



Marketing Science

Publication details, including instructions for authors and subscription information:
<http://pubsonline.informs.org>

The Strategic Implications of Scale in Choice-Based Conjoint Analysis

John R. Hauser, Felix Eggers, Matthew Selove

To cite this article:

John R. Hauser, Felix Eggers, Matthew Selove (2019) The Strategic Implications of Scale in Choice-Based Conjoint Analysis. Marketing Science 38(6):1059–1081. <https://doi.org/10.1287/mksc.2019.1178>

This work is licensed under a Creative Commons Attribution 4.0 International License. You are free to copy, distribute, transmit and adapt this work, but you must attribute this work as “Marketing Science. Copyright © 2019 The Author(s). <https://doi.org/10.1287/mksc.2019.1178>, used under a Creative Commons Attribution License: <https://creativecommons.org/licenses/by/4.0/>.”

Copyright © 2019, The Author(s)

Please scroll down for article—it is on subsequent pages



With 12,500 members from nearly 90 countries, INFORMS is the largest international association of operations research (O.R.) and analytics professionals and students. INFORMS provides unique networking and learning opportunities for individual professionals, and organizations of all types and sizes, to better understand and use O.R. and analytics tools and methods to transform strategic visions and achieve better outcomes. For more information on INFORMS, its publications, membership, or meetings visit <http://www.informs.org>

The Strategic Implications of Scale in Choice-Based Conjoint Analysis

John R. Hauser,^a Felix Eggers,^b Matthew Selove^c

^a Sloan School of Management, Massachusetts Institute of Technology, Cambridge, Massachusetts 02142; ^b Faculty of Economics and Business, University of Groningen, 9747 AE Groningen, Netherlands; ^c The George L. Argyros School of Business and Economics, Chapman University, Orange, California 92866

Contact: hauser@mit.edu,  <http://orcid.org/0000-0001-8510-8640> (JRH); f.eggers@rug.nl,  <https://orcid.org/0000-0001-9753-1227> (FE); selove@chapman.edu,  <http://orcid.org/0000-0001-6706-0049> (MS)

Received: October 3, 2017

Revised: June 19, 2018; November 9, 2018; March 8, 2019; April 26, 2019

Accepted: May 5, 2019

Published Online in Articles in Advance: November 14, 2019

<https://doi.org/10.1287/mksc.2019.1178>

Copyright: © 2019 The Author(s)

Abstract. Choice-based conjoint (CBC) studies have begun to rely on simulators to forecast equilibrium prices for pricing, strategic product positioning, and patent/copyright valuations. Whereas CBC research has long focused on the accuracy of estimated relative partworths of attribute levels, predicted equilibrium prices and strategic positioning are surprisingly and dramatically dependent on scale: the magnitude of the partworths (including the price coefficient) *relative* to the magnitude of the error term. Although the impact of scale on the ability to estimate heterogeneous partworths is well known, neither the literature nor current practice address the sensitivity of pricing and positioning to scale. This sensitivity is important because (estimated) scale depends on seemingly innocuous market-research decisions such as whether attributes are described by text or by realistic images. We demonstrate the strategic implications of scale using a stylized model in which heterogeneity is modeled explicitly. If a firm shirks on the quality of a CBC study and acts on incorrectly observed scale, a follower, but not an innovator, can make costly strategic errors. Externally valid estimates of scale are extremely important. We demonstrate empirically that image realism and incentive alignment affect scale sufficiently to change strategic decisions and affect patent/copyright valuations by hundreds of millions of dollars.

History: Yuxin Chen served as the senior editor and Carl Mela served as associate editor for this article.



Open Access Statement: This work is licensed under a Creative Commons Attribution 4.0 International License. You are free to copy, distribute, transmit and adapt this work, but you must attribute this work as “Marketing Science. Copyright © 2019 The Author(s). <https://doi.org/10.1287/mksc.2019.1178>, used under a Creative Commons Attribution License: <https://creativecommons.org/licenses/by/4.0/>.”

Supplemental Material: Data files and the online appendices are available at <https://doi.org/10.1287/mksc.2019.1178>.

Keywords: conjoint analysis • market research • choice models • scale

1. Scale Affects Strategic Decisions

With an estimated 18,000 applications per year, conjoint analysis is one of the most-used quantitative market research methods (Orme 2014, Sawtooth Software 2015). Over 80% of these conjoint applications are choice based (Sawtooth Software 2016). Firms routinely use choice-based conjoint (CBC) analysis to identify preferred product attributes in the hopes of maximizing profit—for example, General Motors alone spends tens of millions of dollars each year (Urban and Hauser 2004). CBC analysis is increasingly used in litigation, and courts have awarded billion-dollar judgments for patent or copyright infringement based on CBC studies (Mintz 2012, Cameron et al. 2013, McFadden 2014).

Research in CBC analysis has long focused on the ability to estimate accurate *relative* trade-offs among product attribute levels. Improved question

selection, improved estimation, and techniques such as incentive alignment all enhance accuracy of identified relative trade-offs and lead to better managerial decisions. However, with the advancement of CBC simulators and faster computers, researchers have begun to use CBC studies to estimate price equilibria and the resulting equilibrium profits (e.g., Allenby et al. 2014). This use of CBC analysis raises a new concern because, as shown in this paper, the calculated price equilibria depend critically on “scale,” where scale is the magnitude of the partworths (including the price partworths) relative to the magnitude of the error.¹ Whereas the literature has long focused on the impact of scale heterogeneity in CBC estimation, our focus is on a common scale factor in CBC studies. For example, we demonstrate that scale can be quite different if we use realistic images rather than text-only stimuli or if we use incentive alignment rather

than no incentive alignment. (The goal of realism is to represent better choices made by consumers in the marketplace.)

Our research combines formal modeling to understand the phenomena and empirical CBC studies that vary on the realism of the stimuli and on incentive alignment. The empirical studies include a delayed validation task that mimics consumers' marketplace decisions as a proxy to estimate "true" scale. Together, the theory and practice provide complementary insights:

Theory

- Scale affects strategic decisions, such as how to position and set price, even when we account for unobserved attributes and preference heterogeneity (a stylized version of common hierarchical Bayes [HB], latent structure, or machine-learning estimation).

- Equilibria prices are extremely sensitive to true scale; that is, the scale that best describes marketplace decisions.

- For high relative values of true scale, the profit-maximizing strategy is to differentiate. For low relative values of true scale, the profit-maximizing strategy is not to differentiate.

- If a follower shirks on market research and gets a biased estimate of scale, the follower could make the wrong strategic decisions (price and positioning) and forego substantial profits.

- The innovator's strategic decisions do not depend on estimated scale.

Practice

- When the stylized assumptions are relaxed in empirical studies, the identified phenomena and strategic recommendations remain valid.

- Seemingly innocuous aspects of a CBC study can have huge effects on *predicted* equilibrium prices. We test incentive alignment and image realism.

- Aspects of a CBC study can affect strategic positioning, that is, which attribute level maximizes equilibrium profits.

- If estimated scale is adjusted based on a marketplace validation task, then both pricing and positioning decisions are affected. A firm may position differently and choose a different price depending on whether the firm acts on unadjusted scale or validation-adjusted scale.

- Data-based hypotheses for further research are as follows: (1) Image realism is very important. (2) Image realism may be more important than incentive alignment. (3) Validation-adjusted scale implies predicted price equilibria that differ dramatically from price equilibria based on scale estimated from the CBC profile choices.

The practical implications are important. Although a few CBC studies (academic literature and practice)

use highly realistic images and incentive alignment, most do not. Although a very few CBC studies adjust estimates with validation tasks, the vast majority do not. Because our theory and data suggest that such "craft" matters substantially, we also recommend practical decision processes by which firms can decide whether to invest in these elements of CBC craft.

We expect that CBC craft can impact managerial decisions—this is intuitive. But neither the magnitude and direction of the strategic errors nor the large effect of seemingly minor differences in CBC craft are obvious without the insights from the stylized model. (At minimum, many aspects of craft are underappreciated in the academic literature and the vast majority of CBC applications.)

2. Typical Practice in CBC Studies and Recent Changes in Practice

2.1. Typical Current Practice

In CBC analysis, products (or services) are summarized by a set of levels of the attributes. For example, a smartwatch might have a watch face (attribute) that is either round or rectangular (levels), be silver or gold colored, and have a black or brown leather band. By varying the smartwatch attribute levels systematically within an experimental design, CBC analysis estimates preferences for attribute levels (and price), called "partworths," which describe the differential value of the attribute levels. For example, one partworth might represent the differential value of a rectangular watch face relative to a round watch face.

Applied practice focuses on estimating accurately the *relative* partworths. For example, if rectangular and round watch faces are equally costly but the partworth of a rectangular watch face is greater than the partworth of a round watch face for most consumers, then a typical recommendation would be to launch a product with a rectangular watch face. The relative partworths can also be used to calculate willingness to pay (WTP) by comparing differences in partworths to the estimated price coefficient. For example, if a consumer's differential value between a rectangular and a round watch face is higher than the consumer's valuation of a \$100 reduction in the purchase price, firms typically infer that the consumer is willing to pay more than \$100 for a rectangular rather than a round watch face. (There are subtleties in this calculation because of the Bayesian nature of most estimates, but this is the basic concept.)

These calculations depend only on the (posterior distribution of) *relative* partworths. Because attribute-level partworths and the price coefficient are defined relative to one another, if we multiply all partworths and the price coefficient by a constant, the comparative value and WTP calculations remain unchanged. However, the

literature has established that estimated partworths also depend on scale heterogeneity. In particular, if scale varies among consumers, then the accuracy with which the relative partworths can be estimated depends on accounting for heterogeneity in scale during estimation (e.g., Beck et al. 1993, Swait and Louviere 1993, Fiebig et al. 2010, Salisbury and Feinberg 2010, Pancreas et al. 2016). Scale heterogeneity affects partworth estimation and/or aggregation of respondents' WTP, but, once researchers account for heterogeneity, WTP does not depend on a common (across respondents) increase or decrease in scale (e.g., Ofek and Srinivasan 2002, equation 15). The phenomenon we investigate is different from scale heterogeneity; we focus on the strategic implications of a common scale factor in a stylized model assuming accurate relative partworths and assuming the estimation accounts for scale heterogeneity. (The assumptions of accurate relative partworths is relaxed in the empirical analyses.)

The literature recognizes that estimated partworths may need to be adjusted to better represent marketplace choices. One approach is to adjust scale *and relative partworths* to match market shares and use the adjusted scale and partworths in simulations (e.g., Gilbride et al. 2008). The adjustments are motivated by predictive ability rather than strategic implications. A second approach adjusts scale directly or in a procedure known as randomized first choice (RFC), in which an additive error is included in the simulations (Huber et al. 1999). RFC automatically determines the random perturbations to yield “approximately the same scale factor as the [logit] model” (Sawtooth Software 2019). Scale adjustments are easy to implement, but usage is rare—users almost always stick with the scale observed in the CBC estimation (Orme 2017). Many users report that marketplace data, as a benchmark to adjust scale and relative partworths, are often not available, for example, for innovations, or not relevant to the simulated markets. Our stylized model and empirical illustrations suggest that validation adjustments are critical and should be used more often. We also provide an alternative adjustment that does not require marketplace data.

2.2. Current Practice is Changing: The Implications of Price Equilibria

WTP provides valuable diagnostic information for pricing and attribute-level decisions and has been used to motivate and interpret valuations in patent/copyright cases (e.g., Mintz 2012, Cameron et al. 2013, McFadden 2014), but WTP does not account for competitive response. WTP does not indicate how marketplace prices will respond to new products or changes in a product's attributes (Orme 2014, pp. 90–91; Orme and Chrzan 2017, p. 194). Because of the influence of game theory in marketing science, CBC

simulators are beginning to consider competitive response. For example, if an innovator introduces a silver-colored watch face and a follower responds with a gold-colored watch face (and all other attributes are held constant), then CBC simulations can be used to calculate the Nash price equilibrium. Allenby et al. (2014) propose that these methods be used to value patents and copyrights. Courts recognized the issue as early as 2005 for class-action cases (e.g., Whyte 2005; albeit not CBC) and since at least 2012 in patent cases (Koh 2012). Although not proposed previously, simulators can use equilibrium prices to calculate the follower's most-profitable strategic-positioning response (silver versus gold) to the innovator's new product (silver or gold).

We show that scale (and validation-based scale adjustment) plays a central role when predicting price equilibria and predicting optimal competitive reactions. We illustrate the magnitude of the managerial implications. (Sawtooth Software estimates that 80% of managerial CBC applications consider competition in market simulations, although the explicit calculation of equilibrium prices is relatively new (Orme 2017).)

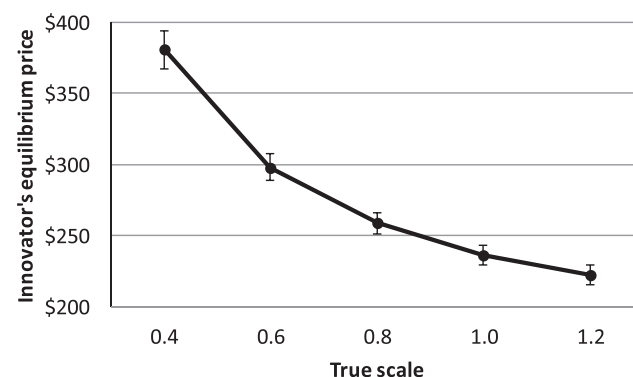
3. Empirical Illustration to Motivate the Phenomena We Seek to Study

Before we derive the stylized model and before we describe fully the empirical tests, it is useful to illustrate the phenomena we seek to study.

3.1. Scale Affects the Price Equilibria That Are Calculated

As an illustration, we plot the predicted equilibrium price of an innovator as a function of the true scale (γ^{true}). Figure 1 illustrates how the predicted price equilibrium might change if estimated scale depends on the craft of a CBC study. We use the distribution of relative partworths obtained in our empirical study

Figure 1. Predicted Equilibrium Price Depends on Scale



Notes. Data are from our empirical study of smartwatches. Error bars are posterior standard deviations.

about smartwatches (HB CBC details in Section 8.5) and calculate the (counterfactual) price equilibria for each level of scale (methods described in Section 8.8). The equilibria are based on a market with two firms whose products differ on the watch color (silver versus gold). We chose the range of the scales to be typical of those reported in the literature and in our empirical studies. (Over the range in Figure 1, equilibrium prices are monotonically decreasing in scale, but there is no guarantee that they do not increase slightly as $\gamma^{true} \rightarrow \infty$. Indeed, they do so in the illustrative example in Online Appendix 1.) We obtain similar results for watch face (round versus rectangular) and watch band (combinations of three levels).

The intuition of Figure 1, shown formally in the stylized model, is that simulated choice probabilities are more sensitive to price changes (or changes in attribute levels) when scale increases even though the relative partworths remain unchanged. Greater sensitivity implies more price competition, which drives down equilibrium prices.

This wide difference in (predicted) equilibrium prices has managerial and litigation implications. For example, suppose that a firm's CBC study reports $scale = 0.4$ but the marketplace acts according to $scale = 1.0$; then the firm would likely earn substantially less profit than it expects. The effect is real. In Section 8.7, data suggest that differences in craft yield estimates of (relative) scale that vary from 0.35 to 1.00.

Using estimates of over 11.9 million Apple Watch sales in 2016 (Reisinger 2017), the calculated price equilibrium swing of \$158 implies a swing of more than \$1.8 billion in revenue. If the predicted multiyear profit were only a small fraction of the revenue swing, it would still be substantial. Profits are based on prices, quantities, and costs, which we address later. In litigation, units sold and costs are often held constant in the "but-for" world; CBC craft would swing damages estimates by \$1.8 billion.

3.2. Scale Affects Strategic Positioning Decisions

We use the same smartwatch empirical data, but report predicted profits for (counterfactual) values of scale. In this illustration, profits are price times share. We consider a two-stage game. In the first stage, firms choose their positioning (silver versus gold). In the second stage, firms launch their products, the marketplace reacts, and the firms obtain equilibrium profits based on equilibrium prices. Table 1 presents the equilibrium profits for all possible positioning decisions by an innovator and a follower. (The innovator's profit is the top number in each subcell of Table 1; the follower's profit is the bottom number.) If scale is higher, in equilibrium, the innovator and follower choose to differentiate their products (the innovator chooses silver, the follower chooses gold),

Table 1. Relative Profits as a Function of Strategic Positioning

Innovator's position	Follower's position	
	Silver	Gold
Higher scale (0.8)		
Silver	72.7	110.8
	72.7	81.2
Gold	81.2	62.8
	110.8	62.8
Lower scale (0.4)		
Silver	112.6	132.9
	112.6	106.6
Gold	106.6	100.2
	132.9	100.2

Notes. Relative HB CBC partworths are heterogeneous, but the same in higher- and lower-scale markets. Innovator's profit is the top number in a subcell; follower's profit the bottom number. Bold indicates an equilibrium.

whereas if scale is lower, the innovator and follower choose to offer the same product (both choose silver). At least for the follower, the recommended attribute level depends on the "true" scale, holding relative partworths constant.

Typical CBC studies make recommendations based on the partworths and scale as estimated based on the CBC design (choice sets). But consumers may choose differently in the marketplace. In Section 8, we use a validation task that mimics the marketplace to adjust scale. We illustrate that strategic recommendations change depending on whether scale is adjusted based on the validation task. Unadjusted scale recommends differentiation; validation-adjusted scale recommends no differentiation for the data in this paper. This is a new reason to consider including realistic validation tasks that go beyond holdout validation in a CBC study.

4. General Formulation and Basic Notation

We begin with notation for a fully heterogeneous model because the empirical studies in Section 8 use a fully heterogeneous model. (Different consumers can have different relative partworths and scale.) Appendix A summarizes notation for both the heterogeneous model and a more stylized formal model. Although empirical studies, including ours, can have many attributes and many levels for each attribute, we focus in the stylized model on a single attribute with two levels. This focus in the stylized model is sufficient to illustrate the impact of scale and is consistent with Irmen and Thisse (1998, p. 78), who conclude that "differentiation in a single dimension is sufficient to relax price competition and to permit firms to enjoy the advantages of a central location in all other characteristics." Our stylized model also applies to simultaneous differentiation of a composite of multiple dimensions, say, a silver smartwatch with a rectangular face and a black leather band versus a gold smartwatch with a

round watch face and a metal band. Both stylistically and empirically, we hold all attributes other than our focal attributes constant across products. In the stylized model, there are no unobserved attributes.

4.1. Formal Definitions

To match typical applications of CBC, we focus on discrete (horizontal) levels of an attribute that we label r and s . A product can have either r or s , but not both. If mnemonics help, think of r as round, regular, routine, ruby, or rust colored, and s as square, small, special, sapphire, or scarlet. Although the empirical model can handle many firms, it is sufficient for the stylized model to focus on two firms, each of which sells one product. We allow an “outside option” to capture other firms and products that are exogenous to the strategic decisions of the two-firm duopoly. In Section 9.4, we show that the insights apply when there are more than two products, more than one attribute, and more than two levels.

Let u_{ij} be consumer i 's utility for firm j 's product, let u_{io} be i 's utility for the outside option, and let p_j be product j 's price. Let β_{ri} and β_{si} be i 's partworths for attribute levels r and s , respectively, and let δ_{rj} and δ_{sj} be indicator functions for whether firm j 's product has r or s , respectively. Let η_i indicate i 's preference for price, let ϵ_{ij} be an extreme value error term with variance $\pi^2/6\gamma_i^2$. If the error terms are independent and identically distributed, we have the standard logit model for the probability, P_{ij} , that consumer i purchases firm j 's product (relative to firm k 's product and the outside option):

$$u_{ij} = \beta_{ri}\delta_{rj} + \beta_{si}\delta_{sj} - \eta_i p_j + \epsilon_{ij},$$

$$P_{ij} = \frac{e^{\gamma_i(\beta_{ri}\delta_{rj} + \beta_{si}\delta_{sj} - \eta_i p_j)}}{e^{\gamma_i(\beta_{ri}\delta_{rj} + \beta_{si}\delta_{sj} - \eta_i p_j)} + e^{\gamma_i(\beta_{ri}\delta_{rk} + \beta_{si}\delta_{sk} - \eta_i p_k)} + e^{\gamma_i u_{io}}}.$$

(1)

Utility (u_{ij}) is unique to at most a positive linear transformation (Train 2009, p. 27); hence, the magnitude of the error term (ϵ_{ij}), the inverse of the error standard deviation (γ_i), and the price and partworth coefficients (η_i , β_{ri} , β_{si}) are defined to at most a multiplicative constant. For a single CBC study, we cannot simultaneously estimate β_{ri} , β_{si} , η_i , and γ_i , nor can we independently interpret the magnitude of any of these constructs. Within a CBC study, the magnitudes of these constructs can be interpreted (and estimated) only relative to one another. (We can, and do, show how estimates can vary *between* different domains such as between higher-cost and lower-cost CBC studies.)

4.2. Relationships Among Different Normalizations

Because β_{ri} , β_{si} , η_i , and γ_i are relative constructs, we must impose one constraint for identification for both interpretation and estimation. The constraint varies in the literature. McFadden (2014) constrains the price

coefficient, η_i , to unity. In the McFadden (2014) normalization, scale is defined as $\eta_i \gamma_i$. Because $\eta_i \equiv 1$, scale becomes $\eta_i \gamma_i = \gamma_i$. The McFadden (2014) normalization has the intuitive advantage that the attribute-level relative partworth differences are measured in currency units and can be interpreted as WTPs. From our perspective, the McFadden (2014) normalization enables the stylized model to manipulate scale independently from the relative partworths.

Sonnier et al. (2007) normalize the CBC model using $\mu_i = 1/\gamma_i$. When $\eta_i = 1$, we define scale as $\eta_i/\mu_i = 1/\mu_i \equiv \gamma_i$. The Sonnier et al. (2007) normalization has no effect for maximum-likelihood estimation, but we must adjust the prior distributions for μ_i when computing Bayesian posterior distributions. For the stylized model, we use the McFadden (2014) normalization because it is more intuitive when greater scale implies that the “signal-to-noise” ratio is larger.

The Allenby et al. (2014) normalization, used commonly in practice, sets $\gamma_i = \mu_i = 1$. In this normalization, WTPs require division by η_i and scale is proportional to the magnitude of the partworths. Formally, in the Allenby et al. (2014) normalization, scale becomes $\eta_i \gamma_i \equiv \eta_i/\mu_i = \eta_i$. Although the Allenby et al. (2014) normalization makes it more difficult to untangle relative partworths and scale, the basic theoretical and practical insights do not change. For the stylized model, all three normalizations are strategically equivalent (Keeney and Raiffa 1976). Empirically, HB, but not maximum likelihood, estimation is slightly different with the Allenby et al. (2014) normalization versus the McFadden (2014) and the Sonnier et al. (2007) normalizations. Section 9.1 summarizes the empirical implications of the three normalizations.

In our stylized model, we focus on the effect of a common scale factor that may be affected by CBC craft. To isolate the effect of scale in the stylized model, we assume relative partworths are not affected by craft. (The impacts on relative partworths are well studied, not new to this paper, and are added back to the empirical model.)

When CBC craft affects both scale and *relative* partworths (Section 9.3), researchers may prefer a different empirical definition of scale. For example, with the Allenby et al. (2014) normalization, researchers have defined scale as the sum of the estimated importances. (The importance of an attribute is defined as the difference between the largest and smallest partworth of an attribute.) This alternative definition does not affect the stylized model, because, in the stylized model, relative partworths do not depend on craft. Empirically, when scale is isolated such that relative partworths are mostly unaffected by craft, the comparisons among experimental conditions do not depend on the normalization-dependent definition of scale.

4.3. Profit Equations

If V is the market volume (including volume due to the outside option), c_j is the marginal cost for product j , C_j is firm j 's fixed cost, and $f(\beta_{ri}, \beta_{si}, \gamma_i)$ is the probability distribution over the relative partworths and scale (posterior if Bayesian), then the profit, π_j , for firm j is given by

$$\pi_j = V(p_j - c_j) \int P_{ij} f(\beta_{ri}, \beta_{si}, \gamma_i) d\beta_{ri} d\beta_{si} d\gamma_i - C_j. \quad (2)$$

(Empirically, if all estimates are Bayesian, we use the posterior distribution in the standard way.)

For the purposes of this paper, we assume that c_j does not depend on the quantity sold nor the choice of r or s . These assumptions can be relaxed and do not reverse the basic intuition in this paper. (The effect of the relative cost of r or s is well studied; see, e.g., Moorthy 1988.)

4.4. Interpretation and Implications of the Error Term

The error term in CBC analysis has many interpretations and implications. It has been interpreted as inherent stochasticity in consumer choice behavior and/or sources that are unobservable to the researcher, such as unobserved heterogeneity, unobserved attributes, functional misspecifications, or consumer stochasticity that is introduced by the CBC experiment (e.g., because of fatigue; see, e.g., Thurstone 1927, Manski 1977). We are most interested in what happens to the (observed) scale when the craft of the CBC study changes, say, by the addition of incentive alignment or images that better approximate the marketplace (more realistic images). To address this issue, we assume that the firm acts strategically on a CBC study anticipating the price equilibria implied by the CBC study. However, after the firm selects its positioning strategy (say a silver versus gold smartwatch) and launches its product, the prices are set by market forces; that is, the marketplace reaches the equilibrium prices because firms adjust price *after launch* until they reach a Nash price equilibrium.

If the firm acts on a CBC study it believes to be correct, the firm will anticipate a price equilibrium based on the scale it believes to be true and will choose its position optimally based on its beliefs. But the actual realized equilibrium prices may differ if the firm's beliefs about scale are not sufficiently accurate. The mechanism by which marketplace prices adjust after positioning decisions is based on market reaction. The mechanism is different from the more common simplifying assumption in modern game theory that "firms compete non-cooperatively in product specifications with instantaneous adjustment to the Nash equilibrium prices" (Economides 1986, p. 67).

The difference is necessary because, unlike typical models, the firm may act based on market research it only believes to be accurate. Our mechanism is similar to that expressed by Hotelling (1929, pp. 48–49):

But understandings between competitors are notoriously fragile. Let one of these business men, say B, find himself suddenly in need of cash. Immediately at hand he will have a resource: Let him lower his price a little, increasing his sales. His profits will be larger until A decides to stop sacrificing business and lowers his price to the point of maximum profit. B will now be likely to go further in an attempt to recoup, and so the system will descend to the equilibrium position. Here neither competitor will have any incentive to lower his price further, since the increased business obtainable would fail to compensate him.

Because actual sales and equilibrium prices depend on how consumers react to the products' chosen positions after the products are introduced to the market, we need the concept of a true scale (γ^{true}) that represents how the marketplace reacts. We purposefully do not define true scale as a philosophical construct—it is defined as the scale that best represents how consumers actually react in the marketplace. Practically, we expect the true scale to be finite because of inherent stochasticity (e.g., Bass 1974), but our stylized theory allows true scale to approach infinity. Our model admits many explanations of inherent uncertainty. The stylized model needs to assume only that, even with the best possible craft, the firm's prediction of consumer behavior includes a (possibly zero) error term. True scale is a latent construct; the firm can at best estimate its value.

4.5. Relationship to Prior Research

Our perspective draws on, but is quite different from the pioneering work by Anderson et al. (1999), de Palma et al. (1985, 1987), and Rhee et al. (1992), who also explore the strategic implications of a normalization constant in a logit model. They represent the marketplace, not individual consumers, by a logit model and interpret the normalization constant ($\mu = 1/\gamma$) as heterogeneity in consumer utility as in the paper by de Palma et al. (1985, p. 779), who state, "the world is pervasively heterogeneous, and we have made it clear how, in a particular model, this restores smoothness [that leads to differentiation]." In their analyses, the firms act strategically on their uncertainty about this heterogeneity. As heterogeneity increases firms on a Hotelling line seek minimum differentiation.

Our stylized model makes different assumptions and has different foci:

- We explicitly constructed the stylized model to model heterogeneity and, hence, rule out unobserved

heterogeneity as an explanation for scale and craft effects.

- We explicitly constructed the stylized model so that there are no unobserved attributes and, hence, rule out unobserved attributes as an explanation for scale and craft effects. (Online Appendix 13 reviews minimum versus maximum differentiation theories that rely on unobserved attributes.)

- We focus on how craft (and external validation) in CBC studies affects scale and, through scale, differentiation. We do not focus on differentiation per se.

- We allow firms to act on different types of information (CBC studies) about consumers; our theory seeks to provide practical suggestions for widely used market research methods.

- We illustrate the effects of craft on scale and provide examples of the effect sizes, using data from professional-quality CBC studies.

- Empirically, we model heterogeneity explicitly and attempt to rule out unobserved attributes.

5. Stylized Formal Model with Two-Segment Heterogeneity

In the stylized model, we focus on two mutually exclusive and collectively exhaustive consumer segments with different relative partworths. This level of heterogeneity is sufficient to enable two firms to target different segments and sufficient to illustrate the strategic effects of scale. The strategic effects survive the more general empirical applications in Section 8, which use standard estimation procedures (HB CBC, tested with three related normalizations).

We label the segments R and S , with segment sizes R and S , respectively. Partworths vary between segments, but are homogeneous within segment ($\beta_{ri} = \beta_{rR}$ and $\beta_{si} = \beta_{sR}$ for all i in segment R ; $\beta_{ri} = \beta_{rS}$ and $\beta_{si} = \beta_{sS}$ for all i in segment S). Scale varies among consumers in the empirical applications, but in the stylized model we focus on a common scale adjustment that might vary among CBC studies of different quality. For this purpose, it is sufficient to assume scale is constant across consumers such that $\gamma_i = \gamma$ for all i .

We investigate trade-offs that firms make between (1) a differentiated strategy in which each firm targets different attribute levels and (2) an undifferentiated strategy in which both firms target the same attribute levels. To do so, we need one attribute level to be more attractive than the other. Given the other symmetries in the model, it is sufficient to model the relative influence of an attribute level by the percent of consumers who prefer that attribute level, R or S . We need partworths to vary between segments. It is sufficient that their relative values reverse ($r > s$ in one segment and $s > r$ in the other segment). Although the partworths differ between segments, it would be redundant to also vary the magnitude of partworth

differences; thus, we set $\beta_{rR} = \beta_{sS} = \beta^h$ and $\beta_{sR} = \beta_{rS} = \beta^l$. We set $\beta^h \geq \beta^l$ and $R \geq S$ without loss of generality. Setting $R \geq S$ assures that the firm prefers $r \geq s$, ceteris paribus. (We can also set $\beta^l = 0$ without loss of generality, but interpretations are more intuitive if we retain β^l in the notation.)

The costs, c_j and C_j , affect strategic decisions in the obvious ways and need not be addressed in this paper. For example, a firm might require a minimum price such that $p_j \geq c_j$ or choose not to enter if C_j is too large. Such effects are well studied and affect firm decisions above and beyond the strategic effect of scale. For focus, we normalize V to a unit market volume, set $C_j = 0$, and roll marginal costs into price by setting $c_j = 0$.

We label the potential strategic positions for firms 1 and 2, respectively, as either rr , rs , sr , or ss . For example, rs means that firm 1 positions at r and firm 2 positions at s . Because prices, market shares, and profits depend on these strategic positioning decisions, we subscript prices, shares, and profits accordingly. For example, p_{1rr} is firm 1's price in a market in which firm 1's position is r and firm 2's position is r .

6. The Effect of Scale on Equilibrium Prices and Strategic Positioning Decisions

6.1. Basic Game to Demonstrate the Impact of True Scale (Inherent Stochasticity)

The price-positioning game is consistent with key references in the strategic positioning literature (see Online Appendix 13) and realistic for most markets. *Temporarily*, we assume the firms believe they know γ^{true} , which may be either finite or approach infinity. (Infinite γ^{true} is equivalent to a first-choice rule in CBC simulators.) Based on this knowledge, the firms first choose their product positions (r or s) sequentially, and then the marketplace sets prices. (If the firms are correct in their beliefs, they correctly anticipate equilibrium prices.) The positioning decisions, once made, are not easily reversible, perhaps because of production capabilities or ephemeral advertising investments. Without loss of generality, firm 1 is the innovator, and firm 2 is the follower. The innovator enters assuming that the follower will choose its positions optimally. (We abstracted away from entry decisions by setting $c_j = C_j = 0$.) After the firms have entered, Nash equilibrium prices, if they exist, are realized. This two-stage game will be embedded in another game in Section 7 in which firms know that the CBC study may be imperfect and choose whether to invest in higher-cost craft to better estimate scale prior to making strategic positioning decisions. We address the relationship to simultaneous entry in Online Appendix 14. We use asterisks to indicate Nash equilibrium prices, shares, and profits.

The equilibria we obtain, and strategies that are best for the innovator and follower, have the flavor of models in the asymmetric competition literature (minimum versus maximum differentiation), but with two important differences: (1) Our results are not driven by unobserved heterogeneity or strategically relevant unobserved attributes. (2) Our results are focused on providing a structure to understand and evaluate the impact of improvements in CBC craft. We develop the formal structure as a practical tool to evaluate whether improvements, such as more realistic images or incentive alignment, affect strategic decisions.

6.2. Price Equilibria in Heterogeneous Logit Models (as in CBC Analysis)

We are not the first to investigate price equilibria in logit models. Choi et al. (1990) demonstrate that price equilibria exist if partworths are homogeneous and consumers are not overly price sensitive. Their condition (Choi et al. 1990, p. 179) suggests that price equilibria are more likely to exist if there is greater uncertainty in consumer preferences—a result consistent with our model which, in addition, accounts for heterogeneity. Choi and DeSarbo (1994) use similar concepts to solve a positioning problem with exhaustive enumeration. Luo et al. (2007) extend the analysis to include heterogeneous partworths and equilibria at the retail level. They use numeric methods to find Stackelberg equilibria if and when the equilibria exist.

We cannot simply assume that price equilibria exist and are unique. For example, Aksoy-Pierson et al. (2013) (hereafter, APAF) warn that price equilibria in heterogeneous logit models may not exist. APAF generalize the analyses of Caplin and Nalebuff (1991) to establish sufficient conditions for price equilibria to exist, to be unique, and to be given by the first-order conditions. The APAF conditions apply to typical HB CBC studies (Aksoy-Pierson et al. 2013, section 6); thus, we check existence and uniqueness in both our stylized model and in our empirical analyses.

6.3. Equilibria in the Price Subgame

Using Equation (1), we obtain implicit first-order and second-order conditions for optimal prices and profits. We use these conditions to derive implicit equations for the equilibrium prices and profits. Differentiating further, we obtain implicit second-order and cross-partial conditions (see Appendix B). We establish that interior equilibria exist and are unique given (mild) sufficient conditions. Equilibria exist and are unique for most posterior draws in the empirical analysis when prices are constrained to be within the range of measurement. When they exist, the empirical equilibria are unique. The equilibria exist and are unique in an illustrative example of the stylized model (Section 7.6).

6.4. True Scale Affects the Relative Profits of the Firms' Positioning Strategies

We temporarily assume the firm believes it knows the true scale, which can be either finite (inherent uncertainty in consumer choices) or approach infinity (no inherent uncertainty). In Section 7, we use the results of this section to explore what happens when the firm does not know the true scale and bases its decisions on CBC market research. All proofs are formalized in Appendix B.

To understand the effect of true scale on firms' positioning strategies (choice of attribute levels in equilibrium), we examine how profit-maximizing attribute levels change as true scale increases from small to large. Because the functions are continuous, we need only show the extremes. Appendix B establishes that, for sufficiently low true scale, price moderation through differentiation does not offset the advantage of targeting the larger segment and both innovator and follower choose the most profitable attribute level, r . The proof is driven by the fact that the logit curve becomes flatter as $\gamma^{\text{true}} \rightarrow 0$. In this regime, the effect of attribute changes or price changes has less effect on choice probabilities.

When price is endogenous, common intuition is not correct. All shares, including the outside option, do not tend toward equality as $\gamma^{\text{true}} \rightarrow 0$. The endogenous increase in equilibrium prices offsets this effect. Instead, while the innovator and follower shares move closer to one another, the equilibrium prices increase and reduce shares relative to the outside option.

As γ^{true} gets large, both the innovator and the follower prefer differentiation. Formally, we use two mild sufficient, but not necessary, conditions: (1) the relative partworth of r is larger than the relative partworth of the outside option and (2) the relative partworth of the outside option is at least as large as the relative partworth of s . We also prove that, among the undifferentiated strategies, both the innovator and follower prefer to target the larger segment and, under the sufficient conditions and large γ^{true} , the innovator prefers the larger segment. These intermediate results produce an equilibrium in product positions. (See Appendix B for proofs.)

6.5. Equilibrium in Product Positions

Proposition 1. *For low true scale ($\gamma^{\text{true}} \rightarrow 0$), the innovator (firm 1) targets the larger segment (r), and the follower chooses not to differentiate. The follower targets the larger segment (r).*

Proposition 2. *If β^h is sufficiently larger than u_o and if $u_o \geq \beta^l$, then there exists a sufficiently large γ^{true} such that the innovator targets the larger segment (r), and the follower chooses to differentiate by targeting the smaller segment (s).*

Because the profit functions are continuous (see also APAF), Propositions 1 and 2 and the mean value theorem imply that there exists a γ^{cutoff} such that the follower is indifferent between rr and rs . We calculate γ^{cutoff} as $\{\gamma : \pi_{2rs}^*(\gamma) = \pi_{2rr}^*(\gamma)\}$. Numerically, for a wide variety of parameter values, the profit functions are smooth, the cutoff value is unique, and $\pi_{2rs}^* - \pi_{2rr}^*$ is monotonically increasing in γ^{true} . We have not found a counterexample.

7. Implications for Investing in the Quality of CBC Studies

7.1. Aspects of Craft in CBC Studies

We reviewed the conjoint analysis papers in *Marketing Science* from the last 16 years (2003–2018). Forty-six papers addressed new estimation methods, new adaptive questioning methods, methods to motivate respondents, more efficient designs, noncompensatory methods, and other improvements. Mostly, papers focused on the improved estimation of relative partworths or implied managerial interpretations. Six of the papers address the implications of scale (or a related concept for non-CBC papers) explicitly, and of those six, three focus on more accurate estimation, one on weighting consumers, one on brand credibility, and one on peer influence. None discuss the strategic (price or positioning) implications of scale (see Online Appendix 15).

There is substantially less focus in the conjoint-analysis literature on data-quality issues such as selecting stimuli to best represent marketplace choices (realistic stimuli). Most papers do not report whether stimuli are text only, pictorial, or animated, but of those that do, the vast majority are text only. Although interest in incentive alignment is growing, no papers discuss the impact of either realistic stimuli or incentive alignment on the scale observed for the estimation data. Furthermore, in practice, defaults in software lead most applications to use text-only stimuli without incentive alignment.

Improving craft in CBC can be expensive. Some firms, such as Procter & Gamble, Chrysler, and General Motors, are sophisticated and spend substantially on CBC. Some CBC studies invest tens of thousands of dollars to create realistic animated descriptions of products and attributes complete with training videos. And some include additional pretests to assure that the stimuli are seen as realistic-to-marketplace by consumers. Incentive alignment can also be expensive: one CBC study gave 1 in 20 respondents \$300 toward a smartphone and another gave every respondent \$30 toward a music-streaming subscription (Koh 2012, McFadden 2014). Firms routinely use high-quality internet panels, often paying as much as \$5–\$10 for each respondent and up to \$50–\$60 for hard-to-reach respondents. Our review of the literature suggests that firms believe that each

of these investments increases the accuracy with which relative partworths are estimated. On the other hand, many firms reduce CBC costs by using text-only attribute descriptions, no incentive alignment, less sophisticated methods, convenience samples, and small sample sizes. We show, in the stylized model and by example empirically, that the managerial implications of these craft decisions (and defaults) are not trivial.

7.2. Modeling Decisions with Respect to CBC Craft

In Section 6.4, we temporarily assumed the firm believed the true scale to be accurate. True scale was the scale that described how consumers would react to r , s , and price in the marketplace. We are interested in what happens if the firms (or testifying experts) shirk on their investments in the craft of CBC studies. We define two additional constructs: $\gamma^{market\ research}$ is the scale estimated by the CBC study, and may or may not equal the true scale, and $\gamma^{asymptotic}$ is the scale that the firm would obtain with the highest possible level of CBC craft. If craft were costless, the firm would always seek the best craft in the hopes that $\gamma^{asymptotic}$ would approximate (unobserved) γ^{true} . But craft is not costless.

We embed the game from Section 6 into a larger game. We assume that if the firm invests more in CBC craft, its estimate of scale becomes better, that is, $|\gamma^{market\ research} - \gamma^{true}|$ becomes smaller. (Strategic errors can be made if γ^{true} is underestimated or overestimated.) To focus on scale in the stylized model, we assume all (reasonable) CBC studies estimate the relative partworths correctly so that the firm knows that $r > s$ in R , $s > r$ in S , and $R > S$. In Section 9.3, we investigate a double whammy whereby craft affects both estimated scale and estimated relative partworths. Our results are complementary to research to improve relative partworth estimates; hence, we need not address the accuracy of relative partworths in the stylized model.

It is sufficient to illustrate the phenomenon in the stylized model if we consider lower-cost and higher-cost CBC studies such that $\gamma^{higher} = \gamma^{true}$ for the higher-cost study and $\gamma^{lower} \neq \gamma^{true}$ for the lower-cost study. (In Sections 8 and 9, we demonstrate empirically that costly craft affects $\gamma^{market\ research}$ and that it is likely that costly craft reduces $|\gamma^{market\ research} - \gamma^{true}|$.) For the stylized model, we formally state the game order even though we can prove the results for other orders and we can relax many assumptions empirically.) The game order is as follows:

1. The innovator decides whether to invest in the lower-cost or the higher-cost CBC study. (To focus on scale, we assumed that both CBC studies reveal correctly that $r > s$ in R , $s > r$ in S , and $R > S$.)

2. The innovator completes its CBC study and observes $\gamma^{\text{market research},i}$.

3. Based on its observed $\gamma^{\text{market research},i}$, the innovator announces and commits to either r or s .

4. The follower decides whether to invest in the lower-cost or the higher-cost CBC study. (By assumption, both CBC studies reveal that $r > s$ in R , $s > r$ in S , and $R > S$.)

5. The follower completes its CBC study and observes $\gamma^{\text{market research},f}$. (The innovator has already acted; the follower observes the innovator's position, r or s .)

6. Based on its observed $\gamma^{\text{market research},f}$, the follower announces and commits to either r or s . (Because the innovator has acted, the follower need not assume anything about the innovator's belief about $\gamma^{\text{market research},i}$.)

7. Both firms launch their products. The marketplace determines sales and price based on γ^{true} —the scale that best describes consumer response. The firms realize their profits.

It will be obvious in Section 7.3 that the follower could have made its craft decision before learning of the innovator's positioning—such a game ordering would give the same results. Commitment to r or s implicitly assumes that positioning decisions are “sticky,” expensive, or based on know-how, patents, or copyrights. Once made, the firm cannot change its positioning even when the market price, market shares, and profits are not as forecast. Propositions 1 and 2 give us sufficient insight to understand the innovator's and the follower's craft decisions. Online Appendix 14 addresses a game in which the innovator and follower move simultaneously. The simultaneous game does not determine which firm positions at r in a differentiated market, but all other implications remain.

7.3 Innovator's Strategic Positioning Decision Does Not Depend on Observed Scale

The innovator chooses to target the larger segment (r) in both Propositions 1 and 2, and thus the innovator makes the same decision whether $\gamma^{\text{market research}} = \gamma^{\text{true}}$ or $\gamma^{\text{market research}} \neq \gamma^{\text{true}}$. Because the innovator's strategic positioning decision is independent of the observed scale, investing in a higher-cost CBC study has no effect on the innovator's positioning strategy. (We state and prove the result formally in Appendix B.) The insight is consistent with recommendations in product development (e.g., Urban and Hauser 1993, Ulrich and Eppinger 2004). These texts advise innovators to use market research to identify the best attributes, but also advise that the accuracy need only be sufficient for a go/no-go decision.

7.4 Follower's Strategic Positioning Decision Depends on Observed Scale

If a naïve follower underinvests in CBC craft and observes $\gamma^{\text{lower}} \neq \gamma^{\text{true}}$, and if either $\gamma^{\text{lower}} < \gamma^{\text{cutoff}} < \gamma^{\text{true}}$

or $\gamma^{\text{lower}} > \gamma^{\text{cutoff}} > \gamma^{\text{true}}$, then the follower makes a strategic error by choosing the wrong strategic position (the wrong attribute level). We state and prove the result formally in Appendix B. For example, if $\gamma^{\text{cutoff}} < \gamma^{\text{true}}$, then Proposition 2 implies that the most profitable attribute level for the follower is s . However, if the follower acts on $\gamma^{\text{market research}} = \gamma^{\text{lower}}$, and if $\gamma^{\text{lower}} < \gamma^{\text{cutoff}}$, then, by Proposition 1, the follower will choose the less profitable attribute level, r . In some cases, the naïve follower may underinvest in CBC studies, but get lucky, say, if $\gamma^{\text{true}} < \gamma^{\text{cutoff}}$ and $\gamma^{\text{lower}} < \gamma^{\text{cutoff}}$. The first inequality implies r is the follower's most profitable attribute level, and the second inequality implies the follower chooses r . The important insight is that if the naïve follower underinvests in the craft of a CBC study, then it is relying on luck to make the right decision.

Although some authors interpret higher scale as a surrogate for higher response accuracy (Toubia et al. 2004, Evgeniou et al. 2005), we interpret scale as more accurate if $|\gamma^{\text{market research}} - \gamma^{\text{true}}|$ is lower. A CBC study that uses less costly craft can have higher estimated scale, but those estimates can be less accurate for representing the marketplace. For example, a CBC study with two convenient attributes, text-only stimuli, and no incentive alignment might estimate that scale is high because respondents answer choice tasks more consistently. But the CBC study with such craft might *overestimate* true scale because two text-based attributes without incentive alignment may not approximate marketplace choices that are more deliberate and externally valid.

7.5 Sophisticated Bayesian Follower's Decision on Investments in CBC Studies

As firms become more sophisticated, they might use Bayesian decision theory to decide whether to invest in a higher-cost or lower-cost craft. For example, if the follower can invest K dollars to learn γ^{true} , the firm can compare expected profits, from acting optimally on γ^{true} , to expected profits based on the prior distribution of γ^{true} . If the higher-cost study updates the prior, the calculations take this into account. The expected-value-of-sample-information calculations are straightforward and provide no incremental insight about craft decisions. For completeness, we provide example calculations in Online Appendix 2.

7.6 Illustrative Example

In Online Appendix 1, we provide an illustrative numerical example with $\beta^h = 2$, $\beta^l = 1$, $u_0 = 1$, and $R = 0.55$. (R programs are available from the authors.) The effect of γ^{true} on equilibrium prices is similar to that observed for the empirical data in Figure 1. For the vast majority of the range of scale, especially in the range we observe in empirical data, equilibrium

prices (and profits) decrease with scale. Prices increase slightly as $\gamma^{true} \rightarrow \infty$. The latter is a result of multiple offsetting forces when the market approaches extreme behavior—very small increases in price relative to competition have large impacts on market shares. As predicted, differentiated positions are most profitable when γ^{true} is large, and undifferentiated positions are most profitable when γ^{true} is small. In the illustrative example, we calculate $\gamma^{cutoff} = \{\gamma : \pi_{2rs}^*(\gamma) = \pi_{2rr}^*(\gamma)\}$ to be approximately 1.0. For the illustrative example, opportunity losses for choosing an incorrect strategic position are quite large.

7.7. Sensitivity of the Stylized Model to Alternative Normalizations

All three normalizations imply the same stylized results. For the Allenby et al. (2014) normalization ($\gamma = \mu = 1$), holding the ratios of β^h/η and β^l/η constant, firms differentiate if $\eta \rightarrow \infty$ and choose not to differentiate if $\eta \rightarrow 0$. For the Sonnier et al. (2007) normalization ($\eta = 1$, $\gamma \equiv 1/\mu$), firms differentiate as $\mu \rightarrow 0$ and choose not to differentiate as μ gets large.

8. Empirical Test: Smartwatches

It is reasonable to ask whether the phenomena we study stylistically are sufficiently strong that they are observable in empirical applications. Our empirical applications relax the formalized assumptions of one strategic attribute, two levels, two products, heterogeneity limited to two segments, homogeneous scale, and homogeneous within-segment partworths. We demonstrate that scale can be manipulated by differences in CBC craft and that recommended strategic price and positioning decisions depend on whether scale is adjusted with validation tasks. Empirically, scale drives strategic decisions even when relative partworths do not vary, when firms do not react to unobserved attributes, and when we allow full heterogeneity.

To test the implications of the stylized theory, we undertake CBC studies in a realistic product category using multiple attributes, some with more than two levels. We vary two representative aspects of craft while maintaining other aspects at professional-level quality. We test the implications of an example validation task.

8.1. Smartwatch CBC Studies

We focused on four attributes of smartwatches: case color (silver or gold), watch face (round or rectangular), watch band (black leather, brown leather, or matching metal color), and price (\$299, \$349, \$399, or \$449). We held all other attributes constant, including brand and operating system. (In Section 9.4, we discuss two studies with more attributes and a multitude of levels.) We designed our stimuli so that any unobserved attributes were unlikely to vary among experimental conditions. By assumption in counterfactual

simulations, unobserved attributes were not used strategically for positioning decisions.

We used 16 choice sets for estimation (and two as internal holdouts) with three profiles per choice set. We included the outside option via a dual-response procedure (Meissner et al. 2016, Wlömert and Eggers 2016). We followed standard survey design principles including extensive pretesting (66 respondents) to assure that (1) the questions, attributes, and tasks were easy to understand; (2) that the manipulation of craft between respondents was not subject to demand artifacts; and (3) that respondents did not report basing decisions on any attributes that were not varied.

8.2. Image Realism and Incentive Alignment

We varied image realism and incentive alignment in a 2×2 between-subjects design. These aspects of CBC craft are chosen as illustrative—we expect many aspects of craft to have strategic implications, including the representativeness of the respondents, the completeness and clarity of the product attributes, the type of questions (simple versus dual response), the number of choice tasks, the number of profiles per choice task, the quality of respondent training, and the quality of partworth estimation. We chose incentive alignment because of the growing academic interest in incentive alignment and because of its proven impact on predictive ability, for example, in Ding (2007) and Ding et al. (2005, 2011). We chose image realism because the product-development literature suggests visual depictions and animations provide nearly the same results as physical prototypes and that rich visual representations are more realistic than text and more likely to evoke marketplace-like responses from respondents (e.g., Vriens et al. 1998, Dahan and Srinivasan 2000, Dahan and Hauser 2002). Furthermore, Dzyabura et al. (2019) suggest that conjoint analysis with physical prototypes provides different conjoint-analysis estimates than less realistic stimuli. Our review of the *Marketing Science* literature (Section 7.1) suggests that realistic images and incentive alignment are rare in the academic literature and in practice.

8.2.1. Image Realism. After the screening questions, respondents entered the CBC section. Following a training task (not used in estimation), each respondent chose repeatedly among three smartwatch profiles and indicated whether he or she would purchase the smartwatch. Respondents in the realistic-image experimental cells saw high-realism images that attempted to represent marketplace stimuli closely (Figure 2). To make the images more realistic, the respondent could toggle among a detailed view, a top view, and an app view (not shown in Figure 2). Respondents in the less-realistic-image cells saw only text-based stimuli (with simple images) and could not toggle among views

Figure 2. Realistic Images: Choice-Based Dual Response Task



Note. The images were animated allowing respondents to toggle views.

(see Figure 3). Text-only stimuli are common in practice and are the defaults in most professional CBC software packages. On the other hand, realistic images are common in marketplace choices among smartwatches (see <https://www.apple.com/watch/compare/>).

8.2.2. Incentive Alignment. In the incentive-aligned experimental cells, respondents saw an animated video to induce incentive alignment (<https://www.youtube.com/watch?v=DBLPfRJo2Ho>). Specifically, respondents were told that 1 in 500 respondents would receive a smartwatch and/or cash with a combined value of \$500, based on their answers to the survey. Image realism in the video was matched to image realism in the experimental cell (see Figure 4). Respondents who were not in incentive-aligned experimental cells received the same cash offer, but the cash was not tied to their answers.

8.3. Validation Task

The ideal external validation is whether the CBC model predicts the choices consumers would make if the hypothetical profiles were to become real products in the marketplace. But most hypothetical profiles will never be market tested. Instead, we mimic marketplace choices by creating a “market” that approximates the marketplace as closely as

feasible while controlling for unmodeled marketing actions. In this validation task, respondents chose among 12 smartwatches and an outside option. Twelve smartwatches represent all possible design combinations. Price was chosen randomly (without replacement) according to minimal overlap regarding the design attributes. The resulting prices are almost orthogonal to the design attributes. The task was delayed three weeks to cleanse memory. We believe, and an empirical posttest confirms, that this validation task is perceived by respondents to be closer to marketplace choices than within-study holdout tasks. (See Online Appendix 12 for an empirical posttest. Marketplace market shares were not available for the hypothetical smartwatch profiles in our experiment.) If scale adjustment based on this validation task affects strategic decisions, then we have demonstrated the phenomenon empirically. Future research can explore other validation tasks such as those proposed by Gilbride et al. (2008) and Wlömert and Eggers (2016).

8.4. Sample

Our sample was drawn from a professional panel.² We screened the sample so that respondents expressed interest in the category but did not own a smartwatch, were based in the United States, were aged 20–69, and agreed to informed consent as required by

Figure 3. Lower-Quality Study: Choice-Based Dual Response Task (No Ability to Toggle)

	Watch 1	Watch 2	Watch 3
Watch face:	 Rectangular	 Round	 Rectangular
Case color:	Gold-colored	Gold-colored	Silver-colored
Band:	Brown leather band	Matching metal band	Black leather band
Price:	\$ 349.-	\$ 399.-	\$ 299.-
Best option:	☐	☐	☐
Would you consider buying your preferred option if it was available?			
☐ Yes			
☐ No			

our institutional review boards. Respondents in both studies received standard panel incentives for participating in the study.

Overall, 1,693 respondents completed the first wave of studies, and, of these, 1,147 completed the delayed validation task (68%). We considered respondents who completed both the study and validation task. We removed respondents who always chose the outside option. There were no significant differences between the experimental cells and the exclusion of respondents ($p = 0.86$). The final sample size was 1,044 with sample sizes varying from 248 to 275 among experimental conditions. To illustrate the effect of CBC craft, we focus on comparisons among the realistic-image, incentive-aligned experimental cell ($n = 270$) and the text-only, not-incentive-aligned experimental cell ($n = 275$). In Section 9.2, we compare the effect of realistic images to the effect of incentive alignment using the full 2×2 design.

8.5. Estimation of Heterogeneous Partworths and Scale: Standard HB CBC Model

We adopt a standard HB CBC estimation method consistent with the stylized model. The basic utility model generalizes the utility model in the stylized model (recall that u_{ij} is consumer i 's utility for product profile j and p_j is the price). For notational simplicity, we state the utility for binary attributes recognizing the standard generalization to multilevel attributes (as in our empirical CBC studies). If profile j has attribute k , then $a_{jk} = 1$; otherwise $a_{jk} = -1$. The utility model is

$$u_{ij} = \gamma_i \left(\sum_{k=1}^K \beta_{ki} a_{jk} - p_j \right) + \epsilon_{ij}. \quad (3)$$

The probability of choosing each profile (or the outside option) is given by the standard logit model analogous to that used for the stylized model. This

Figure 4. Incentive Alignment Screenshot

There is one more thing. We are giving away one of these products you are evaluating. Please watch the following video to learn more.



Conditions:

- 1 out of every 500 respondents will get the \$ 500.- budget to buy the smartwatch
- If you are the winner we will offer you a watch with the specific watch face, case color, band, and price you have chosen in a randomly determined choice set.
- This watch will be from your preferred brand: Apple
- If your exact preference will not be available on the market in about three weeks from now, we will match it as close as possible based on the available options and from what we know about your preferences.
- In order to take part in the lottery we need to know your email address that we will use only to contact you if you have won. We will not contact you otherwise and will not share it with anyone else.
- The reward can only be transferred to the USA, Canada, or Europe.
- Remember, you must be one of the lucky winners to be eligible for this gift.

You will be able to proceed after watching this video.

McFadden (2014) normalization is similar to the normalization used by Sonnier et al. (2007) with the exception that the latter estimate $\mu_i \equiv 1/\gamma_i$. The Allenby et al. (2014) normalization estimates an explicit price coefficient η_i by setting $\gamma_i = \mu_i = 1$; hence, scale is quantified by η_i . Empirically, strategic implications from the three normalizations are not significantly different (see Online Appendices 6, 7, and 8).

Like Allenby et al. (2014, p. 436), we use a hierarchical estimation that assumes the observed data are given by the choice model (as a function of the β_{ki} 's, γ_i 's, and a_{jk} 's). The β_{ki} 's and $\ln(\gamma_i)$'s are distributed multivariate normal. We use a random-effects specification for scale allowing the means of the distribution to vary according to the experimental condition (see Section 8.6). The second-stage prior is the standard Normal-inverted-Wishart conditionally conjugate prior. Allenby et al. (2014) use the standard relatively diffuse prior for the β_{ki} 's, but modify the prior for $\ln(\gamma_i)$ to be more diffuse ($\ln(\eta_i)$ in their model). Details are provided in Online Appendix 5 and by Allenby et al. (2014), who provide graphical motivation for the prior.

To avoid misspecification errors, we tested for interaction effects. We did not detect significant improvements, and hence our final model is based on main effects. All settings not specified by Allenby et al. (2014) followed standard procedures as in Sawtooth Software (2015). For example, we used 10,000 burn-in iterations for convergence and a subsequent 10,000 iterations to draw partworths and scale, from which we kept every 10th draw. All subsequent summaries, profits, and other reported quantities are based on the posterior distributions.

8.6. Identification of Relative Scale as a Function of Craft and Validation

We identify how scale changes as a function of craft by using an experimental design. The ratio of scale among experimental conditions is well defined and identified for all three normalizations. With two experimental cells times two types of choice tasks (estimation and validation), we identify three scale adjustments, all relative to the text-only, not-incentive-aligned, no-validation-adjustment factor, which we normalize to 1.0. Accordingly, we estimate scale-adjustment factors for the realistic-image, incentive-aligned condition, λ_{Q^h} ; the validation task, λ_V ; and their interaction, λ_{Q^hV} . Following Fiebig et al. (2010), we use an exponential transformation to assure that all scale factors are positive.

Let $Q_i^h = 1$ if respondent i was exposed to the realistic-image, incentive-aligned condition (0, otherwise), and

let $V_i = 1$ for respondent i 's validation task (0 for the estimation tasks). Then we obtain

$$u_{ij} = \gamma^{QV} \gamma_i \left(\sum_{k=1}^K \beta_{ki} a_{jk} - p_j \right) + \epsilon_{ij}, \quad (4)$$

where $\ln(\gamma^{QV}) = \lambda_{Q^h} Q_i^h + \lambda_V V_i + \lambda_{Q^hV} Q_i^h V_i$.

This specification was estimated as a random-effects model within a HB framework that assumes a normal distribution for $\ln(\gamma_i)$ with means according to $\ln(\gamma^{QV})$. The priors are otherwise consistent. The full specification can be found in Online Appendix 6.

Following Bayesian principles, this specification uses all of the data simultaneously and rigorously. We compared this specification to an ad hoc method in which we estimate parameters for each experimental cell using the CBC choice tasks and then use a single-parameter logit model to estimate a scale-adjustment factor between choice tasks and the validation task. The ad hoc specification has the advantage of separating relative partworth estimation from scale-adjustment because the relative partworths are estimated independently for each experimental cell. When we compared the results, the specification in Equation (4) was highly correlated with the ad hoc method ($\rho = 0.995$).

8.7. CBC Market-Research Quality and Validation Affect Scale as Observed by the Firm

The posterior means and standard deviations of the scale-adjustment posterior distributions of γ^{QV} are given in Table 2. First, we notice that in the majority of posterior draws (99%) for the estimation choice profiles only, relative scale is higher for text-only questions without incentive alignment than it is for more realistic images with incentive alignment. If scale is used as a surrogate for response accuracy as in Evgeniou et al. 2005, Toubia et al. 2004, and others, the firm might conclude that investments in realistic images and incentive alignment reduced response accuracy among the CBC profiles. But the goal is not a higher scale based on CBC profiles; the goal is to minimize $|\gamma^{\text{market research}} - \gamma^{\text{true}}|$.

Scale might be artificially inflated among text-only choice tasks because it is easier for respondents to answer such questions consistently, but at the same time text-only choice tasks might be less predictive of choices in a marketplace than incentive-aligned questions based on stimuli that match the marketplace. To the extent that scale based on realistic images and incentive alignment and adjusted for the validation task is our best estimate of γ^{true} , then $|\gamma^{\text{market research}} - \gamma^{\text{true}}|$ is best, by assumption, for the

Table 2. Posterior Means of Relative Scale Adjustment

	Text only, no incentive alignment	Realistic images, incentive alignment
Scale is based on estimation choice tasks	1.00 ^a (n.a.)	0.86 (0.06)
Scale is adjusted to validation task	0.35 (0.04)	0.61 (0.06)

Notes. Standard deviations are in parentheses. The full posterior distribution is available from the authors. n.a., not applicable.

^aNormalized to 1.00 for identification.

realistic-image, incentive-aligned, validation-adjusted estimates. All relative comparisons make intuitive sense. The next-best estimate is for realistic-image, incentive-aligned, estimation-only scale, then text-only, not-incentive-aligned, validation-adjusted scale. The worst estimate is text-only, not-incentive-aligned, estimation-only scale.

Table 2 isolates a scale effect. A common measure, hit rates, isolate a relative-partworth effect. As expected, hit rates are substantially improved for the realistic-image, incentive-aligned condition—hit rates increase from 24% to 39% (chance is 7.7%) for the validation task and from 64% to 77% (chance is 25%) for the estimation task.

Uncertainty explained (U^2 ; Hauser 1978) is based on the joint accuracy of scale and relative partworths. In our data, U^2 increases for the realistic-image, incentive-aligned condition—from 0.16 to 0.33 for the validation task and from 0.34 to 0.53 for the estimation task. Based on the posterior distribution, all differences (hit rates and U^2) are significant (see Online Appendix 11). There was no draw in which the text-only, not-incentive-aligned condition performed better. Taken together, these results imply that $\gamma^{\text{market research}}$ is closer to γ^{true} for the realistic-image, incentive-aligned condition.

The effects appear to be robust. For example, when we use a mixture of normal distributions to estimate upper-level heterogeneity or random splits of the sample or the choice tasks used for the estimation, we obtain the same basic results. Scale adjustment factors are also not affected when using less data, neither via splits of the sample nor choice tasks; only posterior standard deviations increase for subsets of the sample (see Online Appendix 8). The results are robust to alternative model normalizations (see Section 9.1).

Table 2 is important for practice because the vast majority of CBC studies rely on unadjusted CBC-choice-task-only estimates of scale. Text-only, not-incentive-aligned measures based on estimation data alone might give the firm false confidence because the analysis overestimates scale, but increases $|\gamma^{\text{market research}} - \gamma^{\text{true}}|$. We next show that errors due to over- or underestimating scale have substantial strategic implications.

8.8. The Empirical Data Produce Strategic Effects Analogous to Those in the Stylized Model

Table 1 previewed relative profits as a function of strategic positioning. We created Table 1 by holding constant the (heterogeneous) relative partworths from the smartwatch study, but counterfactually varying the level of scale adjustment. (Unadjusted γ_i continues to vary among respondents.) For each combination of strategic positioning attributes (silver versus gold color), we use the root-finding method described in Allenby et al. (2014) to find the price equilibria. In order to avoid extrapolation beyond the price range used in the CBC experiment, we cap prices at the upper limit of the data (\$449). Because more respondents preferred silver to gold (65.7%) than vice versa, the analogy to the stylized model is $r = \text{silver}$, even though “ r ” is mnemonically cumbersome for silver.

Using the same heterogeneous relative partworths, we calculate γ^{cutoff} as the scale adjustment for which the follower’s undifferentiated profits (π_{2r}^*) equal its differentiated profits (π_{2rs}^*). Numerically, $\gamma^{\text{cutoff}} \cong 0.6$. As an illustration only, we choose a true scale above the cutoff ($\gamma^{\text{true}} = 0.8$) and a true scale below the cutoff ($\gamma^{\text{true}} = 0.4$). If we assume that the true scale is 0.8 and the market is 11.9 million units (Reisinger 2017), then misestimating the true scale to be below the cutoff and not differentiating from the innovator would result in over a \$100 million opportunity loss for the follower. We obtained similar results when we used CBC simulators for watch face (rectangular versus round), watch band (black versus brown or other combinations), or alternative model normalizations. In all counterfactual tests using empirical HB CBC partworths, the market always shifted from differentiated to undifferentiated as (true) scale decreased through a critical value.

With $\gamma^{\text{cutoff}} \cong 0.6$, we interpret the implications of Table 2. For the text-only, no-incentive CBC study, estimation-based scale implies differentiation, whereas validation-based scale reverses the strategic recommendation to no differentiation. For the realistic-image, incentive-aligned CBC study, estimation-based scale implies differentiation, whereas validation-based scale implies that scale is close to the cutoff where differentiation and no differentiation are equally profitable. Validation adjustment has strategic implications.

9. Robustness Tests

9.1. Alternative Normalizations of Scale Do Not Change the Results

We compare empirical estimates obtained from the McFadden (2014) normalization in the stylized model ($\eta_i = 1$ and γ_i log-normally distributed), the Sonnier et al. (2007) normalization ($\eta_i = 1$ and $\mu_i = 1/\gamma_i$ log-normally distributed), and the Allenby et al. (2014) normalization ($\gamma_i = 1$ and η_i log-normally distributed). The posterior means of the scale adjustments vary slightly, but well within posterior confidence intervals. The implications of the stylized model are not dependent on the empirical normalization. Ratio-based WTP posterior means and medians are almost identical between the McFadden (2014) normalization, and the Sonnier et al. (2007) normalization. As anticipated by Sonnier et al. (2007, pp. 315–317), ratio-based WTP posterior means vary more for the Allenby et al. (2014) normalization, although median WTP estimates reduce this variation. Detailed estimates are provided in Online Appendix 10.

9.2. Realistic Images and Incentive Alignment, Each Acting Alone, Affect Relative Scale

Table 3 extends the analyses in Table 2 to provide the posterior means of the scale adjustments separately for realistic images, incentive alignment, and their interaction. The results suggest that using realistic images impacts scale at least as much as incentive alignment—more for validation-based adjustments. The relative improvement due to realistic images is about three times that of incentive alignment for validation-based adjustments: $0.53 - 0.35 = 0.18$ versus $0.41 - 0.35 = 0.06$. Interactions increase both effects. If the hypothesis that image realism is more important than incentive alignment holds up, the results are important. Whereas incentive alignment is gaining traction in academia and in practice, much less attention has been devoted to image realism.

9.3. Results Survive a Double Whammy If CBC Craft Also Affects Relative Partworths

Although we focus on a common scale adjustment due to CBC craft, CBC craft might also affect the

relative partworth distributions. To examine this potential double whammy, we drew 1,000 times from the posterior distributions to compare the relative partworths between experimental conditions. The importances of the attributes are given by Table 4. (Importance is the largest partworth minus the smallest partworth for each attribute.) The price coefficient for \$150 (the price range in the experiment) is normalized to 1.0 in Table 4 so that the importances are relative to price. The effect of craft on relative partworth distributions reinforces the effect on scale, except for color, which is not significantly different between conditions. The estimated importances relative to price are larger for watch band and watch face when the study uses realistic images and incentive alignment.

One interpretation is that the realistic images and incentive alignment encouraged respondents to evaluate attribute importances more carefully (see also Vriens et al. 1998). However, we cannot rule out situations where greater respondent motivation and more realistic descriptions cause respondents to decrease valuations of attribute importances.

9.4. The Stylized Model and Empirical Results Apply for More Products and/or Attributes

The smartwatch application focused on two products and four attributes, but empirical studies often have more products, more attributes, and more levels. For example, Allenby et al. (2014) estimate price equilibria for a digital camera market with four brands and seven attributes, representing a total of 17 levels, plus an outside option. We also obtained data from a nationwide study of student preferences for dormitories with seven attributes representing a total of 24 levels. These data replicate a CBC study that a U.S. university used to design new dormitories.

Online Appendix 4 computes counterfactual equilibria prices as scale adjustment varies. For both applications, the equilibria prices vary, as in Figure 1. For the camera application, equilibria prices vary from \$275 to \$195 as scale increases from 0.6 to 1.2. For the dormitory application, equilibria rents vary from \$1,500 to \$1,180 as scale increases from 0.5 to 1.2.

Table 3. Posterior Means of Scale Adjustment for Realistic Images and Incentive Alignment

	Text-only no incentive alignment	Main effect of realistic images	Main effect of incentive alignment	Realistic images $\times$ incentive alignment
Scale is based on estimation data	1.00 ^a (n.a.)	0.89 (0.04)	0.96 (0.04)	0.86 (0.06)
Scale is adjusted to validation task	0.35 (0.04)	0.53 (0.05)	0.41 (0.04)	0.61 (0.06)

Notes. Standard deviations are in parentheses. The full posterior distribution is available from the authors. n.a., not applicable.

^aNormalized to 1.00 for identification.

Table 4. Posterior Means of Relative Importances

	Text only, no incentive alignment	Realistic images, incentive alignment
Color	1.39 (0.05)	1.33 (0.05)
Watch band	1.88 (0.07)	2.46 (0.08)
Watch face	1.38 (0.06)	1.60 (0.07)
Price	1.00 (n.a.)	1.00 (n.a.)

Notes. Standard deviations are in parentheses. The full posterior distribution is available from the authors. n.a., not applicable.

9.5. Computation is Feasible

The empirical equilibrium calculations require that we solve a fixed-point problem for every draw from the posterior distribution of partworths. This procedure is computationally intensive, but feasible. For example, on a standard Apple MacBook Pro computer with a 2.7 GHz Intel Core i5 processor and 8 GB of memory, using programs written in R, the equilibrium prices for the Allenby et al. (2014) camera data with five alternatives and $n = 10,000$ draws of the hyperparameters were computed in an average of 2.85 seconds per draw (standard deviation = 0.99 seconds, ~48 minutes for 1,000 draws).

10. Managerial Implications and Future Research

10.1. Summary of Implications

The stylized model and our empirical tests highlight the large impact of scale-factor differences driven by seemingly innocuous differences in CBC craft. Whereas many researchers focus on the impact of heterogeneous scale in CBC estimation, few CBC researchers explore the impact of a common scale factor on equilibrium prices and profits.

Moreover, although many researchers focus on the impact of scale in logit models on strategic positioning, most explanations involve heterogeneity in preferences or unobserved attributes. We demonstrate that neither are necessary and that scale affects strategic decisions even when modern (HB CBC, latent structure, or machine learning) estimation is used and researchers are careful to include a complete set of attributes.

Our results suggest that when equilibrium prices are used to replace WTP calculations, equilibrium-price estimates are extremely sensitive to craft. Image realism, incentive alignment, and likely other seemingly minor craft investments have impacts in the range of tens to hundreds of millions of dollars. Adjusting scale using a validation task likewise has a huge impact.

10.2. Recommendations for Practice

If craft were costless, we would recommend that firms use the best possible craft including realistic images and incentive alignment (and other yet-to-be-tested aspects of craft). We also recommend validation adjustment. Better craft and validation-adjustment likely minimize $|\gamma^{\text{market research}} - \gamma^{\text{true}}|$. But γ^{true} is latent until the product is actually launched to the marketplace and firms, particularly followers, must decide whether to invest in costly craft and validation. Fortunately, for strategic positioning, firms need not know γ^{true} exactly. Firms need only compare the posterior distributions of $\gamma^{\text{market research}}$ to γ^{cutoff} to be reasonably confident that they can distinguish among $\pi_{2rs}^*(\gamma) \gg \pi_{2rr}^*(\gamma)$, $\pi_{2rs}^*(\gamma) \ll \pi_{2rr}^*(\gamma)$, and $\pi_{2rs}^*(\gamma) \approx \pi_{2rr}^*(\gamma)$. Firms can use formal expected-value-of-sample-information calculations, but we expect that managerial judgment on $|\gamma^{\text{market research}} - \gamma^{\text{cutoff}}|$ will be more common and will improve with further research. See also Online Appendix 3.

10.3. Recommendations for Research

Our empirical tests suggest research to explore the implications of craft, validation adjustment, scale, equilibrium prices, and strategic positioning. Specifically, we propose the following: (1) Test other aspects of craft to see whether they impact strategic decisions dramatically. (2) Improve the validation task to better estimate γ^{true} . (3) Attempt to estimate γ^{true} in the marketplace. (4) Compare validation-adjusted scale factors. (5) Test the sensitivity of equilibrium prices beyond the three empirical applications. (6) Test the sensitivity of strategic positioning beyond the smartwatch study. (7) Test whether image realism is more important than incentive alignment. (8) Test under which conditions validation adjustment lowers estimated scale. (9) Develop rules of thumb about the impact on scale of craft and validation adjustment. (10) Develop experiments that isolate and explore person-specific (and/or time-specific) scale effects that are not otherwise modeled.

Acknowledgments

The authors thank the editor, the area editor, and the anonymous reviewers for their comments during the revision process. They are grateful for comments and suggestions by

participants of the 2016 Sawtooth Software Conference and 2017 Marketing Science Conference. They thank Greg Allenby for sharing the data and code from the camera study completed by him and his co-authors.

Appendix A. Summary of Notation

i	Indexes consumers
j	Indexes firms; firm 1 is the innovator, and firm 2 is the follower
a_{jk}	Indicator function; $a_{jk} = 1$ if profile j has attribute k , $a_{jk} = -1$ otherwise
c_j	Firm j 's marginal cost
C_j	Firm j 's fixed costs
r	A product attribute; we can think of r as red (or rose, regular, round, or routine)
s	A product attribute; we can think of s as silver (or sapphire, small, square, or special); a firm's product can have either r or s , but it cannot have both or neither
p_j	Firm j 's price
p_{jrr}^*	Nash equilibrium price for firm j given that firm 1 chooses r and firm 2 chooses r ; define p_{jrs}^* , p_{jsr}^* , and p_{jss}^* analogously
P_{ijrr}	Probability that consumer i purchases product from firm j given that firm 1 chooses r and firm 2 chooses r ; define P_{ijrs} , P_{ijsr} , and P_{ijss} analogously
P_{Rjrr}	Probability that a consumer in segment R purchases product from firm j given that firm 1 chooses r and firm 2 chooses r ; define P_{Rjrs} , P_{Rjsr} , P_{Rjss} , P_{Sjrs} , P_{Sjsr} , and P_{Sjss} analogously
R	Size of segment R ; we use italics for the size of the segment; non-italics to name the segment
S	Size of segment S
WTP	Willingness to pay
HB CBC	Hierarchical Bayes choice-based conjoint
u_{ij}	Utility that consumer i perceives for firm j 's product
u_{io}	Utility that consumer i perceives for the outside option
u_o	Utility of outside option for segments R and S
u_{Rj}	Utility of firm j 's product among consumers in segment R
u_{Sj}	Utility of firm j 's product among consumers in segment S
V	Number (measure) of consumers
β_{ri}	Relative partworth for r for consumer i
β_{si}	Relative partworth for s for consumer i
β_{rR}	Relative partworth of r for all $i \in R$; define β_{sR} , β_{rS} , and β_{sS} analogously
β^h	Higher partworth, $\beta_{rR} = \beta_{sS} = \beta^h$
β^ℓ	Lower partworth, $\beta_{rS} = \beta_{sR} = \beta^\ell$; theory holds if β^ℓ normalized to zero, but is less intuitive
β_{ki}	Relative partworth for attribute k and consumer i
δ_{rj}	Indicator function for whether firm j 's product has attribute r ; define δ_{sj} analogously
ϵ_{ij}	Error term for consumer i for firm j 's product; errors are independent and identically distributed extreme value random variables
η_i	Price coefficient, normalized to 1 in the stylized model and some empirical applications
γ_i	Scale when η_i normalized to 1; larger values imply smaller relative magnitude of the error term
$\gamma^{\text{asymptotic}}$	Scale obtained with theoretically best quality market research
γ^{cutoff}	cutoff value for scale; $\gamma > \gamma^{\text{cutoff}}$ implies differentiation; $\gamma < \gamma^{\text{cutoff}}$ no differentiation
$\gamma^{\text{higher}}, \gamma^{\text{lower}}$	Scale as affected by higher- or lower-cost market research
γ^{QV}	Scale adjustment due to experimental cell and/or validation task
γ^{true}	The true scale (sometimes γ for notational simplicity in proofs if not confused with γ_i)
$\lambda_{Q^h}, \lambda_V, \lambda_{Q^hV}$	Used to identify scale effects for market-research-quality conditions (Q_i^h, V_i indicators)
μ_i	Sonnier et al. (2007) renormalization such that $\gamma_i \equiv 1/\mu_i$
π_j	Profits for firm j
π_{jrr}^*	Profits for firm j at the Nash equilibrium prices; define π_{jrs}^* , π_{jsr}^* , and π_{jss}^* analogously
Δ_{R2rr}	Defined in the proof to Result B.1; Δ_{S2rr} and other terms for rs , sr , and ss are defined analogously

Appendix B. Proofs of Results and Propositions

Throughout this appendix, for notational simplicity, we drop the superscript on γ^{true} and write it simply as γ . Results in this appendix are stated in notational shorthand, but are the same as those in the text. All proofs assume η is normalized to 1.

Result B.1. For $\gamma \rightarrow 0$, $\pi_{2rr}^* > \pi_{2rs}^*, \pi_{1rs}^* > \pi_{1rr}^*$, and $\pi_{1rs}^* > \pi_{2rs}^*$.

Proof. This proof addresses first-order conditions. We address second-order and cross-partial conditions when we examine existence and uniqueness later in this appendix. As $\gamma \rightarrow 0$, the logit curve becomes extremely flat, which motivates a Taylor's series expansion of market share around $\beta^h = \beta^\ell$. When $\beta^h = \beta^\ell$, the logit equations for the market shares are identical for firms 1 and 2; identical for all

strategies, rr , rs , sr , and ss ; and symmetric with respect to firm 1 and firm 2. Thus, at $\beta^h = \beta^\ell$, we have

$$\begin{aligned} p_{1rr}^* &= p_{2rr}^* = p_{1rs}^* = p_{2rs}^* = p \text{ at } \beta^h = \beta^\ell, \\ P_{R1rr}^* &= P_{R2rr}^* = P_{R1rs}^* = P_{R2rs}^* = P \text{ at } \beta^h = \beta^\ell, \\ P_{S1rr}^* &= P_{S2rr}^* = P_{S1rs}^* = P_{S2rs}^* = P \text{ at } \beta^h = \beta^\ell. \end{aligned}$$

Because the prices and shares are identical, we have

$$\pi_{1rr}^* = \pi_{2rr}^* = \pi_{1rs}^* = \pi_{2rs}^* = \frac{1}{\gamma} \frac{P}{1-P} \text{ at } \beta^h = \beta^\ell,$$

where the last step comes from substituting the equalities for P in the implicit first-order conditions and simplifying using $R + S = 1$. Similar equations apply for rs , sr , and ss and firm 2:

$$\begin{aligned} \frac{\partial P_{R1rr}}{\partial p_{1rr}} &= \frac{-\gamma^{true} e^{\gamma^{true}(\beta^h - p_{1rr})} [e^{\gamma^{true}(\beta^h - p_{2rr})} + e^{\gamma^{true} u_0}]}{[e^{\gamma^{true}(\beta^h - p_{1rr})} + e^{\gamma^{true}(\beta^h - p_{2rr})} + e^{\gamma^{true} u_0}]^2} \\ &= -\gamma^{true} P_{R1rr} (1 - P_{R1rr}), \\ \frac{\partial \pi_{1rr}}{\partial p_{1rr}} &= RP_{R1rr} + SP_{S1rr} - \gamma^{true} p_{1rr} \{RP_{R1rr} (1 - P_{R1rr}) \\ &\quad + SP_{S1rr} (1 - P_{S1rr})\} = 0, \\ p_{1rr}^* &= \frac{1}{\gamma^{true}} \frac{RP_{R1rr}^* + SP_{S1rr}^*}{RP_{R1rr}^* (1 - P_{R1rr}^*) + SP_{S1rr}^* (1 - P_{S1rr}^*)}, \\ \pi_{1rr}^* &= \frac{1}{\gamma^{true}} \frac{(RP_{R1rr}^* + SP_{S1rr}^*)^2}{RP_{R1rr}^* (1 - P_{R1rr}^*) + SP_{S1rr}^* (1 - P_{S1rr}^*)}. \end{aligned}$$

We obtain the optimal price by solving the following fixed-point problem in p :

$$\gamma p = \frac{1}{1-P} = \frac{2e^{-\gamma p} + e^{\gamma u_0}}{e^{-\gamma p} + e^{\gamma u_0}} \text{ using } P = \frac{e^{-\gamma p}}{2e^{-\gamma p} + e^{\gamma u_0}}.$$

Because the right-hand side is decreasing in p on the range $[1, 1.5]$, there will be exactly one solution in the range of $\gamma p \in [1, 1.5]$ for small γ . We compute the partial derivatives of the P 's at $\beta^h = \beta^\ell$:

$$\begin{aligned} \frac{\partial P_{R2rr}}{\partial \beta^h} &= \gamma P (1 - 2P) \equiv \gamma \Delta_{R2rr}, \quad \frac{\partial P_{S2rr}}{\partial \beta^h} = 0 \equiv \gamma \Delta_{S2rr}, \\ \frac{\partial P_{R2rs}}{\partial \beta^h} &= -\gamma P^2 \equiv \gamma \Delta_{R2rs}, \quad \frac{\partial P_{S2rs}}{\partial \beta^h} = \gamma P (1 - P) \equiv \gamma \Delta_{S2rs}, \\ \Delta &= \beta^h - \beta^\ell. \end{aligned}$$

We now use a Taylor's series expansion with respect to β^h . Using standard mathematical arguments, higher-order terms that are $O(\gamma^2)$ or higher vanish as $\gamma \rightarrow 0$. (The ratio of terms $O(\gamma^2)$ or higher to terms $O(\gamma)$ goes to zero as $\gamma \rightarrow 0$.) Substituting the expressions for the partial derivatives into the first-order conditions, multiplying by γ , and using the above notation, we obtain

$$\begin{aligned} \gamma \pi_{2rr}^* &= \frac{[R(P + \gamma \Delta_{R2rr} \Delta) + S(P + \gamma \Delta_{S2rr} \Delta)]^2 + O(\gamma^2)}{[R(P + \gamma \Delta_{R2rr} \Delta)((1 - P) - \gamma \Delta_{R2rr} \Delta) + S(P + \gamma \Delta_{S2rr} \Delta)((1 - P) - \gamma \Delta_{S2rr} \Delta) + O(\gamma^2)]}, \\ \gamma \pi_{2rs}^* &= \frac{P^2 + 2\gamma \Delta (R \Delta_{R2rr} + S \Delta_{S2rr}) + O(\gamma^2)}{P(1 - P) + \gamma \Delta (1 - 2P)(R \Delta_{R2rr} + S \Delta_{S2rr}) + O(\gamma^2)}. \end{aligned}$$

Similarly,

$$\gamma \pi_{2rs}^* = \frac{P^2 + 2\gamma \Delta (R \Delta_{R2rs} + S \Delta_{S2rs}) + O(\gamma^2)}{P(1 - P) + \gamma \Delta (1 - 2P)(R \Delta_{R2rs} + S \Delta_{S2rs}) + O(\gamma^2)}.$$

Because all terms in the numerators and denominators of $\gamma \pi_{2rr}^*$ and $\gamma \pi_{2rs}^*$ are clearly positive, the condition for $\gamma \pi_{2rr}^* > \gamma \pi_{2rs}^*$ for $\gamma \rightarrow 0$ becomes

$$\begin{aligned} P^2 + 2\gamma \Delta (R \Delta_{R2rr} + S \Delta_{S2rr}) [P(1 - P) + \gamma \Delta (1 - 2P)(R \Delta_{R2rs} \\ + S \Delta_{S2rs})] > P^2 + 2\gamma \Delta (R \Delta_{R2rs} + S \Delta_{S2rs}) [P(1 - P) \\ + \gamma \Delta (1 - 2P)(R \Delta_{R2rs} + S \Delta_{S2rs})]. \end{aligned}$$

After simplification and ignoring terms that are $O(\gamma^2)$, this expression reduces to

$$\gamma \Delta P [(R \Delta_{R2rr} + S \Delta_{S2rr}) - (R \Delta_{R2rs} + S \Delta_{S2rs})] [2 - 3P + 2P^2] > 0.$$

We need only show that both terms in brackets are positive. We show the first term in brackets is positive because

$$\begin{aligned} (R \Delta_{R2rr} + S \Delta_{S2rr}) - (R \Delta_{R2rs} + S \Delta_{S2rs}) \\ = (RP(1 - P) - RP^2) - (SP(1 - P) - RP^2) > 0. \end{aligned}$$

The last step follows from $R > S$. We show the second term is positive because its minimum occurs at $P = \frac{3}{4}$ and its value at this minimum is $2 - 3P + 2P^2 = \frac{7}{8}$. Thus, $2 - 3P + 2P^2$ is positive for all $P \in [0, 1]$.

To prove that $\pi_{1rs}^* > \pi_{1rr}^*$ for $\gamma \rightarrow 0$, we use another Taylor's series expansion and simplify by the same procedures that recognize that higher-order terms vanish. Most of the algebra is the same until we come down to the following term in brackets (now reversed because rs is more profitable for firm 1 than rr as $\gamma \rightarrow 0$). Taking derivatives gives

$$\begin{aligned} \frac{\partial P_{R1rr}}{\partial \beta^h} &= \gamma P (1 - 2P) \equiv \gamma \Delta_{R1rr}, \quad \frac{\partial P_{S1rr}}{\partial \beta^h} = 0 \equiv \gamma \Delta_{S1rr}, \\ \frac{\partial P_{R1rs}}{\partial \beta^h} &= \gamma P (1 - P) \equiv \gamma \Delta_{R1rs}, \quad \frac{\partial P_{S1rs}}{\partial \beta^h} = -\gamma P^2 \equiv \gamma \Delta_{S1rs}. \end{aligned}$$

The corresponding expression in brackets becomes (for $\gamma \pi_{1rs}^* - \gamma \pi_{1rr}^*$)

$$\begin{aligned} (R \Delta_{R1rs} + S \Delta_{S1rs}) - (R \Delta_{R1rr} + S \Delta_{S1rr}) \\ = (RP(1 - P) - SP^2) - (RP(1 - P) - RP^2) > 0, \end{aligned}$$

where the last step is true because $R > S$.

By exploiting symmetry, we have $\pi_{1rr}^* = \pi_{2rr}^*$, yielding the result that $\pi_{1rs}^* > \pi_{1rr}^* = \pi_{2rr}^* > \pi_{2rs}^*$. $\square$

Lemma B.1. $\gamma p_{1rs}^* < (1 - P_{R1rs}^*)^{-1}$ and $\gamma p_{2rs}^* < (1 - P_{S2rs}^*)^{-1}$. Related conditions hold for rr , ss , and sr .

Proof. We use the first-order conditions (for rs) given in the proof to Result B.1. All terms are positive, so we cross multiply. After cross multiplying, the first expression is equivalent to $RP_{R1rs}^* (1 - P_{R1rs}^*) + SP_{S1rs}^* (1 - P_{S1rs}^*) > RP_{R1rs}^* (1 - P_{R1rs}^*) + SP_{S1rs}^* (1 - P_{R1rs}^*)$, which is true if $P_{R1rs}^* > P_{S1rs}^*$. The latter holds whenever $\beta^h > \beta^\ell$ for all γ by substituting directly into the logit equation. We prove the second expression by using the first-order

conditions for p_{2rs}^* . Related expressions hold for other positionings. For example, for the rr positions, $\gamma p_{1rr}^* < (1 - P_{R1rr}^*)^{-1}$ and $\gamma p_{2rr}^* < (1 - P_{R2rr}^*)^{-1}$.

Result B.2. Suppose β^h is sufficiently larger than u_o and $u_o \geq \beta^\ell$. Then, there exists a sufficiently large γ such that $\pi_{2rs}^* > \pi_{2rr}^*$, $\pi_{1rs}^* > \pi_{1rr}^*$, and $\pi_{1rs}^* > \pi_{2rs}^*$.

Proof. In this proof, we examine the first-order conditions. Second-order and cross-partial conditions are addressed when we consider existence and uniqueness later in this appendix. We first recognize that

$$\begin{aligned} P_{S1rs} &= \frac{e^{\gamma(\beta^\ell - p_1)}}{e^{\gamma(\beta^\ell - p_1)} + e^{\gamma(\beta^h - p_2)} + e^{\gamma u_o}}, \\ P_{R1rs} &= \frac{e^{\gamma(\beta^h - p_1)}}{e^{\gamma(\beta^h - p_1)} + e^{\gamma(\beta^\ell - p_2)} + e^{\gamma u_o}}, \\ P_{R2rs} &= \frac{e^{\gamma(\beta^\ell - p_2)}}{e^{\gamma(\beta^h - p_1)} + e^{\gamma(\beta^\ell - p_2)} + e^{\gamma u_o}}, \\ P_{S2rs} &= \frac{e^{\gamma(\beta^h - p_2)}}{e^{\gamma(\beta^\ell - p_1)} + e^{\gamma(\beta^h - p_2)} + e^{\gamma u_o}}, \\ P_{R2rr} &= \frac{e^{\gamma(\beta^h - p_1)}}{e^{\gamma(\beta^h - p_1)} + e^{\gamma(\beta^h - p_2)} + e^{\gamma u_o}}, \\ P_{S2rr} &= \frac{e^{\gamma(\beta^\ell - p_2)}}{e^{\gamma(\beta^\ell - p_1)} + e^{\gamma(\beta^\ell - p_2)} + e^{\gamma u_o}}. \end{aligned}$$

When γ is large relative to β and u_o , $P_{S1rr} = P_{S2rr} \approx 0$, $P_{R2rs} \approx 0$, and $P_{S1rs} \approx 0$. Substituting and using algebra to simplify the first-order conditions gives us

$$\begin{aligned} \gamma p_{2rs}^* &= \frac{RP_{R2rs}^* + SP_{S2rs}^*}{RP_{R2rs}^*(1 - P_{R2rs}^*) + SP_{S2rs}^*(1 - P_{S2rs}^*)} \\ &\cong \frac{SP_{S2rs}^*}{SP_{S2rs}^*(1 - P_{S2rs}^*)} = \frac{1}{1 - P_{S2rs}^*}. \end{aligned}$$

We substitute the logit model directly for P_{S2rs} and simplify algebraically to obtain

$$\gamma p_{2rs}^* \cong \frac{e^{\gamma(\beta^h - p_{2rs}^*)} + e^{\gamma(\beta^\ell - p_{1rs}^*)} + e^{\gamma u_o}}{e^{\gamma(\beta^\ell - p_{1rs}^*)} + e^{\gamma u_o}} \cong e^{\gamma(\beta^h - u_o - p_{2rs}^*)} + 1.$$

As γ gets large and positive, the effect of γ as an exponent is much larger than the effect of γ as a multiplier; thus, the expression in parentheses in the exponent must converge toward zero for the equality to hold. As the expression approaches zero, the solution to this fixed point problem approaches $p_{2rs}^* = \beta^h - u_o - \epsilon$ where $\epsilon > 0$, ϵ is but a fraction of $\beta^h - u_o$, and $\epsilon \rightarrow 0$ as $\gamma \rightarrow \infty$. Thus, $\pi_{2rs}^* = p_{2rs}^*(RP_{R2rs}^* + SP_{S2rs}^*) \cong p_{2rs}^* SP_{S2rs}^* \cong SP_{S2rs}^*(\beta^h - u_o - \epsilon)$. (The first expression is by the definition of π_{2rs}^* .) Substituting p_{2rs}^* into the expression for P_{S2rs}^* , we get

$$P_{S2rs}^* = \frac{e^{\gamma(u_o + \epsilon)}}{e^{\gamma(u_o + \epsilon)} + e^{\gamma u_o} + e^{\gamma(\beta^\ell - p_{1rs}^*)}} > \frac{e^{\gamma(u_o + \epsilon)}}{e^{\gamma(u_o + \epsilon)} + e^{\gamma u_o} + e^{\gamma(u_o - p_{1rs}^*)}} > \frac{1}{3}.$$

Thus, using $P_{R2rs} \approx 0$, the solution to the fixed point problem, and the definition of π_{2rs}^* , we have shown that π_{2rs}^* is greater than $S(\beta^h - u_o)/3$ as $\gamma \rightarrow \infty$. (P_{S2rs}^* actually gets close to 1 and π_{2rs}^* gets close to $S(\beta^h - u_o)$ as $\gamma \rightarrow \infty$, but we only need the weaker lower bound.)

Thus, for sufficiently large γ (relative to β^h and u_o), the solution of π_{2rs}^* is greater than $S(\beta^h - u_o)/3$. Similar arguments establish that $\pi_{1rs}^* \cong R(\beta^h - u_o - \epsilon)P_{R1rs}^*$ and that π_{1rs}^* is greater than $R(\beta^h - u_o)/3$. (Recall that $\epsilon \rightarrow 0$ as $\gamma \rightarrow \infty$.)

We examine the price equilibrium when both firm 1 and firm 2 choose r . We first recognize that, by symmetry, $p_{1rr}^* = p_{2rr}^*$. Hence,

$$\begin{aligned} P_{R2rr} &= \frac{e^{\gamma(\beta^h - p_{2rr}^*)}}{2e^{\gamma(\beta^h - p_{2rr}^*)} + e^{\gamma u_o}} \text{ and} \\ P_{S2rr} &= \frac{e^{\gamma(\beta^\ell - p_{2rr}^*)}}{2e^{\gamma(\beta^\ell - p_{2rr}^*)} + e^{\gamma u_o}}. \end{aligned}$$

We seek to show that there is a p_{2rr}^* with the properties that $p_{2rr}^* \ll \beta^h - u_o$ and $p_{2rr}^* < u_o$, which satisfies the first-order conditions. In this case, as $\gamma \rightarrow \infty$, $P_{R2rr}^* \cong \frac{1}{2}$. The first-order conditions become

$$\begin{aligned} \gamma p_{2rr}^* &= \frac{RP_{R2rr}^* + SP_{S2rr}^*}{RP_{R2rr}^*(1 - P_{R2rr}^*) + SP_{S2rr}^*(1 - P_{S2rr}^*)} \\ &\cong \frac{\frac{1}{2}R + SP_{S2rr}^*}{\frac{1}{4}R + SP_{S2rr}^*(1 - P_{S2rr}^*)} \\ &\leq \frac{\frac{1}{2}R + S}{\frac{1}{4}R} = 2 + 4\frac{S}{R} < 6. \end{aligned}$$

The third to last step, setting $P_{S2rr}^* = 1$ for the inequality, is possible because the fraction increases in P_{S2rr}^* to obtain its maximum at $P_{S2rr}^* = 1$, as shown with simple calculus. Thus, if p_{2rr}^* satisfies the first-order conditions, then $p_{2rr}^* < 6/\gamma$. Putting the upper bound on π_{2rr}^* together with the lower bound on π_{2rs}^* , $\pi_{2rr}^* < \frac{6}{\gamma}(\frac{1}{2}R + S) < \frac{9}{2\gamma} < \frac{1}{3}S(\beta^h - u_o) < \pi_{2rs}^*$ for γ sufficiently large. (We use the condition that $\beta^h > u_o$ by a sufficient amount.) We establish $\pi_{1rr}^* < \pi_{1rs}^*$ by similar arguments recognizing that, by symmetry, $\pi_{1rr}^* = \pi_{2rr}^*$ and using the proven result that π_{1rs}^* is greater than $\frac{1}{3}R(\beta^h - u_o)$ for sufficiently large γ . $\square$

Result B.3. $\pi_{1rr}^* = \pi_{2rr}^* > \pi_{1ss}^* = \pi_{2ss}^*$.

Proof. We examine the equations for the segment-based market shares to recognize that $P_{R1rr}(p_{1ss}^*, p_{2ss}^*) = P_{S1ss}^*(p_{1ss}^*, p_{2ss}^*)$ and $P_{S1rr}(p_{1ss}^*, p_{2ss}^*) = P_{R1ss}^*(p_{1ss}^*, p_{2ss}^*)$, and $P_{S1ss}^*(p_{1ss}^*, p_{2ss}^*) > P_{R1ss}^*(p_{1ss}^*, p_{2ss}^*)$. Thus, $\pi_{1rr}^* = \pi_{1rr}(p_{1rr}^*, p_{2rr}^*) \geq \pi_{1rr}(p_{1ss}^*, p_{2ss}^*) = p_{1ss}^*[RP_{R1rr}(p_{1ss}^*, p_{2ss}^*) + SP_{S1rr}(p_{1ss}^*, p_{2ss}^*)] = p_{1ss}^*[RP_{S1ss}^* + SP_{R1ss}^*] > p_{1ss}^*[SP_{S1ss}^* + RP_{R1ss}^*] = \pi_{1ss}^*$. The second inequality is by the principle of optimality. The last inequality uses $R > S$ and $P_{S1ss}^* > P_{R1ss}^*$. The equalities, $\pi_{1rr}^* = \pi_{2rr}^*$ and $\pi_{1ss}^* = \pi_{2ss}^*$, are by symmetry. $\square$

Result B.4. Suppose β^h is sufficiently larger than u_o and $u_o \geq \beta^\ell$. Then, there exists a sufficiently large γ such that $\pi_{1rs}^* > \pi_{1sr}^*$.

Proof. By symmetry, we recognize that $\pi_{1sr}^* = \pi_{2rs}^*$. In the proof to Result B.2, we established that $\pi_{2rs}^* \cong S(\beta^h - u_o)P_{S2rs}^*$ and $\pi_{1rs}^* \cong R(\beta^h - u_o)P_{R1rs}^*$ because $\epsilon \rightarrow 0$ as $\gamma \rightarrow \infty$. We also see that the fixed-point problems are identical for p_{1rs}^*

and p_{2rs}^* ; thus, as $\gamma \rightarrow \infty$, $p_{1rs}^* \cong p_{2rs}^*$, which implies that $P_{R1rs}^* \cong P_{S2rs}^*$. Putting these relationships together implies that $\pi_{1rs}^* \cong R(\beta^h - u_o)P_{R1rs}^* > S(\beta^h - u_o)P_{R1rs}^* \cong S(\beta^h - u_o)P_{S2rs}^* \cong \pi_{2rs}^* = \pi_{1sr}^*$. $\square$

Proposition 1. For low true scale ($\gamma^{true} \rightarrow 0$), the innovator (firm 1) targets the larger segment (r), and the follower chooses not to differentiate. The follower targets the larger segment (r).

Proposition 2. If β^h is sufficiently larger than u_o and if $u_o \geq \beta^l$, then there exists a sufficiently large γ^{true} such that the innovator targets the larger segment (r), and the follower chooses to differentiate by targeting the smaller segment (s).

Proof of Propositions 1 and 2. We prove the two propositions together. Result B.1 establishes that $\pi_{2rr}^* > \pi_{2rs}^*$ as $\gamma \rightarrow 0$. Result B.2 establishes that $\pi_{2rs}^* > \pi_{2rr}^*$ when γ is sufficiently large. Thus, if firm 1 chooses r , firm 2 chooses r as $\gamma \rightarrow 0$ and chooses s when γ gets sufficiently large.

To prove that firm 1 always chooses r , we first consider the case where $\gamma \rightarrow 0$. If firm 1 chooses r , then firm 2 chooses r by Proposition 1. Suppose instead that firm 1 chooses s ; then firm 2 will choose r . Firm 2 will choose r in this case because, by Result B.1, $\pi_{1rs}^* > \pi_{1rr}^*$, and by symmetry, $\pi_{2sr}^* = \pi_{1rs}^*$; hence, $\pi_{2sr}^* > \pi_{1rr}^* = \pi_{2rr}^*$. If firm 2 would choose r whenever firm 1 chooses s , firm 1 would earn π_{1sr}^* . But $\pi_{1sr}^* = \pi_{2rs}^*$ by symmetry and $\pi_{2rs}^* < \pi_{2rr}^* = \pi_{1rr}^*$ by Result B.1. Thus, firm 1 earns more profits (π_{1rr}^*) by choosing r than the profits it would obtain (π_{1sr}^*) by choosing s .

We now consider the case where γ is sufficiently large. Suppose firm 1 chooses r ; then firm 2 will choose s by Result B.2. Firm 1 receives π_{1rs}^* . Suppose instead that firm 1 chooses s ; then firm 2 will choose r because $\pi_{2sr}^* = \pi_{1rs}^*$ by symmetry and $\pi_{1rs}^* > \pi_{1ss}^* = \pi_{2ss}^*$ under the conditions of Result B.2. Thus, if firm 1 chooses s , it receives π_{1sr}^* . Because $\pi_{1rs}^* > \pi_{1sr}^*$ by Result B.4, firm 1 will choose r . $\square$

Existence and Uniqueness

The existence and uniqueness arguments require substantial algebra. To avoid an excessively long appendix, we provide the basic insight. Detailed calculations are available from the authors. The proofs to Result B.1–Result B.4 rely on the first-order conditions; thus we must show that a solution to the first-order conditions, if it exists, satisfies the second-order conditions. We seek to show that the second-order conditions for the rs positions are negative at equilibrium. Taking derivatives, we obtain the following second-order conditions for the rs positions:

$$\begin{aligned} \frac{\partial^2 \pi_{1rs}^*}{\partial p_{1rs}^2} = & -\gamma R P_{R1rs}^* (1 - P_{R1rs}^*) [2 - \gamma p_{1rs}^* (1 - 2P_{R1rs}^*)] \\ & - \gamma S P_{S1rs}^* (1 - P_{S1rs}^*) [2 - \gamma p_{1rs}^* (1 - 2P_{S1rs}^*)]. \end{aligned}$$

We use Lemma B.1 to substitute $(1 - P_{R1rs}^*)^{-1}$ for γp_{1rs}^* . The former is a larger value, so if the conditions hold for the larger value, they hold for γp_{1rs}^* . Algebra simplifies the right-hand side of the second-order condition to $-\gamma \{R P_{R1rs}^* (1 - P_{R1rs}^*) + S P_{S1rs}^* (1 - P_{S1rs}^*) (1 - 2P_{R1rs}^* + 2P_{S1rs}^*)\}$. With direct substitution in the logit model, recognizing $p_{1rs}^* \geq p_{2rs}^*$, we show $P_{S2rs}^* \geq P_{R1rs}^* \geq P_{R2rs}^* \geq P_{S1rs}^*$. (We show

$p_{1rs}^* \geq p_{2rs}^*$ with implicit differentiation of the first-order conditions with respect to R .) These inequalities imply that $P_{S1rs}^* < \min\{P_{R1rs}^*, 1 - P_{R1rs}^*\}$. Hence, $R P_{R1rs}^* (1 - P_{R1rs}^*) \geq S P_{S1rs}^* (1 - P_{S1rs}^*)$ whenever $R > S$. Thus, the second-order condition is more negative than $-\gamma S P_{S1rs}^* (1 - P_{S1rs}^*) (2 - 2P_{R1rs}^* + 2P_{S1rs}^*) < 0$. We repeat the analysis for p_{2rs}^* using a sufficient technical condition that either $P_{S2rs}^* \leq \frac{1}{2}$ or that the ratio of S/R is above a minimum value. (The condition, not shown here, requires only $S > 0$ as $\gamma \rightarrow \infty$.) Although our proof formally imposes the technical sufficient condition, we have not found any violation of the second-order conditions at equilibrium, even with small S . Thus, with a (possible) mild restriction on S , the second-order conditions are satisfied whenever the first-order conditions hold.

We now establish that the second-order conditions are satisfied on a compact set. We begin by showing algebraically that $(1 - P_{R1rs}^*)^{-1}$ is decreasing in p_{1rs} and that it decreases from a finite positive value, which we call $F_{R1rs}(p_{1rs} = 0) > 1$. As $p_{1rs} \rightarrow \infty$, $(1 - P_{R1rs}^*)^{-1}$ decreases to 1. But γp_{1rs} increases from 0 to ∞ ; thus, there must be a solution to $\gamma p_{1rs} = (1 - P_{R1rs}^*)^{-1}$ for every p_{2rs} . Call this solution $p_{1rs}^m(p_{2rs})$. Because $(1 - P_{R1rs}^*)^{-1}$ is decreasing in γp_{1rs} , it must be true that $\gamma p_{1rs} \leq (1 - P_{R1rs}^*)^{-1}$ for all $p_{1rs} \in [0, p_{1rs}^m(p_{2rs})]$. Using similar arguments, we show there exists a $p_{2rs}^m(p_{1rs})$ such that $\gamma p_{2rs} \leq (1 - P_{S2rs}^*)^{-1}$ for all $p_{2rs} \in [0, p_{2rs}^m(p_{1rs})]$. Together, $p_{1rs} \in [0, p_{1rs}^m(p_{2rs})]$ and $p_{2rs} \in [0, p_{2rs}^m(p_{1rs})]$ define a compact set that is a subset of $p_{1rs} \in [0, p_{1rs}^m(0)]$ and $p_{2rs} \in [0, p_{2rs}^m(0)]$. (The term $p_{1rs}^m(p_{2rs})$ is continuous and decreasing in p_{2rs} , and $p_{2rs}^m(p_{1rs})$ is continuous and decreasing in p_{1rs} ; $p_{1rs}^m(p_{2rs}), p_{2rs}^m(p_{1rs}) > 0$.) We have already established that $P_{S2rs}^* \geq P_{R1rs}^* \geq P_{R2rs}^* \geq P_{S1rs}^*$ when $p_{1rs} \geq p_{2rs}^*$. If we restrict the compact set to $p_{1rs} \geq p_{2rs}$ and the price difference is not too large, we have $P_{S2rs}^* \geq P_{R1rs}^* \geq P_{R2rs}^* \geq P_{S1rs}^*$ on the set. This simplifies the proof, but is not necessary. Thus, we can choose a compact set such that $\gamma p_{1rs} = (1 - P_{R1rs}^*)^{-1}$, $\gamma p_{2rs} \leq (1 - P_{S2rs}^*)^{-1}$, and $P_{S2rs}^* \geq P_{R1rs}^* \geq P_{R2rs}^* \geq P_{S1rs}^*$ on the set. This set contains the interior solution to the first-order conditions. Using arguments similar to those we used for the equilibrium prices, we establish that the second-order conditions hold on this compact set. If necessary, we impose a weak technical condition on S/R . This implies that both profit functions are concave on the compact set. Concavity on a compact set guarantees that the solution exists and, by the arguments in the previous paragraph, that the solution is an interior solution. Numerical calculations, for a wide variety of parameter values, suggest that the second-order conditions hold on the compact set, that the second-order conditions hold outside the set (the restrictions are sufficient but not necessary), that the second-order conditions hold for prices satisfying $p_{2rs} > p_{1rs}$, and that, at equilibrium, the second-order conditions hold for all S .

The proof for the rr positions follows arguments that are similar to those for the rs positions. We do not need the technical condition on S because $P_{S2rr}^* \leq \frac{1}{2}$ implies that $S > 0$ is sufficient. The compact set is simpler because $p_{1rr}^* = p_{2rr}^*$ by symmetry. The proofs for the sr and ss positions use related conditions and follow the logic of the proofs for the rs and rr positions. $\square$

Uniqueness requires that we examine the cross-partial derivatives, illustrated here for rs :

$$\frac{\partial^2 \pi_{1rs}}{\partial p_{1rs} \partial p_{2rs}} = \gamma R P_{R1rs} P_{R2rs} [1 - \gamma p_{1rs} (1 - 2P_{R1rs})] \\ + \gamma R P_{S1rs} P_{S2rs} [1 - \gamma p_{1rs} (1 - 2P_{S1rs})].$$

Restricting ourselves to use the a compact set as in the existence arguments, we can use $\gamma p_{1rs} \leq 1/(1 - P_{R1rs})$, $\gamma p_{2rs} \leq 1/(1 - P_{S2rs})$, and $P_{S2rs} \geq P_{R1rs} \geq P_{R2rs} \geq P_{S1rs}$. We substitute to show that when the cross-partial derivative is positive (similar conditions and a similar proof apply when it is negative),

$$\left| \frac{\partial^2 \pi_{1rs}}{\partial p_{1rs}^2} \right| - \left| \frac{\partial^2 \pi_{1rs}}{\partial p_{1rs} \partial p_{2rs}} \right| \geq \frac{\gamma}{1 - P_{R1rs}} \{ R P_{R1rs} (1 - P_{R1rs})^2 \\ + R(1 - P_{R1rs} - P_{R2rs}) P_{R1rs}^2 \\ + S P_{S1rs} (1 - P_{S1rs}) (1 - P_{R1rs}) \\ + S P_{S1rs} (1 - P_{S1rs} - P_{S2rs}) \\ \cdot (2P_{S1rs} - P_{R1rs}) \}.$$

We substitute further to show the third term on the right-hand side is larger than the, possibly negative, fourth term. Hence, the cross-partial condition is positive for π_{1rs} on the compact set. The cross-partial condition for π_{2rs} is satisfied with a technical condition on S . Numerical calculations, for a wide variety of parameter values, suggest that the cross-partial conditions hold on the compact set, that the cross-partial conditions hold outside the set (the restrictions are sufficient but not necessary), that the cross-partial conditions hold for prices satisfying $p_{2rs} > p_{1rs}$, and that, at equilibrium, the cross-partial conditions hold for all S .

In summary, subject to (possible) technical conditions on the magnitude of S , we have proven that interior-solution price equilibria exist and are unique. At minimum, we have shown that this is true for many, if not most, markets. We have proven that the equilibria exist and are unique for markets satisfying the technical conditions on S/R . □

Corollary B.1. Firm 1 selects r for both γ^{lower} and γ^{higher} .

Proof. The result follows directly from Propositions 1 and 2. Firm chooses r if $\gamma^{\text{lower}} < \gamma^{\text{cutoff}}$ by Proposition 1 and chooses r if $\gamma^{\text{lower}} \geq \gamma^{\text{cutoff}}$ by Proposition 2. Thus, firm 1 chooses r independently of γ^{lower} . We use the same arguments to show that firm 1 chooses r independently of γ^{higher} . (The result also requires continuity of the profit functions, proven elsewhere.) □

Corollary B.2. If firm 2 acts on γ^{lower} (believes $\gamma^{\text{lower}} = \gamma^{\text{true}}$) and if, in the marketplace, $\gamma^{\text{lower}} \neq \gamma^{\text{true}}$, then firm 2 might choose the strategy that does not maximize profits.

Proof. We provide two examples. If $\gamma^{\text{lower}} < \gamma^{\text{cutoff}} < \gamma^{\text{true}}$, then, if firm 2 acts on γ^{lower} , it will choose r by Proposition 1 because $\gamma^{\text{lower}} < \gamma^{\text{cutoff}}$, but the profit-maximizing decision is s by Proposition 2 because $\gamma^{\text{cutoff}} < \gamma^{\text{true}}$. If $\gamma^{\text{true}} < \gamma^{\text{cutoff}} < \gamma^{\text{lower}}$, then firm 2 will choose s by Proposition 2 because $\gamma^{\text{cutoff}} < \gamma^{\text{lower}}$, but the profit-maximizing decision is to choose r by Proposition 1 because $\gamma^{\text{true}} < \gamma^{\text{cutoff}}$. The word “might” is important. Firm 2 might choose the correct strategy, even if $\gamma^{\text{lower}} \neq \gamma^{\text{true}}$ when both γ^{lower} and γ^{true} are on the same side of γ^{cutoff} . □

Appendix C. List of Online Appendices

1. Numerical Example to Illustrate Stylized Model
2. Numerical Example of Craft Decisions by a Sophisticated Follower
3. Practical Recommendations for CBC Craft
4. Equilibrium Prices and Brief Descriptions for the Camera and Dormitory Studies
5. Brief Summary of the McFadden (2014) (Used in Stylized Model), Sonnier et al. (2007), and Allenby et al. (2014) HB CBC Normalizations
6. Specifications of the Bayesian Methods to Estimate the Scale-Adjustment Factors
7. Comparison of Estimates for Scale Adjustment Factors from the Three Normalizations
8. Alternative Estimations Accounting for Gender, for Split Sample, for Split Choice Task, and for a Mixture of Normal Distributions
9. Posterior Distributions for Scale Adjustment Factors and Attribute Importances
10. Posterior WTP Estimates from the Three Normalizations
11. Hit Rates and Uncertainty Explained (U^2) for Holdout Tests and Validation Tests
12. Empirical Posttest for Validation Task
13. Relationship of the Minimum vs. Maximum Differentiation Literature to the Stylized Model
14. Comments on a Simultaneous Positioning Game
15. Additional Citations: Six *Marketing Science* Papers That Discuss Scale Explicitly

Endnotes

¹ Following McFadden (2014), we define scale as the magnitude of the price coefficient relative to the standard deviation of the error. Other authors use alternative normalizations (e.g., Allenby et al. 2014, p. 427; Sonnier et al. 2007, p. 315; Train 2009, p. 40). We address the impact of these normalizations in later sections.

² Peanut Labs is an international panel with 15 million prescreened panelists from 36 countries. Their many corporate clients cumulatively gather data from approximately 450,000 completed surveys per month. Peanut Labs is a member of the Advertising Research Foundation, Council of American Survey Research Organizations, European Society for Opinion and Market Research, and Marketing Research Association and has won many awards (see web.peanutlabs.com).

References

- Aksoy-Pierson M, Allon G, Federgruen A (2013) Price competition under mixed multinomial logit demand functions. *Management Sci.* 59(8):1817–1835.
- Allenby GM, Brazell J, Howell JR, Rossi PE (2014) Economic valuation of product features. *Quant. Marketing Econom.* 12(4):421–456.
- Anderson SP, de Palma A, Thisse JF (1999) *Discrete Choice Theory of Product Differentiation* (MIT Press, Cambridge, MA).
- Bass FM (1974) The theory of stochastic preference and brand switching. *J. Marketing Res.* 11(1):1–20.
- Beck MJ, Rose JM, Hensher DA (1993) Consistently inconsistent: The role of certainty, acceptability and scale in choice. *Transportation Res. Part E: Logist. Transportation Rev.* 56(September): 81–93.
- Cameron L, Cragg M, McFadden DL (2013) The role of conjoint surveys in reasonable royalty cases. *Law360* (October 16), <https://www.law360.com/articles/475390/the-role-of-conjoint-surveys-in-reasonable-royalty-cases>.

- Caplin A, Nalebuff B (1991) Aggregation and imperfect competition: On the existence of equilibrium. *Econometrica* 59(1):25–59.
- Choi SC, DeSarbo WS (1994) A conjoint simulation model incorporating short-run price competition. *J. Product Innovation Management* 11(5):451–459.
- Choi SC, DeSarbo WS, Harker PT (1990) Product positioning under price competition. *Management Sci.* 36(2):175–199.
- Dahan E, Hauser JR (2002) The virtual customer. *J. Product Innovation Management* 19(5):332–354.
- Dahan E, Srinivasan V (2000) The predictive power of Internet-based product concept testing using visual depiction and animation. *J. Product Innovation Management* 17(2):99–109.
- de Palma A, Ginsburgh V, Thisse JF (1987) On existence of location equilibria in the 3-firm Hotelling problem. *J. Indust. Econom.* 36(2):245–252.
- de Palma A, Ginsburgh V, Papageorgiou YY, Thisse JF (1985) The principle of minimum differentiation holds under sufficient heterogeneity. *Econometrica* 53(4):767–781.
- Ding M (2007) An incentive-aligned mechanism for conjoint analysis. *J. Marketing Res.* 54(May):214–223.
- Ding M, Grewal R, Liechty J (2005) Incentive-aligned conjoint analysis. *J. Marketing Res.* 42(February):67–82.
- Ding M, Hauser JR, Dong S, Dzyabura D, Yang Z, Su C, Gaskin S (2011) Unstructured direct elicitation of decision rules. *J. Marketing Res.* 48(February):116–127.
- Dzyabura D, Jagabathula S, Muller E (2019) Accounting for discrepancies between online and offline shopping behavior. *Marketing Sci.* 38(1):88–106.
- Economides N (1986) Minimal and maximal product differentiation in Hotelling's duopoly. *Econom. Lett.* 21(1):67–71.
- Evgeniou T, Boussios C, Zacharia G (2005) Generalized robust conjoint estimation. *Marketing Sci.* 24(3):415–429.
- Fiebig DG, Keane MP, Louviere J, Wasi N (2010) The generalized multinomial logit model: Accounting for scale and coefficient heterogeneity. *Marketing Sci.* 29(3):393–421.
- Gilbride TJ, Lenk PJ, Brazell JD (2008) Market share constraints and the loss function in choice-based conjoint analysis. *Marketing Sci.* 27(6):995–1011.
- Hauser JR (1978) Testing the accuracy, usefulness, and significance of probabilistic models: An information theoretic approach. *Oper. Res.* 26(3):406–421.
- Hotelling H (1929) Stability in competition. *Econom. J.* 39(153):41–57.
- Huber J, Orme BK, Miller R (1999) Dealing with product similarity in conjoint simulations. *Sawtooth Software: Research Paper Series*, <https://www.sawtoothsoftware.com/download/techpap/prodsim.pdf>.
- Irmen A, Thisse JF (1998) Competition in multi-characteristics spaces: Hotelling was almost right. *J. Econom. Theory* 78(1):76–102.
- Keeney RL, Raiffa H (1976) *Decisions with Multiple Objectives: Preferences and Value Tradeoffs* (John Wiley & Sons, New York).
- Koh L (2012) Order granting in part and denying in part motions to exclude certain expert opinions: Public redacted version. Apple, Inc. v. Samsung Elecs. Co., Case No. 12-CV-00630-LHK (N.D. Cal. Feb. 25, 2014).
- Luo L, Kannan PK, Ratchford BT (2007) New product development under channel acceptance. *Marketing Sci.* 26(2):149–163.
- Manski CF (1977) The structure of random utility models. *Theory Decision* 8(3):229–254.
- McFadden DL (2014) Testimony of Daniel L. McFadden in the matter of determination of rates and terms for digital performance in sound recordings and ephemeral recordings (WEB IV). Before the Copyright Royalty Board Library of Congress, Washington DC, Docket No. 14-CRB-0001-WR, October 6.
- Meissner M, Oppewal H, Huber J (2016) How many options? behavioral responses to two vs. five alternatives per choice. *Proc. Sawtooth Software Conf.: September 2016* (Sawtooth Software, Park City, UT), 19–36.
- Mintz H (2012) Apple wins \$1 billion victory over Samsung. *San Jose Mercury News* (August 24), <https://www.mercurynews.com/2012/08/24/2012-apple-wins-1-billion-victory-over-samsung/>.
- Moorthy KS (1988) Product and price competition in a duopoly. *Marketing Sci.* 7(2):141–168.
- Ofek E, Srinivasan V (2002) How much does the market value an improvement in a product attribute? *Marketing Sci.* 21(4):398–411.
- Orme B (2014) *Getting Started with Conjoint Analysis: Strategies for Product Design and Pricing Research*, 3rd ed. (Research Publishers LLC, Manhattan Beach, CA).
- Orme B (2017) Personal email to the authors, July 25, 2017.
- Orme B, Chrzan K (2017) *Becoming an Expert in Conjoint Analysis: Choice Modelling for Pros* (Sawtooth Software, Orem, UT).
- Pancreas J, Wang X, Dey DK (2016) Investigating the impact of customer stochasticity on firm price discrimination strategies using a new Bayesian mixture scale heterogeneity model. *Marketing Lett.* 27(3):537–552.
- Reisinger D (2017) Here's how popular Apple Watch was last quarter. *Fortune* (February 8), <http://fortune.com/2017/02/08/apple-watch-2016-sales/>.
- Rhee BD, de Palma A, Fornell C, Thisse JF (1992) Restoring the principle of minimum differentiation in product positioning. *J. Econom. Management Strategy* 1(3):475–505.
- Salisbury LC, Feinberg FM (2010) Alleviating the constant stochastic variance assumption in decision research: Theory, measurement, and experimental test. *Marketing Sci.* 29(1):1–17.
- Sawtooth Software (2015) Report on conjoint analysis usage among Sawtooth Software customers. Accessed May 9, 2019, http://www.sawtoothsoftware.com/download/Conjoint_Report_2015.pdf.
- Sawtooth Software (2016) Results of Sawtooth Software user survey. Accessed May 9, 2019, <https://www.sawtoothsoftware.com/about-us/news-and-events/news/1693-results-of-2016-sawtooth-software-user-survey>.
- Sawtooth Software (2019) Randomized first choice settings. Accessed May 9, 2019, <https://www.sawtoothsoftware.com/help/lighthouse-studio/manual/randomizedfirstchoicestettingswindow.html>.
- Sonnier G, Ainslie A, Otter T (2007) Heterogeneity distributions of willingness-to-pay in choice models. *Quant. Marketing Econom.* 5(3):313–331.
- Swait J, Louviere J (1993) The role of the scale parameter in the estimation and comparison of multinomial logit models. *J. Marketing Res.* 30(3):305–314.
- Thurstone LL (1927) A law of comparative judgment. *Psych. Rev.* 34(4):273–286.
- Toubia O, Hauser JR, Simester DI (2004) Polyhedral methods for adaptive choice-based conjoint analysis. *J. Marketing Res.* 41(1):116–131.
- Train KE (2009) *Discrete Choice Methods with Simulation* (Cambridge University Press, Cambridge, UK).
- Ulrich KT, Eppinger SD (2004) *Product Design and Development*, 3rd ed. (McGraw-Hill, New York).
- Urban GL, Hauser JR (1993) *Design and Marketing of New Products*, 2nd ed. (Prentice-Hall, Englewood Cliffs, NJ).
- Urban GL, Hauser JR (2004) “Listening-in” to find and explore new combinations of customer needs. *J. Marketing* 68(April):72–87.
- Vriens M, Loosschilder GH, Rosbergen E, Wittink DR (1998) Verbal vs. realistic pictorial representations in conjoint analysis with design attributes. *J. Product Innovation Management* 15(5):455–467.
- Whyte RM (2005) Order granting in part and denying in part Olin's motion to exclude the testimony of John Kilpatrick. *Palmisano et al. v. Olin Corporation et al.*, Case No. C-03-01607 RMW (N.D. Cal. July 5, 2005).
- Wlömert N, Eggers F (2016) Predicting new service adoption with conjoint analysis: External validity of BDM-based incentive-aligned and dual-response choice designs. *Marketing Lett.* 27(1):195–210.