu_B(\beta_0, \beta_{\bar{v}_B}) = \frac{p\beta_{\bar{v}_B}}{p\beta_{\bar{v}_B}+(1-p)\beta_0}$  respectively. (If  $\beta_0 = \beta_{\bar{v}_B} = 1$ , then viewing Report  $A$  is a zero-probability event. If  $\beta_0 = \beta_{\bar{v}_B} = 0$ , then viewing Report  $B$  is a zero-probability event. In these cases, we assign belief that the probability of  $\bar{v}_B$  equals the prior  $p$ .) The consumer's expected utilities from choosing Products  $A$  and  $B$  after viewing Report  $A$  are  $\bar{v}_A + r$  and  $\mu_A(\beta_0, \beta_{\bar{v}_B})\bar{v}_B$  respectively, and those after viewing Report  $B$  are  $\bar{v}_A$  and  $\mu_B(\beta_0, \beta_{\bar{v}_B})\bar{v}_B + r$  respectively. Note also that  $\mu_A(\beta_0, \beta_{\bar{v}_B})$  achieves the maximum and  $\mu_B(\beta_0, \beta_{\bar{v}_B})$  achieves the minimum at  $\beta_0 = \beta_{\bar{v}_B} = \frac{1}{2}$ , with resulting expected utility  $p\bar{v}_B$  in both cases. It follows that  $a(A) = 1$  and  $a(B) = 0$  is the optimal choice for any  $(\beta_0, \beta_{\bar{v}_B}) \in \mathcal{B}$  given the tie-breaking rule in Assumption 2 if and only if  $\bar{v}_A + r \geq p\bar{v}_B$  and  $\bar{v}_A < p\bar{v}_B + r$ , which are equivalent to  $0 < p\bar{v}_B + r - \bar{v}_A \leq 2r$ .

For part (b), we first note that the derivative of  $G((\beta_0, \beta_{\bar{v}_B}), a_A, a_B)$  in (C.6) with respect to  $\beta_0$  is  $\frac{\partial G((\beta_0, \beta_{\bar{v}_B}), a_A, a_B)}{\partial \beta_0} = -2(1-p)r < 0$ , which implies that given  $(\phi_{AB}(\beta_{\bar{v}_B}), \beta_{\bar{v}_B}) \in \mathcal{B}$ ,  $G(\beta'_0, \beta_{\bar{v}_B}), a_A, a_B) \geq G((\phi_{AB}(\beta_{\bar{v}_B}), \beta_{\bar{v}_B}), a_A, a_B) = 0$  if and only if  $\beta'_0 \leq \phi_{AB}(\beta_{\bar{v}_B})$ , in which case Product  $A$  is the optimal default under  $(\beta'_0, \beta_{\bar{v}_B})$ . We next note that the derivative of

$\phi_{AB}(\beta_{\bar{v}_B})$  in (C.9) with respect to  $\beta_{\bar{v}_B}$  is

$$\frac{\partial \phi_{AB}(\beta_{\bar{v}_B})}{\partial \beta_{\bar{v}_B}} = -\frac{p}{1-p} < 0. \quad (\text{C.10})$$

Thus,  $\phi_{AB}(\beta_{\bar{v}_B})$  is monotonically decreasing in  $\beta_{\bar{v}_B}$ . If at its minimum, which is achieved at  $\beta_{\bar{v}_B} = 1$ ,  $\phi_{AB}(1) = \beta_{AB} \geq 0$ , then for any  $\beta'_{\bar{v}_B} \leq 1$ , there exists  $\beta''_0 \in [0, \phi_{AB}(\beta'_{\bar{v}_B})]$  such that Product A is the optimal default under  $(\beta''_0, \beta'_{\bar{v}_B})$ . Note that the tie-breaking rule in Assumption 2 is used for the boundary case where  $\phi_{AB}(1) = 0$  and  $\beta'_{\bar{v}_B} = 1$ . □

**Proof of Proposition C.1.** In equilibrium, the expert chooses a  $(\beta_0, \beta_{\bar{v}_B}) \in \mathcal{B}$ , if one exists, so that the consumer acquires the ranking report. We prove the proposition by characterizing the consumer's equilibrium (sequentially rational) strategies under all influential  $(\beta_0, \beta_{\bar{v}_B}) \in \mathcal{B}$  ( $0 < p\bar{v}_B + r - \bar{v}_A \leq 2r$  per Lemma C.1). We continue to use the tie-breaking rule in Assumption 2. The proof utilizes the following derivatives of  $G$  specified in (C.4) and (C.5) and of  $\phi_A$  and  $\phi_B$  specified in (C.7) and (C.8):

$$\frac{\partial G((\beta_0, \beta_{\bar{v}_B}), a^{TP}, a_A)}{\partial \beta_0} = (1-p)(r - \bar{v}_A) \geq 0, \quad (\text{C.11})$$

$$\frac{\partial G((\beta_0, \beta_{\bar{v}_B}), a^{TP}, a_B)}{\partial \beta_0} = -(1-p)(\bar{v}_A + r) < 0, \quad (\text{C.12})$$

$$\frac{\partial \phi_A(\beta_{\bar{v}_B})}{\partial \beta_{\bar{v}_B}} = -\left(\frac{p}{1-p}\right) \left(\frac{\bar{v}_B + r - \bar{v}_A}{r - \bar{v}_A}\right) \geq 0, \text{ and} \quad (\text{C.13})$$

$$\frac{\partial \phi_B(\beta_{\bar{v}_B})}{\partial \beta_{\bar{v}_B}} = -\left(\frac{p}{1-p}\right) \left(\frac{\bar{v}_A + r - \bar{v}_B}{\bar{v}_A + r}\right) \geq 0. \quad (\text{C.14})$$

For part (a) with  $r < \bar{v}_A$ , (C.11) and (C.12) imply respectively the following two preference cases: (1) given  $(\phi_A(\beta_{\bar{v}_B}), \beta_{\bar{v}_B}) \in \mathcal{B}$ ,  $G((\beta'_0, \beta_{\bar{v}_B}), a^{TP}, a_A) \geq G((\phi_A(\beta_{\bar{v}_B}), \beta_{\bar{v}_B}), a^{TP}, a_A) = 0$  if and only if  $\beta'_0 \leq \phi_A(\beta_{\bar{v}_B})$ , in which case the consumer prefers acquiring the report under  $(\beta'_0, \beta_{\bar{v}_B})$  over not acquiring with Product A as the default, and (2) given  $(\phi_B(\beta_{\bar{v}_B}), \beta_{\bar{v}_B}) \in \mathcal{B}$ ,  $G((\beta''_0, \beta_{\bar{v}_B}), a^{TP}, a_B) \geq G((\phi_B(\beta_{\bar{v}_B}), \beta_{\bar{v}_B}), a^{TP}, a_B) = 0$  if and only if  $\beta''_0 \leq \phi_B(\beta_{\bar{v}_B})$ , in which case the consumer prefers acquiring the report under  $(\beta''_0, \beta_{\bar{v}_B})$  over not acquiring with Product B as the default. These preference cases are established by fixing a default product as alternative to acquiring the report. Sequential rationality requires the default alternative to be optimal. We have established in the proof of Lemma C.1 that Product A is the optimal default under  $(\hat{\beta}_0, \beta_{\bar{v}_B})$  if and only if  $\hat{\beta}_0 \leq \phi_{AB}(\beta_{\bar{v}_B})$ .

Whether the above preferences are supported by sequentially rational default alternative depends on the relative sizes of  $\phi_A(\beta_{\bar{v}_B})$ ,  $\phi_B(\beta_{\bar{v}_B})$ , and  $\phi_{AB}(\beta_{\bar{v}_B})$ . By definition,  $\phi_A(\beta_{\bar{v}_B}) = \phi_B(\beta_{\bar{v}_B}) = \phi_{AB}(\beta_{\bar{v}_B})$  at  $\beta_{\bar{v}_B} = I_{\beta_{\bar{v}_B}}$ . For  $r < \bar{v}_A$ , the derivatives in (C.10), (C.13), and (C.14) satisfy  $\frac{\partial \phi_{AB}(\beta_{\bar{v}_B})}{\partial \beta_{\bar{v}_B}} < \frac{\partial \phi_B(\beta_{\bar{v}_B})}{\partial \beta_{\bar{v}_B}} < \frac{\partial \phi_A(\beta_{\bar{v}_B})}{\partial \beta_{\bar{v}_B}}$ . It follows that for  $\beta_{\bar{v}_B} \geq I_{\beta_{\bar{v}_B}}$ ,  $\phi_{AB}(\beta_{\bar{v}_B}) \leq \phi_B(\beta_{\bar{v}_B}) \leq \phi_A(\beta_{\bar{v}_B})$ , and for  $\beta_{\bar{v}_B} < I_{\beta_{\bar{v}_B}}$ ,  $\phi_A(\beta_{\bar{v}_B}) < \phi_B(\beta_{\bar{v}_B}) < \phi_{AB}(\beta_{\bar{v}_B})$ . Consequently, both preference cases (1) and (2) are sequentially rational under  $\beta_{\bar{v}_B} \geq I_{\beta_{\bar{v}_B}}$ , and only case (1) is so under  $\beta_{\bar{v}_B} < I_{\beta_{\bar{v}_B}}$ . The rest of the proof of part (a) involves verifying the ranges of the relevant values.

We first note that our restriction  $\phi_{AB}(1) \geq 0$  implies that  $\phi_{AB}(\beta_{\bar{v}_B}) \geq 0$  for any  $\beta_{\bar{v}_B} \in [0, 1]$ . If  $f \in (0, f_2]$ , then  $I_{\beta_{\bar{v}_B}} \in (0, 1]$ . For  $\beta_{\bar{v}_B} \in [I_{\beta_{\bar{v}_B}}, 1]$ ,  $\phi_B(\beta_{\bar{v}_B}) \geq 0$ . For  $\beta_{\bar{v}_B} \in [0, \phi_A^{-1}(0))$ ,  $\phi_A(\beta_{\bar{v}_B}) < 0$ , and for  $\beta_{\bar{v}_B} \in [\phi_A^{-1}(0), I_{\beta_{\bar{v}_B}})$ ,  $\phi_A(\beta_{\bar{v}_B}) \geq 0$ . The following thus constitutes the sequentially rational strategy of the consumer for  $f \in (0, f_2]$  in part (a)(i):

- for  $\beta_{\bar{v}_B} \in [0, \phi_A^{-1}(0))$ ,
  - $s(\beta_0, \beta_{\bar{v}_B}) = 0$  with  $a_A^{TP}$  if  $\beta_0 \in [0, \min\{\phi_{AB}(\beta_{\bar{v}_B}), 1\}]$ , and
  - $s(\beta_0, \beta_{\bar{v}_B}) = 0$  with  $a_B^{TP}$  if  $\beta_0 \in (\phi_{AB}(\beta_{\bar{v}_B}), 1]$  and  $\phi_{AB}(\beta_{\bar{v}_B}) < 1$ ;
- for  $\beta_{\bar{v}_B} \in [\phi_A^{-1}(0), I_{\beta_{\bar{v}_B}})$ ,
  - $s(\beta_0, \beta_{\bar{v}_B}) = 1$  with  $a_A^{TP}$  if  $\beta_0 \in [0, \min\{\phi_A(\beta_{\bar{v}_B}), 1\}]$ ,
  - $s(\beta_0, \beta_{\bar{v}_B}) = 0$  with  $a_A^{TP}$  if  $\beta_0 \in (\phi_A(\beta_{\bar{v}_B}), \min\{\phi_{AB}(\beta_{\bar{v}_B}), 1\}]$  and  $\phi_A(\beta_{\bar{v}_B}) < 1$ , and
  - $s(\beta_0, \beta_{\bar{v}_B}) = 0$  with  $a_B^{TP}$  if  $\beta_0 \in (\phi_{AB}(\beta_{\bar{v}_B}), 1]$  and  $\phi_{AB}(\beta_{\bar{v}_B}) < 1$ ;
- for  $\beta_{\bar{v}_B} \in [I_{\beta_{\bar{v}_B}}, 1]$ ,
  - $s(\beta_0, \beta_{\bar{v}_B}) = 1$  with  $a_A^{TP}$  if  $\beta_0 \in [0, \min\{\phi_{AB}(\beta_{\bar{v}_B}), 1\}]$ ,
  - $s(\beta_0, \beta_{\bar{v}_B}) = 1$  with  $a_B^{TP}$  if  $\beta_0 \in (\phi_{AB}(\beta_{\bar{v}_B}), \min\{\phi_B(\beta_{\bar{v}_B}), 1\}]$  and  $\phi_{AB}(\beta_{\bar{v}_B}) < 1$ , and
  - $s(\beta_0, \beta_{\bar{v}_B}) = 0$  with  $a_B^{TP}$  if  $\beta_0 \in (\phi_B(\beta_{\bar{v}_B}), 1]$  and  $\phi_B(\beta_{\bar{v}_B}) < 1$ .

If  $f \in (f_2, f_1]$ , then  $I_{\beta_{\bar{v}_B}} > 1$ . For  $\beta_{\bar{v}_B} \in [0, \phi_A^{-1}(0))$ ,  $\phi_A(\beta_{\bar{v}_B}) < 0$ , and for  $\beta_{\bar{v}_B} \in [\phi_A^{-1}(0), 1]$ ,  $\phi_A(\beta_{\bar{v}_B}) \in [0, 1]$ . The following thus constitutes the sequentially rational strategy of the consumer for  $f \in (f_2, f_1]$  in part (a)(ii):

- for  $\beta_{\bar{v}_B} \in [0, \phi_A^{-1}(0))$ ,
  - $s(\beta_0, \beta_{\bar{v}_B}) = 0$  with  $a_A^{TP}$  if  $\beta_0 \in [0, \min\{\phi_{AB}(\beta_{\bar{v}_B}), 1\}]$ , and
  - $s(\beta_0, \beta_{\bar{v}_B}) = 0$  with  $a_B^{TP}$  if  $\beta_0 \in (\phi_{AB}(\beta_{\bar{v}_B}), 1]$  and  $\phi_{AB}(\beta_{\bar{v}_B}) < 1$ ;



- for  $\beta_{\bar{v}_B} \in [\phi_A^{-1}(0), 1]$ ,
  - $s(\beta_0, \beta_{\bar{v}_B}) = 1$  with  $a_A^{TP}$  if  $\beta_0 \in [0, \phi_A(\beta_{\bar{v}_B})]$ ,
  - $s(\beta_0, \beta_{\bar{v}_B}) = 0$  with  $a_A^{TP}$  if  $\beta_0 \in (\phi_A(\beta_{\bar{v}_B}), \min\{\phi_{AB}(\beta_{\bar{v}_B}), 1\}]$ , and
  - $s(\beta_0, \beta_{\bar{v}_B}) = 0$  with  $a_B^{TP}$  if  $\beta_0 \in (\phi_{AB}(\beta_{\bar{v}_B}), 1]$  and  $\phi_{AB}(\beta_{\bar{v}_B}) < 1$ .

If  $f \in (f_1, \infty)$ , then  $I_{\beta_{\bar{v}_B}} > 1$  and  $\phi_A(\beta_{\bar{v}_B}) < 0$  for all  $\beta_{\bar{v}_B} \in [0, 1]$ . The sequentially rational strategy of the consumer in part (a)(iii) is therefore: for any  $\beta_{\bar{v}_B} \in [0, 1]$ ,  $s(\beta_0, \beta_{\bar{v}_B}) = 0$  with  $a_A^{TP}$  if  $\beta_0 \in [0, \phi_{AB}(\beta_{\bar{v}_B})]$ , and  $s(\beta_0, \beta_{\bar{v}_B}) = 0$  with  $a_B^{TP}$  if  $\beta_0 \in (\phi_{AB}(\beta_{\bar{v}_B}), 1]$ .

For part (b) with  $r > \bar{v}_A$ , (C.11) implies a different preference case: (3) given any influential  $(\phi_A(\beta_{\bar{v}_B}), \beta_{\bar{v}_B}) \in \mathcal{B}$ ,  $G((\tilde{\beta}_0, \beta_{\bar{v}_B}), a^{TP}, a_A) \geq G((\phi_A(\beta_{\bar{v}_B}), \beta_{\bar{v}_B}), a^{TP}, a_A) = 0$  if and only if  $\tilde{\beta}_0 \geq \phi_A(\beta_{\bar{v}_B})$ , in which case the consumer prefers acquiring the report under  $(\tilde{\beta}_0, \beta_{\bar{v}_B})$  over not acquiring with Product A as the default. Preference case (2) above implied by (C.12) remains.

For  $r > \bar{v}_A$ , the derivatives in (C.10), (C.13), and (C.14) satisfy  $\frac{\partial \phi_A(\beta_{\bar{v}_B})}{\partial \beta_{\bar{v}_B}} < \frac{\partial \phi_{AB}(\beta_{\bar{v}_B})}{\partial \beta_{\bar{v}_B}} < \frac{\partial \phi_B(\beta_{\bar{v}_B})}{\partial \beta_{\bar{v}_B}}$ . It follows that for  $\beta_{\bar{v}_B} \geq I_{\beta_{\bar{v}_B}}$ ,  $\phi_A(\beta_{\bar{v}_B}) \leq \phi_{AB}(\beta_{\bar{v}_B}) \leq \phi_B(\beta_{\bar{v}_B})$ , and for  $\beta_{\bar{v}_B} < I_{\beta_{\bar{v}_B}}$ ,  $\phi_B(\beta_{\bar{v}_B}) < \phi_{AB}(\beta_{\bar{v}_B}) < \phi_A(\beta_{\bar{v}_B})$ . Consequently, both preference cases (2) and (3) are sequentially rational under  $\beta_{\bar{v}_B} \geq I_{\beta_{\bar{v}_B}}$ , while none is so under  $\beta_{\bar{v}_B} < I_{\beta_{\bar{v}_B}}$ . The rest of the proof of part (b) involves verifying the ranges of the relevant values.

It remains the case that  $\phi_{AB}(\beta_{\bar{v}_B}) \geq 0$  for any  $\beta_{\bar{v}_B} \in [0, 1]$ . We consider two subcases for  $f \in (0, f_1]$ . Let  $\hat{f} = p(\bar{v}_A + r - \bar{v}_B)$ , where  $\hat{f} \gtrless 0$  and  $\hat{f} < f_1$ . If  $\hat{f} > 0$  and  $f \in (0, \hat{f}]$ , then  $I_{\beta_{\bar{v}_B}} \gtrless 0$  and  $I_{\beta_{\bar{v}_B}} \leq 1$ . For  $\beta_{\bar{v}_B} \in [\max\{0, I_{\beta_{\bar{v}_B}}\}, \phi_A^{-1}(0))$ ,  $\phi_A(\beta_{\bar{v}_B}) > 0$ , and for  $\beta_{\bar{v}_B} \in [\phi_A^{-1}(0), 1]$ ,  $\phi_A(\beta_{\bar{v}_B}) \leq 0$ ; for  $\beta_{\bar{v}_B} \in [\max\{0, I_{\beta_{\bar{v}_B}}\}, \phi_B^{-1}(1))$ ,  $\phi_B(\beta_{\bar{v}_B}) > 1$ , and for  $\beta_{\bar{v}_B} \in [\phi_B^{-1}(1), 1]$ ,  $\phi_B(\beta_{\bar{v}_B}) \in (0, 1]$ . If  $f \in (\hat{f}, f_1]$ , then  $I_{\beta_{\bar{v}_B}} \gtrless 0$  and  $I_{\beta_{\bar{v}_B}} \leq 1$  no matter the sign of  $\hat{f}$ . For  $\beta_{\bar{v}_B} \in [\max\{0, I_{\beta_{\bar{v}_B}}\}, \phi_A^{-1}(0))$ ,  $\phi_A(\beta_{\bar{v}_B}) \in (0, 1)$ , and for  $\beta_{\bar{v}_B} \in [\phi_A^{-1}(0), 1]$ ,  $\phi_A(\beta_{\bar{v}_B}) \leq 0$ ; for  $\beta_{\bar{v}_B} \in [\max\{0, I_{\beta_{\bar{v}_B}}\}, 1]$ ,  $\phi_B(\beta_{\bar{v}_B}) \in [0, 1)$ . The sequentially rational strategies of the consumer under these subcases for  $f \in (0, f_1]$  in part (b)(i) can be succinctly stated as:

- for  $\beta_{\bar{v}_B} \in [0, I_{\beta_{\bar{v}_B}})$  if  $I_{\beta_{\bar{v}_B}} > 0$ ,
  - $s(\beta_0, \beta_{\bar{v}_B}) = 0$  with  $a_A^{TP}$  if  $\beta_0 \in [0, \min\{\phi_{AB}(\beta_{\bar{v}_B}), 1\}]$ , and
  - $s(\beta_0, \beta_{\bar{v}_B}) = 0$  with  $a_B^{TP}$  if  $\beta_0 \in (\phi_{AB}(\beta_{\bar{v}_B}), 1]$  and  $\phi_{AB}(\beta_{\bar{v}_B}) < 1$ ;
- for  $\beta_{\bar{v}_B} \in [\max\{0, I_{\beta_{\bar{v}_B}}\}, 1]$ ,
  - $s(\beta_0, \beta_{\bar{v}_B}) = 0$  with  $a_A^{TP}$  if  $\beta_0 \in [0, \phi_A(\beta_{\bar{v}_B}))$  and  $\phi_A(\beta_{\bar{v}_B}) > 0$ ,
  - $s(\beta_0, \beta_{\bar{v}_B}) = 1$  with  $a_A^{TP}$  if  $\beta_0 \in [\max\{0, \phi_A(\beta_{\bar{v}_B})\}, \min\{\phi_{AB}(\beta_{\bar{v}_B}), 1\}]$  and  $\phi_A(\beta_{\bar{v}_B}) \leq 1$ , and  $s(\beta_0, \beta_{\bar{v}_B}) = 0$  with  $a_A^{TP}$  if  $\phi_A(\beta_{\bar{v}_B}) > 1$

- $s(\beta_0, \beta_{\bar{v}_B}) = 1$  with  $a_B^{TP}$  if  $\beta_0 \in (\phi_{AB}(\beta_{\bar{v}_B}), \min\{\phi_B(\beta_{\bar{v}_B}), 1\}]$  and  $\phi_{AB}(\beta_{\bar{v}_B}) < 1$ , and
- $s(\beta_0, \beta_{\bar{v}_B}) = 0$  with  $a_B^{TP}$  if  $\beta_0 \in (\phi_B(\beta_{\bar{v}_B}), 1]$  and  $\phi_B(\beta_{\bar{v}_B}) < 1$ .

Note that  $\phi_A(\beta_{\bar{v}_B}) \leq 1$  is equivalent to  $\beta_{\bar{v}_B} \geq \phi_A^{-1}(1)$ , where  $\phi_A^{-1}(1) < 1$ . Thus, the case where  $\phi_A(\beta_{\bar{v}_B}) > 1$  does not arise for  $\beta_{\bar{v}_B} \in [\max\{0, \phi_A^{-1}(1), I_{\beta_{\bar{v}_B}}\}, 1]$ .

If  $f \in (f_1, f_2]$ , then  $I_{\beta_{\bar{v}_B}} \geq 0$  and  $I_{\beta_{\bar{v}_B}} \leq 1$ . For  $\beta_{\bar{v}_B} \in [\max\{0, I_{\beta_{\bar{v}_B}}\}, 1]$ ,  $\phi_A(\beta_{\bar{v}_B}) \in (0, 1)$  and  $\phi_B(\beta_{\bar{v}_B}) \in (1)$ . The following thus constitutes the sequentially rational strategy of the consumer for  $f \in (f_1, f_2]$  in part (b)(ii):

- for  $\beta_{\bar{v}_B} \in [0, I_{\beta_{\bar{v}_B}})$  if  $I_{\beta_{\bar{v}_B}} > 0$ ,
  - $s(\beta_0, \beta_{\bar{v}_B}) = 0$  with  $a_A^{TP}$  if  $\beta_0 \in [0, \phi_{AB}(\beta_{\bar{v}_B})]$ , and
  - $s(\beta_0, \beta_{\bar{v}_B}) = 0$  with  $a_B^{TP}$  if  $\beta_0 \in (\phi_{AB}(\beta_{\bar{v}_B}), 1]$ ;
- for  $\beta_{\bar{v}_B} \in [\max\{0, I_{\beta_{\bar{v}_B}}\}, 1]$ ,
  - $s(\beta_0, \beta_{\bar{v}_B}) = 0$  with  $a_A^{TP}$  if  $\beta_0 \in [0, \phi_A(\beta_{\bar{v}_B}))$ ,
  - $s(\beta_0, \beta_{\bar{v}_B}) = 1$  with  $a_A^{TP}$  if  $\beta_0 \in [\phi_A(\beta_{\bar{v}_B}), \phi_{AB}(\beta_{\bar{v}_B})]$ ,
  - $s(\beta_0, \beta_{\bar{v}_B}) = 1$  with  $a_B^{TP}$  if  $\beta_0 \in (\phi_{AB}(\beta_{\bar{v}_B}), \phi_B(\beta_{\bar{v}_B})]$ , and
  - $s(\beta_0, \beta_{\bar{v}_B}) = 0$  with  $a_B^{TP}$  if  $\beta_0 \in (\phi_B(\beta_{\bar{v}_B}), 1]$ .

Finally, if  $f \in (f_2, \infty)$ , then  $I_{\beta_{\bar{v}_B}} > 1$ . The sequentially rational strategy of the consumer in part (b)(iii) is therefore: for any  $\beta_{\bar{v}_B} \in [0, 1]$ ,  $s(\beta_0, \beta_{\bar{v}_B}) = 0$  with  $a_A^{TP}$  if  $\beta_0 \in [0, \phi_{AB}(\beta_{\bar{v}_B})]$ , and  $s(\beta_0, \beta_{\bar{v}_B}) = 0$  with  $a_B^{TP}$  if  $\beta_0 \in (\phi_{AB}(\beta_{\bar{v}_B}), 1]$ . □

**Proof of Proposition C.2.** We begin with the efficient acquisition equilibrium, in which the consumer's expected payoff is the highest among all subgame-perfect acquisition equilibria. Throughout the proof, we refer to the sets of subgame-perfect acquisition equilibrium ranking methods  $\mathcal{B}_1 \cup \mathcal{B}_2$ ,  $\mathcal{B}_3$ ,  $\mathcal{B}_4$ , and  $\mathcal{B}_5$  specified in the different cases in Proposition C.1. The derivatives of  $U((\beta_0, \beta_{\bar{v}_B}), 1, a^{TP})$  in (C.3) with respect to  $\beta_0$  and  $\beta_{\bar{v}_B}$  are  $\frac{\partial U((\beta_0, \beta_{\bar{v}_B}), 1, a^{TP})}{\partial \beta_0} = -(1-p)\bar{v}_A < 0$  and  $\frac{\partial U((\beta_0, \beta_{\bar{v}_B}), 1, a^{TP})}{\partial \beta_{\bar{v}_B}} = p(\bar{v}_B - \bar{v}_A) > 0$  respectively. It follows that, for  $r < \bar{v}_A$ , the ranking method in each of  $\mathcal{B}_1 \cup \mathcal{B}_2$  and  $\mathcal{B}_3$  that maximizes the consumer's expected payoff is  $(\beta_0, \beta_{\bar{v}_B}) = (0, 1)$ . For  $r > \bar{v}_A$  and  $f \in (0, f_1]$ , the derivatives imply that, with  $\phi_A(1) < 0$ , the ranking method in  $\mathcal{B}_4$  that maximizes the consumer's expected payoff is also  $(\beta_0, \beta_{\bar{v}_B}) = (0, 1)$ . Finally, for  $r > \bar{v}_A$  and  $f \in (f_1, f_2]$ , the derivatives imply that, with  $\frac{\partial \phi_A(\beta_{\bar{v}_B})}{\partial \beta_{\bar{v}_B}} < 0$ , the ranking method in  $\mathcal{B}_5$  that maximizes the consumer's expected payoff is  $(\beta_0, \beta_{\bar{v}_B}) = (\phi_A(1), 1) = (\beta_A, 1)$ .

To prove the part for the robust acquisition equilibrium, we denote by  $\mathcal{B}^{\text{SPE}}$  the set of subgame-perfect acquisition equilibrium ranking methods and, slightly modifying the notation used in defining strict loss monotonicity, let  $G((\beta_0, \beta_{\bar{v}_B}), 0)$  be the consumer's expected loss from not acquiring the ranking report under  $(\beta_0, \beta_{\bar{v}_B})$ , where it equals the expression in either (C.4) or (C.5). We first note that the claim used in the proof of Proposition 3 extends to the two-dimensional game: if  $(\beta_0, \beta_{\bar{v}_B})$  is a robust acquisition equilibrium ranking method, then  $(\beta_0, \beta_{\bar{v}_B}) \in \operatorname{argmax}_{(\beta'_0, \beta'_{\bar{v}_B}) \in \mathcal{B}^{\text{SPE}}} G((\beta'_0, \beta'_{\bar{v}_B}), 0)$ . We do not repeat the proof of this claim, which is essentially the same.

We complete the proof by solving  $\max_{(\beta_0, \beta_{\bar{v}_B}) \in \mathcal{B}^{\text{SPE}}} G((\beta_0, \beta_{\bar{v}_B}), 0)$ . There are two instances for the derivative of  $G((\beta_0, \beta_{\bar{v}_B}), 0)$  with respect to  $\beta_0$ : (i)  $\frac{\partial G((\beta_0, \beta_{\bar{v}_B}), 0)}{\partial \beta_0} = (1-p)(r - \bar{v}_A)$  for the case where  $U((\beta_0, \beta_{\bar{v}_B}), 0, a_A) \geq U((\beta_0, \beta_{\bar{v}_B}), 0, a_B)$ , and (ii)  $\frac{\partial G((\beta_0, \beta_{\bar{v}_B}), 0)}{\partial \beta_0} = -(1-p)(\bar{v}_A + r) < 0$  for the case where  $U((\beta_0, \beta_{\bar{v}_B}), 0, a_A) < U((\beta_0, \beta_{\bar{v}_B}), 0, a_B)$ , with  $U((\beta_0, \beta_{\bar{v}_B}), 0, a_A)$  and  $U((\beta_0, \beta_{\bar{v}_B}), 0, a_B)$  defined in (C.1) and (C.2). Similarly, there are two instances of the derivative with respect to  $\beta_{\bar{v}_B}$ : (iii)  $\frac{\partial G((\beta_0, \beta_{\bar{v}_B}), 0)}{\partial \beta_{\bar{v}_B}} = p(\bar{v}_B + r - \bar{v}_A) = f_1 > 0$  for the case where  $U((\beta_0, \beta_{\bar{v}_B}), 0, a_A) \geq U((\beta_0, \beta_{\bar{v}_B}), 0, a_B)$ , and (iv)  $\frac{\partial G((\beta_0, \beta_{\bar{v}_B}), 0)}{\partial \beta_{\bar{v}_B}} = -p(\bar{v}_A + r - \bar{v}_B)$  for the case where  $U((\beta_0, \beta_{\bar{v}_B}), 0, a_A) < U((\beta_0, \beta_{\bar{v}_B}), 0, a_B)$ .

If  $r < \bar{v}_A$ , then  $\frac{\partial G((\beta_0, \beta_{\bar{v}_B}), 0)}{\partial \beta_0} < 0$  in derivative case (i). Given that the derivative in case (iii)  $\frac{\partial G((\beta_0, \beta_{\bar{v}_B}), 0)}{\partial \beta_{\bar{v}_B}} > 0$ ,  $G((\beta_0, \beta_{\bar{v}_B}), 0)$  achieves the maximum at  $(\beta_0, \beta_{\bar{v}_B}) = (0, 1)$  among the subgame-perfect acquisition equilibria that are supported by optimal default Product A. We show that  $G((\beta_0, \beta_{\bar{v}_B}), 0)$  does not attain a higher value when the optimal default alternative is Product B. From the proof of part (a) of Proposition C.1, the consumer's sequentially rational decision to acquire the report is supported by default Product B if and only if the following condition (M) is satisfied:  $f \in (0, f_2]$ ,  $\beta_{\bar{v}_B} \in [I_{\beta_{\bar{v}_B}}, 1]$ ,  $\beta_0 \in (\phi_{AB}(\beta_{\bar{v}_B}), \min\{\phi_B(\beta_{\bar{v}_B}), 1\}]$ , and  $\phi_{AB}(\beta_{\bar{v}_B}) < 1$ . If the derivative in case (iv)  $\frac{\partial G((\beta_0, \beta_{\bar{v}_B}), 0)}{\partial \beta_{\bar{v}_B}} > 0$ , then the maximum  $G((\beta_0, \beta_{\bar{v}_B}), 0)$  subject to (M) involves  $\beta_{\bar{v}_B} = 1$ ; if  $\frac{\partial G((\beta_0, \beta_{\bar{v}_B}), 0)}{\partial \beta_{\bar{v}_B}} < 0$ , then it involves  $\beta_{\bar{v}_B} = I_{\beta_{\bar{v}_B}}$ ; and if  $\frac{\partial G((\beta_0, \beta_{\bar{v}_B}), 0)}{\partial \beta_{\bar{v}_B}} = 0$ , then it involves any  $\beta_{\bar{v}_B} \in [I_{\beta_{\bar{v}_B}}, 1]$ . Given that  $\frac{\partial G((\beta_0, \beta_{\bar{v}_B}), 0)}{\partial \beta_0} < 0$  in both derivative cases (i) and (ii) and  $U(\phi_{AB}(\beta_{\bar{v}_B}), \beta_{\bar{v}_B}, 0, a_A) = U(\phi_{AB}(\beta_{\bar{v}_B}), \beta_{\bar{v}_B}, 0, a_B)$ ,  $G((\beta_0, \bar{\beta}_{\bar{v}_B}), 0) < G((0, \bar{\beta}_{\bar{v}_B}), 0) < G((0, 1), 0)$  for any  $\beta_0$  that satisfies (M) and  $\bar{\beta}_{\bar{v}_B} \in \{I_{\beta_{\bar{v}_B}}, 1\}$ .

If  $r > \bar{v}_A$ , then  $\frac{\partial G((\beta_0, \beta_{\bar{v}_B}), 0)}{\partial \beta_0} > 0$  in derivative case (i). Given that the derivative in case (iii)  $\frac{\partial G((\beta_0, \beta_{\bar{v}_B}), 0)}{\partial \beta_{\bar{v}_B}} > 0$ ,  $G((\beta_0, \beta_{\bar{v}_B}), 0)$  achieves the maximum at  $(\beta_0, \beta_{\bar{v}_B}) = (\phi_{AB}(1), 1) = (\beta_{AB}, 1)$  among the subgame-perfect acquisition equilibria that are supported by optimal default Product A. We again show that  $G((\beta_0, \beta_{\bar{v}_B}), 0)$  does not attain a higher value when the optimal default alternative is Product B. From the proof of part (b) of Proposition C.1, the consumer's sequentially rational decision to acquire the report is supported by default Product B if and only if the following condition (M') is satisfied: either  $f \in (0, f_1]$ ,  $\beta_{\bar{v}_B} \in [\max\{0, I_{\beta_{\bar{v}_B}}\}, 1]$ ,  $\beta_0 \in (\phi_{AB}(\beta_{\bar{v}_B}), \min\{\phi_B(\beta_{\bar{v}_B}), 1\}]$ , and  $\phi_{AB}(\beta_{\bar{v}_B}) < 1$ , or  $f \in (f_1, f_2]$ ,  $\beta_{\bar{v}_B} \in [\max\{0, I_{\beta_{\bar{v}_B}}\}, 1]$ ,

and  $\beta_0 \in (\phi_{AB}(\beta_{\bar{v}_B}), \phi_B(\beta_{\bar{v}_B})]$ . If the derivative in case (iv)  $\frac{\partial G((\beta_0, \beta_{\bar{v}_B}), 0)}{\partial \beta_{\bar{v}_B}} > 0$ , then the maximum  $G((\beta_0, \beta_{\bar{v}_B}), 0)$  subject to (M') involves  $\beta_{\bar{v}_B} = 1$ ; if  $\frac{\partial G((\beta_0, \beta_{\bar{v}_B}), 0)}{\partial \beta_{\bar{v}_B}} < 0$ , then it involves  $\beta_{\bar{v}_B} = \max\{0, I_{\beta_{\bar{v}_B}}\}$ ; and if  $\frac{\partial G((\beta_0, \beta_{\bar{v}_B}), 0)}{\partial \beta_{\bar{v}_B}} = 0$ , then it involves any  $\beta_{\bar{v}_B} \in [\max\{0, I_{\beta_{\bar{v}_B}}\}, 1]$ . Given that  $\frac{\partial G((\beta_0, \beta_{\bar{v}_B}), 0)}{\partial \beta_0} < 0$  in derivative case (ii) and  $U(\phi_{AB}(\beta_{\bar{v}_B}), \beta_{\bar{v}_B}, 0, a_A) = U(\phi_{AB}(\beta_{\bar{v}_B}), \beta_{\bar{v}_B}, 0, a_B)$ ,  $G((\beta_0, \tilde{\beta}_{\bar{v}_B}), 0) < G((\phi_{AB}(\tilde{\beta}_{\bar{v}_B}), \tilde{\beta}_{\bar{v}_B}), 0) < G((\phi_{AB}(1), 1), 0)$  for any  $\beta_0$  that satisfies (M') and  $\tilde{\beta}_{\bar{v}_B} \in \{\max\{0, I_{\beta_{\bar{v}_B}}\}, 1\}$ .

Finally, the unique solution to the maximization problem implies that the robust acquisition equilibrium in each case of  $r < \bar{v}_A$  and  $r > \bar{v}_A$  is unique. □

**Proof of Corollary C.3.** For any  $(\beta_0, \beta_{\bar{v}_B}) \in \mathcal{B}$ , the consumer acquires the ranking report if and only if  $f \leq U((\beta_0, \beta_{\bar{v}_B}), 1, a^{TP}) - \max\{U((\beta_0, \beta_{\bar{v}_B}), 0, a_A), U((\beta_0, \beta_{\bar{v}_B}), 0, a_B)\}$ . Therefore, the expert maximizes payoff subject to given  $(\beta_0, \beta_{\bar{v}_B})$  by setting  $f_e = U((\beta_0, \beta_{\bar{v}_B}), 1, a^{TP}) - \max\{U((\beta_0, \beta_{\bar{v}_B}), 0, a_A), U((\beta_0, \beta_{\bar{v}_B}), 0, a_B)\}$ , which is the consumer's willingness to pay for the ranking report under  $(\beta_0, \beta_{\bar{v}_B})$ . The corollary then follows from the fact that  $(\beta_0, \beta_{\bar{v}_B})$  maximizes  $f_e$  if and only if it maximizes  $G((\beta_0, \beta_{\bar{v}_B}), 0)$  used in the proof of Proposition C.2 for the robust acquisition equilibrium. □