Online Appendices for

The Strategic Implications of Scale in Choice-Based Conjoint Analysis, *Marketing Science*

John R. Hauser, MIT Management

Felix Eggers, University of Groningen

Matthew Selove, Chapman University

May 2019

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, Ainslie, and Otter (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 Mixtures 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 Post-Test 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.

Online Appendix 1
Numerical Example to Illustrate Stylized Model.

We illustrate the formal insights with a numerical example in which $\beta^h = 2$, $\beta^\ell = 1$, $u_o = 1$, and $R = 0.55$. We obtain the fixed-point price equilibria by simple iteration combined with grid search. In all cases, we check that the second-order and cross-partial conditions are satisfied. (R program available from the authors.)

Table OA1.1 reports price equilibria for differentiated strategies (rs) for different values of scale (γ^{true}). In practice we expect γ^{true} to be the order of magnitude of the partworths, but to illustrate key issues we vary γ^{true}over a wider range. For very small values of true scale ($\gamma^{true} = 0.05$), the market is less sensitive to price allowing firms to price highly and earn substantial profits. Profits and prices decrease with γ^{true} over most of the range. For very large values of γ^{true}, the innovator's share in segment S (P^*_{S1rs}) approaches zero as does the follower's share in Segment R (P^*_{R2rs}). The market becomes more segmented when true scale increases.

Table OA1.2 reports equilibria for undifferentiated strategies (rr) using the same values of true scale as in Table OA1.1. The second-order conditions are always satisfied for undifferentiated strategies. Low true scale implies high prices and profits. When true scale is large, the market is very sensitive to price and the shares in Segment R approach 50%. If the firms do not differentiate, the high price sensitivity due to large scale drives profits to zero. The last two columns of Table OA1.2 compare profits between a differentiated (rs) strategy and an undifferentiated strategy (rr). For low scale (below $\gamma^{cutoff} \cong 1.0$), strategy rr is more profitable than rs for the follower. This is shown in a **red bold font**.

Table OA1.3 reports the shares of the outside option in Segment R, Segment S, and overall for both a differentiated market and an undifferentiated market. Figure OA1.1 plots equilibrium prices for the innovator as a function of scale over a range similar to that of Table 1 in the text. Conceptually, the plots are similar suggesting the stylized model captures the sensitivity of equilibrium prices to scale. Figure OA1.2 plots the relative equilibrium profits of differentiated vs. undifferentiated positioning strategies for both the innovator and the follower as a function of scale. Notice that the innovator would always prefer to differentiate but the follower would prefer to differentiate only when scale is above γ^{cutoff}, which in Figure OA1.2 is approximately 1.0.

Table OA1.1. Prices, Shares, Profits, and Second-order Conditions: Differentiated Market

Scale	**Prices**		**Shares in Segment R**		**Shares in Segment S**		**Profits**		**Second Order Conditions**	
γ^{true}	p^*_{1rs}	p^*_{2rs}	P^*_{R1rs}	P^*_{R2rs}	P^*_{S1rs}	P^*_{S2rs}	π^*_{1rs}	π^*_{2rs}	$\frac{\partial^2 \pi^*_{1rs}}{\partial p^2_{1rs}}$	$\frac{\partial^2 \pi^*_{2rs}}{\partial p^2_{2rs}}$
0.05	24.625	24.603	0.192	0.183	0.183	0.192	4.622	4.600	-0.009	-0.009
0.50	2.588	2.564	0.261	0.160	0.158	0.264	0.556	0.531	-0.103	-0.107
0.60	2.190	2.166	0.278	0.155	0.146	0.299	0.485	0.459	-0.132	-0.126
0.70	1.909	1.885	0.295	0.149	0.139	0.316	0.435	0.408	-0.157	-0.149
0.80	1.701	1.677	0.311	0.143	0.133	0.334	0.398	0.370	-0.184	-0.173
0.90	1.543	1.519	0.328	0.136	0.195	0.275	0.371	0.342	-0.212	-0.198
1.0	1.418	1.394	0.345	0.130	0.126	0.352	0.349	0.316	-0.137	-0.144
2.0	0.923	0.905	0.501	0.070	0.067	0.511	0.282	0.243	-0.491	-0.573
3.0	0.817	0.807	0.614	0.031	0.030	0.621	0.287	0.240	-0.808	-0.589
4.0	0.787	0.783	0.692	0.013	0.013	0.696	0.304	0.251	-1.200	-1.481
5.0	0.779	0.778	0.747	0.005	0.005	0.747	0.322	0.264	-1.639	-2.018
10	0.805	0.805	0.876	0.000	0.000	0.876	0.388	0.317	-3.938	-4.815
20	0.861	0.861	0.942	0.000	0.000	0.942	0.446	0.365	-8.477	-10.36

Table OA1.2. Prices, Shares, Profits, and Relative Profits: Undifferentiated Market

Scale	Prices		Shares in Segment R		Shares in Segment S		Profits		Relative Profits	
γ^{true}	p^*_{1rr}	p^*_{2rr}	P^*_{R1rr}	P^*_{R2rr}	P^*_{S1rr}	P^*_{S2rr}	π^*_{1rr}	π^*_{2rr}	$\pi^*_{1rs} - \pi^*_{1rr}$	$\pi^*_{2rs} - \pi^*_{2rr}$
0.05	24.619	24.619	0.190	0.190	0.184	0.184	4.618	4.618	0.004	**-0.018**
0.50	2.553	2.553	0.240	0.240	0.179	0.179	0.542	0.542	0.014	**-0.011**
0.60	2.147	2.147	0.251	0.251	0.178	0.178	0.468	0.468	0.017	**-0.009**
0.70	1.858	1.858	0.262	0.262	0.176	0.176	0.415	0.415	0.020	**-0.007**
0.80	1.642	1.642	0.272	0.272	0.175	0.175	0.375	0.375	0.023	**-0.005**
0.90	1.474	1.474	0.283	0.283	0.173	0.173	0.345	0.345	0.026	**-0.002**
1.0	1.341	1.341	0.294	0.294	0.172	0.172	0.320	0.320	0.029	0.004
2.0	0.744	0.744	0.385	0.385	0.156	0.156	0.209	0.209	0.072	0.034
3.0	0.539	0.539	0.444	0.444	0.142	0.142	0.166	0.166	0.121	0.074
4.0	0.425	0.425	0.476	0.476	0.134	0.134	0.137	0.137	0.167	0.114
5.0	0.349	0.349	0.491	0.491	0.130	0.130	0.114	0.114	0.208	0.150
10	0.177	0.177	0.500	0.500	0.127	0.127	0.059	0.059	0.329	0.258
20	0.089	0.089	0.500	0.500	0.127	0.127	0.029	0.029	0.416	0.335

Table OA1.3. Shares of the Outside Option

Scale	Outside Option Segment R		Outside Option Segment S		Outside Option Net Share	
γ^{true}	P^*_{R0rs}	P^*_{R0rr}	P^*_{S0rs}	P^*_{S0rr}	P^*_{0rs}	P^*_{0rr}
0.05	0.625	0.626	0.625	0.626	0.625	0.626
0.50	0.581	0.581	0.576	0.581	0.579	0.581
0.60	0.576	0.571	0.546	0.571	0.563	0.571
0.70	0.566	0.562	0.535	0.562	0.552	0.562
0.80	0.556	0.553	0.523	0.553	0.541	0.553
0.90	0.477	0.544	0.589	0.544	0.527	0.544
1.0	0.529	0.534	0.518	0.534	0.524	0.534
2.0	0.432	0.459	0.419	0.459	0.426	0.459
3.0	0.356	0.414	0.348	0.414	0.352	0.414
4.0	0.295	0.390	0.291	0.390	0.293	0.390
5.0	0.248	0.379	0.248	0.379	0.248	0.379
10	0.124	0.373	0.124	0.373	0.124	0.373
20	0.058	0.373	0.058	0.373	0.058	0.373

Figure OA1.1. Plot of Innovator's Equilibrium Price as a Function of Scale

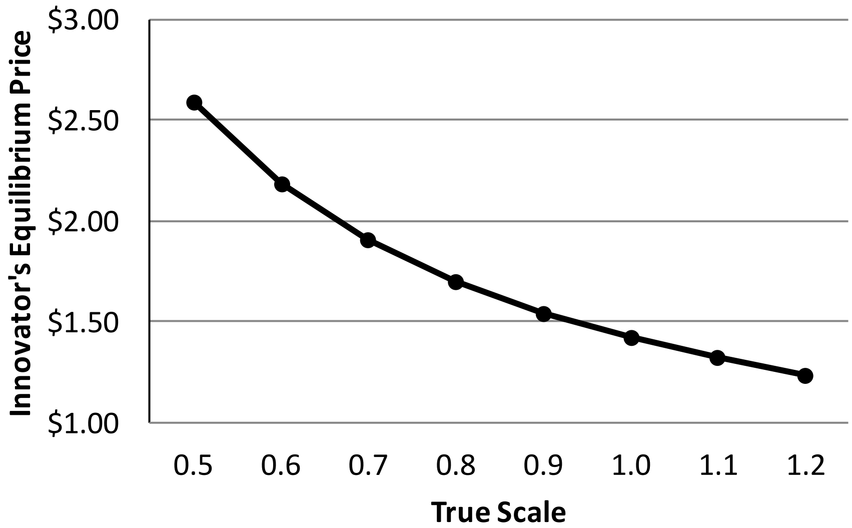
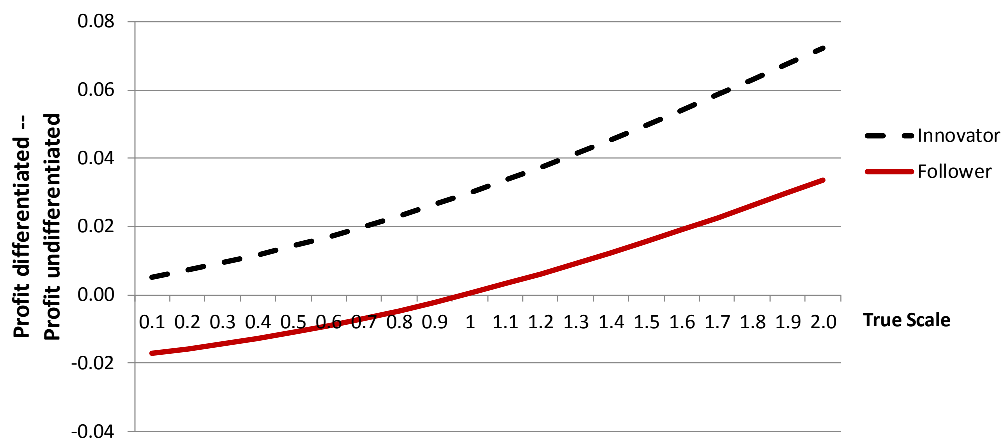


Figure OA1.2. Relative Profits of Differentiated vs. Undifferentiated Positioning Strategies



Online Appendix 2
Numerical Example of Craft Decisions by a Sophisticated Follower

Sophisticated followers might anticipate that higher-cost CBC studies resolve their uncertainty about true scale. Such sophisticated followers would make optimal decisions on whether or not to invest in higher-cost CBC studies. Suppose that the follower has prior beliefs, $g(\gamma^{true})$, about the true scale and can pay M dollars to resolve that uncertainty ($\gamma^{higher} = \gamma^{true}$). (For simplicity of exposition, we normalize the cost of the lower-cost CBC study to zero.) Suppose further that the estimates of the relative partworths are the same for both the higher- and lower-cost CBC studies, but only the higher-cost study resolves γ^{true}. Because the follower knows the relative partworths and is sophisticated, we assume the follower can calculate anticipated $\pi^*_{2rs}(\gamma^{true})$ and $\pi^*_{2rr}(\gamma^{true})$ for all values of γ^{true}. The sophisticated follower must decide whether or not to invest M dollars for higher cost.

If a sophisticated follower invests only in the lower-cost CBC study, it does not resolve $g(\gamma^{true})$ and its expected profits are given by an expectation over $g(\gamma^{true})$. The risk-neutral follower's expected profits with lower-cost research are:

(OA2.1) $$E[\pi^*_2(lower\ quality\ research)]$$

$$= max\left\{\int \pi^*_{2rr}(\gamma^{true})g(\gamma^{true})d\gamma^{true}, \int \pi^*_{2rs}(\gamma^{true})g(\gamma^{true})d\gamma^{true}\right\}$$

On the other hand, if the follower invests in a higher-cost CBC study, it resolves its estimate of scale such that $\gamma^{higher} = \gamma^{true}$. For each observed γ^{true}, the follower anticipates that it will choose r if $\pi^*_{2rs}(\gamma^{true}) < \pi^*_{2rr}(\gamma^{true})$, s if $\pi^*_{2rs}(\gamma^{true}) > \pi^*_{2rr}(\gamma^{true})$, and choose randomly if $\pi^*_{2rs}(\gamma^{true}) = \pi^*_{2rr}(\gamma^{true})$. Let $\Delta_2(\gamma^{true}) = 1$ indicate that it is optimal for the follower to choose r for an observed γ^{true} and $\Delta_2(\gamma^{true}) = 0$ indicate that it is optimal to choose s after γ^{true} is revealed by higher-cost market research. The risk neutral follower will use the maximum-profit-indicator function (Δ_2) to integrate over $g(\gamma^{true})$. The expected profits when the sophisticated risk-neutral follower invests in higher-cost market research are:

$$E[\pi_2^*(higher\ quality\ research)]$$

(OA2.2)
$$= \int \{\pi_{2rs}^*(\gamma^{true})\Delta_2(\gamma^{true}) + \pi_{2rr}^*(\gamma^{true})[1-\Delta_2(\gamma^{true})]\} f(\gamma^{true}) d\gamma^{true} - M$$

To decide on whether or not to invest in the higher-cost CBC study, the sophisticated follower need only compare the profits given by Equations OA2.1 and OA2.2. Because the notation in Equations OA2.1 and OA2.2 is cumbersome, we illustrate the comparison more simply and intuitively below using the illustrative example.

As argued in the text, the solution to the larger game is that the innovator never invests to resolve scale (γ^{true}). Lower-cost market research is sufficient as long as the CBC study reveals sufficiently accurate relative partworths ($r > s$ in R, $s > r$ in S, and $R > S$). The sophisticated follower chooses whether to invest by choosing the market research that maximizes profits comparing Equations OA2.1 and OA2.2). Naively relying on the scale observed in a lower-cost CBC study might lead to substantial opportunity losses. Unfortunately, our experience suggests that many firms make “gut” decisions on CBC investments and choose aspects of CBC studies that we suspect are lower-cost. To the extend such firms are unaware of the implications of scale on strategic decisions, such “gut” decisions may or may not be optimal.

Suppose, for the sake of illustration, that the market potential is 10 million units and that prices are scaled in dollars. Suppose further that the follower anticipates that the higher-cost CBC study reveals the true scale, $\gamma^{higher} = \gamma^{true}$. It will act on the γ^{true} that is revealed. It uses its prior to anticipate the γ^{true} that will be revealed. The lower-cost CBC study does not reveal γ^{true}, therefore the follower must act based on its prior. If the follower chooses the lower-cost CBC study, the follower bases its positioning strategy based on expected profits, integrating over $g(\gamma^{true})$. The calculations are given in Table OA2.1.

Based on Table OA2.1, an undifferentiated strategy with a lower-cost CBC study has a higher expected value than a differentiated strategy, hence the follower using a lower-cost CBC study would choose r as per Equation OA2.1. If the follower invests in the higher-cost CBC study, the follower can choose its strategy (r or s) depending upon the γ^{true} it observes. The follower's decision after observing γ^{true} is indicated by the "Best Strategy" column. Choosing the best strategy for each realized γ^{true} yields higher expected profits ($5,034,722) compared to the best strategy based only on the lower-cost study ($4,981,407). The difference, $53,315, is the most that a sophisticated follower would pay for a higher-cost CBC study.

Table OA2.1 also illustrates that a naïve follower can make strategic errors. Suppose the follower invests in a lower-cost CBC study that tells the firm (incorrectly) that $\gamma^{true} = 0.1$. Believing and acting on the lower-cost CBC study, the follower would choose not to differentiate (r) and forecast a profit of over $23.5M. If true scale were really $\gamma^{true} = 2.0$, then the firm would (1) position the product incorrectly (r rather than s), (2) bear an opportunity cost of $335,010, and (3) not realize anywhere near its anticipated profit ($2.1M vs. $23.5M).

Table OA2.1. Illustration of the Follower's Decisions and Outcomes Based on Either a Lower-Cost CBC Study (Columns 3&4) or a Higher-Cost CBC Study (Column 6)

Prior, $g(\gamma^{true})$	**True Scale, γ^{true}**	**Follower Chooses s Based on Lower-Cost CBC Study**	**Follower Chooses r Based on Lower-Cost CBC Study**	**Best Strategy After γ^{true} Revealed**	**Follower Chooses r or s after Higher-Cost CBC Study**
0.03	0.1	$23,337,834	$23,509,998	***r***	$23,509,998
0.03	0.2	$12,027,032	$12,186,344	***r***	$12,186,344
0.08	0.3	$8,275,610	$8,420,431	***r***	$8,420,431
0.08	0.4	$6,414,787	$6,543,437	***r***	$6,543,437
0.08	0.5	$5,310,777	$5,421,558	***r***	$5,421,558
0.08	0.6	$4,585,625	$4,676,841	***r***	$4,676,841
0.08	0.7	$4,077,318	$4,147,275	***r***	$4,147,275
0.08	0.8	$3,704,817	$3,751,862	***r***	$3,751,862
0.08	0.9	$3,423,066	$3,445,561	***r***	$3,445,561
0.08	1.0	$3,204,993	$3,201,369	***s***	$3,204,993
0.03	1.1	$3,033,356	$3,002,089	***s***	$3,033,356
0.03	1.2	$2,896,596	$2,836,255	***s***	$2,896,596
0.03	1.3	$2,786,715	$2,695,922	***s***	$2,786,715
0.03	1.4	$2,697,959	$2,575,425	***s***	$2,697,959
0.03	1.5	$2,626,085	$2,470,611	***s***	$2,626,085
0.03	1.6	$2,567,891	$2,378,368	***s***	$2,567,891
0.03	1.7	$2,520,907	$2,296,323	***s***	$2,520,907
0.03	1.8	$2,483,216	$2,222,635	***s***	$2,483,216
0.03	1.9	$2,453,264	$2,155,856	***s***	$2,453,264
0.03	2.0	$2,429,844	$2,094,834	***s***	$2,429,844
Expected Profits		$4,975,580	$4,981,407		$5,034,722

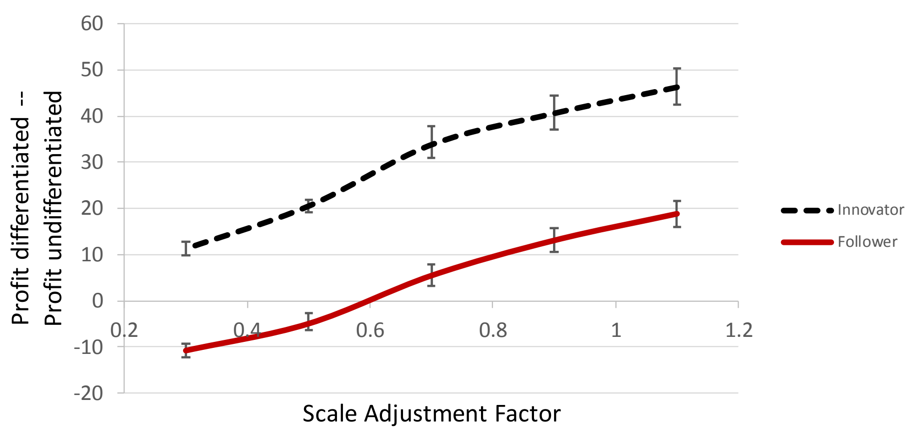
Online Appendix 3
Practical Recommendations for CBC Craft

Although γ^{true} is a latent construct and, hence, not directly observable, the stylized theory and smartwatch empirical test provide insights for practical recommendations. There is substantial research in marketing science and substantial practical experience to aid the firm in making decisions with respect to the accuracy of the relative partworths. For the purpose of this online appendix, we assume the firm has invested wisely to identify relative partworths and is only focused on the decision of whether to invest in more costly craft to improve its estimate ($\gamma^{market\ research}$) of γ^{true}.

By assumption, the firm's estimates of the relative partworths (β_{ki}'s) are accurate. Using these relative partworths and any value of γ, the firm can use Equations 1 and 2 to estimate (a posterior distribution of) the profits it would obtain for differentiation and for no differentiation: $\pi^*_{2rs}(\gamma)$ and $\pi^*_{2rr}(\gamma)$ in the stylized model. (Empirically, these calculations apply for many-product markets.) The firm can either plot $\pi^*_{2rs}(\gamma) - \pi^*_{2rr}(\gamma)$ to identify γ^{cutoff} or compute numerically $\gamma^{cutoff} = \{\gamma: \pi^*_{2rs}(\gamma) = \pi^*_{2rr}(\gamma)\}$. Figure OA1.2 provides an example plot for the illustrative example and Figure OA3.1 provides an example plot for the smartwatch data. From Figure OA3.1, $\gamma^{cutoff} \cong 0.6$. (If the firm uses a posterior distribution for the relative partworths, it obtains a posterior distribution for γ^{cutoff}.)

Figure OA3.1. Relative Profits Based on the Smartwatch Data

(vertical bars indicate posterior confidence intervals)



Using its priors for γ^{true} as in Online Appendix 2, or using the posterior distribution for γ^{true} after a pre-study, the firm can compare γ^{true} to the posterior distribution of γ^{cutoff}. If the firm is reasonably confident that it can distinguish among $\pi_{2rs}^*(\gamma) \gg \pi_{2rr}^*(\gamma)$, $\pi_{2rs}^*(\gamma) \ll \pi_{2rr}^*(\gamma)$, and $\pi_{2rs}^*(\gamma) \approx \pi_{2rr}^*(\gamma)$, then it differentiates in the first case and does not differentiate in the second case. In the third case both positioning strategies give similar profit and the firm can choose among strategies for other (unmodeled) reasons.

Perhaps after sufficient empirical studies to examine how CBC craft affects scale, we might develop rules of thumb to suggest which elements of craft have a large impact on scale and which have a small impact of scale. Meta analyses could then suggest best practices to trade off the cost and benefits of craft.

Online Appendix 4
Equilibrium Prices and Brief Description for the Camera and Dormitory Studies

Allenby et al. (2014) propose that price equilibria be used to compute damages in patent litigation. They illustrate their proposed procedure using data from a CBC study of digital camera choices. Their application considers a market of four brands using a CBC study of seven attributes:

- Brand: Canon, Sony, Nikon, Panasonic
- Pixels: 10, 16 mega-pixels
- Zoom: 4x, 10x optical
- Video: HD (720p), Full HD (1080p) and mike
- Swivel Screen: No, Yes
- Wi-Fi: No, Yes
- Price: $79-$279

The survey was fielded by Sampling Surveys International in August 2013 and the data are based on 501 questionnaires. They eliminated two "straight-liners" as well as twenty-three respondents who always selected the outside option. The final sample was 469 respondents. They do not indicate whether realistic images or incentive alignment was used.

Although Allenby et al. (2014) do not consider scale effects, we use their data to estimate counterfactuals for scale adjustment. Figure OA4.1a demonstrates that the price equilibria can be identified and that the effect of scale on price equilibria is conceptually similar to that observed for the smartwatch application (Figure 1 in the text). Plots for the other three brands are similar.

In Fall 2018, a major university, which we will call UrbanTech, collected CBC data from its target market. Those data were key to UrbanTech's decisions about new dormitories. Although the actual data are proprietary, we received permission to replicate the CBC study on a more-national target of students and potential students.

In Spring 2018, we collected data from 985 students. The data came from three sources. The first source was students who had taken the GMAT or GRE and expressed interest in business schools. (They were screened to have UrbanTech-level scores.) The second source came from a professional panel, ProdegeMR. Members of professional panels are screened to have interest in taking questionnaires. Although survey takers are compensated, a good panel company uses a variety of quality-control measures to assure that the data are accurate and representative. The third source was students in a management course at UrbanTech. The sample sizes from the three sources are GMAT—386 students, ProdegeMR—533 students, and UrbanTech—66 students. Naturally, the GMAT and UrbanTech course samples are overly rich in graduate students interested in management, but the data can be used to compute hypothetical equilibrium prices as if the sample were representative of UrbanTech's population.

The CBC study asked students about seven attributes broken down into twenty-four levels:

1. Unit type (students with families saw the following)
    a. studio: private bathroom, compact kitchen, no walls separating living areas.
    b. 1-bedroom apartment: private bathroom, full-sized kitchen, includes living room.
    c. 2-bedroom apartment: two bedrooms, full-sized kitchen, includes living room.

    Or, Unit type (single students saw the following)
    a. twin or triple, shared bathroom, shared kitchen
    b. single bedroom, shared bathroom, shared kitchen
    c. 2-3 bedroom apartment with one student per room. Unit includes living room, one shared bathroom, and a full-size kitchen
2. Commute time
    a. 10 minute walk, 3-5 minute bike, 0.5 miles or fewer away
    b. 20 minute walk, 6-10 minute bike, 1 mile away
    c. 20 minute bike, driving might be necessary, 3 miles away
3. Access to grocery stores and bars/cafes/restaurants
    a. no grocery or bar/café/restaurant in neighborhood
    b. grocery store, but no bar/café/restaurant in neighborhood

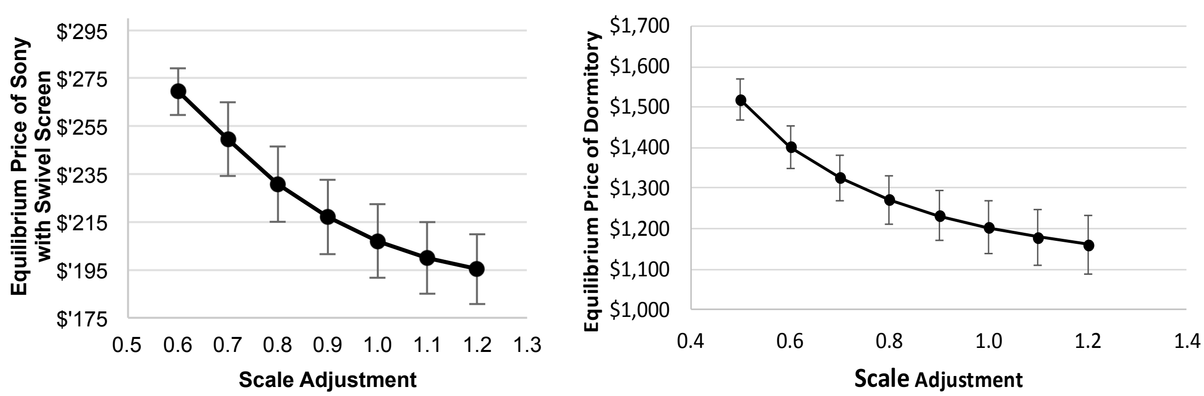
   c. grocery store and bar/café/restaurant in neighborhood
4. Bedroom size
   a. fits twin-size bed, 150 sq. ft. (14 sq. m)
   b. fits double-size bed, 200 sq. ft. (18.5 sq. m)
   c. fits queen-size bed, 250 sq. ft. (23 sq. m)
   d. fits king-size bed, 300 sq. ft. (28 sq. m)
5. Building amenities
   a. no amenities
   b. some: small community lounge, small fitness center, outdoor area, front desk, same-day maintenance service
   c. many: large community lounge, large fitness center, study lounge, music room, recreation/game room, outdoor area, barbecue in outdoor area, front desk, same-day maintenance service
6. Parking
   a. no parking
   b. paid uncovered parking
   c. paid covered parking
7. Rent (the data provide a single parameter to represent utility per dollar)
   a. \$500 per month
   b. \$1,000 per month
   c. \$1,500 per month
   d. \$2,000 per month
   e. \$2,500 per month

Each respondent was asked to evaluate 16 choice sets using a dual response choice task. To encourage respondents to think hard about their choices, the tasks were incentive aligned. Specifically, respondents were told (accurately) that one respondent would be selected and that that respondent would be given a reasonable chance at winning \$30,000 toward rent for one year. However, the dormitory (or off-campus living) option, for which the rent could be used, would be chosen by us and based upon the respondent's answers to the choice questions. If the respondent's data indicated that he or she would prefer a dormitory, we would offer the dormitory predicted by the conjoint analysis and any remaining cash if the annual rent was below $30,000. If the respondent's data indicated that he or she would prefer to live off campus, then the rent would only apply off campus. (The respondent could still live on campus, but would forego the $30,000.)

We used images whenever possible to enhance realism and to illustrate the levels of the dormitory attributes. Attributes and levels were explained and illustrated with high-realism images before the respondents completed any choice tasks. Respondents also viewed training screens. Figure OA4.2 gives an example dual-response choice task.

In this case, there is but one "firm," but it competes against average rents in the immediate vicinity of the university, i.e., the outside option. The new dormitories are sufficiently large (and built at the request of city government) that their presence could affect those rents. Figure OA4.1b plots the price equilibria and posterior standard deviations of a specific dormitory characterized by all attributes (1 bedroom, 20 min walk commute, access to grocery stores, queen size bed, no amenities and no parking) as a function of counterfactual values of scale adjustments. The equilibria are feasible to compute in the majority of draws; the implications are conceptually similar to those from the smartwatch application.

Figure OA4.1. Predicted Equilibrium Price as a Function of Scale for Camera and Dormitories



a. Four Cameras **b. New Dormitory (vs. Outside Option)**

Figure OA4.2. Dual-Reponse Choice Task from the Dormitory Study

Imagine that you are in the market and making the decision of where to live as at your college or university. You are choosing where would be best for you based on a number of alternatives.

If there were no other options available AND all other features not mentioned in the exercise were the same across the dormitory living arrangements shown, which would you choose?

You may click on any attribute to review the levels at any time.

Choose by clicking one of the buttons below:

1 / 16

Unit Type	Studio, private bathroom, compact kitchen	2-bedroom apartment, private bedroom, full-size kitchen	1-bedroom apartment, private bedroom, full-size kitchen	Studio, private bathroom, compact kitchen
Commute Time	20 min walk, 6-10 min bike	20 min bike, driving may be necessary	10 min walk, 3-5 min bike	10 min walk, 3-5 min bike
Access to Grocery Stores and Bars/Cafes /Restaurants	Nothing in Neighborhood	Grocery store nearby	Grocery store & bars/cafes /restaurants nearby	Nothing in Neighborhood
Bedroom Size	Bedroom fits twin-size bed	Bedroom fits queen-size bed	Bedroom fits king-size bed	Bedroom fits double-size bed
Building Amenities	Some	Many	None	None
Parking	Paid uncovered parking	No parking	Paid covered parking	No parking
Rent per Household	$1000	$2000	$2500	$500
	Select	Select	Select	Select

Given your knowledge of the real-estate market, would you actually be willing to live in the dormitory living arrangement you chose at the price indicated?

(Please assume that if you choose not to live at the option you chose above, you would be choosing to live off-campus at a residence you found on your own.)

◯ Yes, I would be live in the dormitory living arrangement that I chose above.

◯ No, I would rather live off-campus than live in the dormitory living arrangement I chose above.

Online Appendix 5

Brief summary of the McFadden (2014, used in stylized-model), Sonnier, Ainslie, and Otter (2007), and Allenby et al. (2014) HB CBC Normalizations.

Stylized model (McFadden 2014 based) specification. In the stylized model specification we model consumer i's utility u_{ij} for product profile j as:

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

where a_{jk} refers to the level of attribute k (effect-coded) and p_j to the price (in $150 units). We apply a multinomial logit model to consumer i's choices, y_i, given attribute levels, price, and preference parameters (β_i, γ_i), within a hierarchical Bayes framework. The β_i's and $\ln(\gamma_i)$ are assumed multivariate normally distributed with mean θ and covariance matrix V (we assume mean 0 for β_i and we allow the means for $\ln(\gamma_i)$ to vary according to the experimental condition and validation task; see Online Appendix 6). The second-stage prior is the standard Normal-Inverted-Wishart conditionally conjugate prior. The hierarchical model is then specified as:

$$y_i | a_j, p_j, \beta_i, \gamma_i$$

$$\beta_i, \ln(\gamma_i) \sim N(\theta, V)$$

$$V \sim IW(\nu, \nu V_0)$$

We apply Allenby et al.'s "default" settings (p. 438) and use a relatively diffuse prior with the following parameters: $\theta = 0$, $\nu = \dim(\beta_i) + 6$, and $V_0 = I$. Consistent with Allenby et al. (2014) we lower the diagonal element of V_0 corresponding to γ_i to 0.5 to account for its logarithmic scale.

Sonnier, Ainslie, and Otter (2007) specification. Sonnier et al. model consumer i's utility u_{ij} as:

$$u_{ij} = \frac{1}{\mu_i}(\sum_{k=1}^{K} \beta_{ki} a_{jk} - p_j) + \epsilon_{ij}$$

In the first stage prior the β_{ki}'s are assumed normally distributed, $\ln(\mu_i)$ is assumed normally distributed. The second-stage prior and hyper-priors remain consistent to the stylized model (replacing the hyper-prior for γ_i with an equivalent hyper-prior for μ_i to account for the effects of craft and validation.).

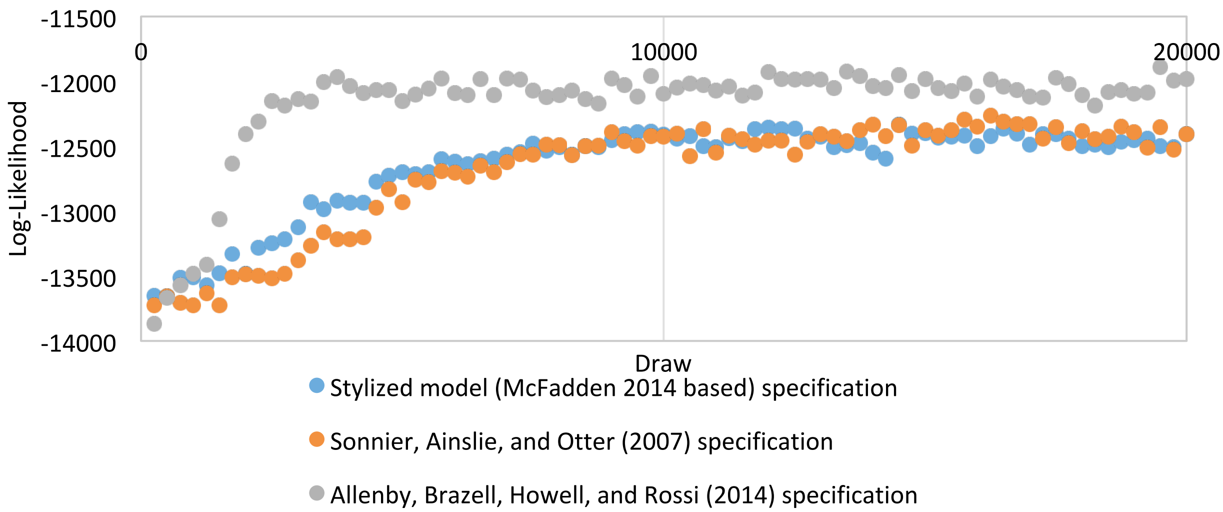
Allenby, Brazell, Howell, and Rossi (2014) specification. Allenby et al. do not employ a scaling parameter but estimate a price parameter, β_{pi}, in their utility specification:

$$u_{ij} = \sum_{k=1}^{K} \beta_{ki} a_{jk} - \beta_{pi} p_j + \epsilon_{ij}$$

The β_{ki}'s are assumed normally distributed, $\ln(\beta_{pi})$ is assumed normally distributed. The second-stage prior and hyper-priors remain consistent to the stylized model (replacing the hyper-prior for γ_i with an equivalent hyper-prior for β_{pi} and accounting for craft and validation). We tested other prior specifications, e.g., $\nu = \dim(\beta_i) + 16$, and the results remained consistent (see Online Appendix 9.).

HB settings. All settings not specified by Allenby et al. followed standard procedures, e.g., as in Sawtooth Software (2015). For example, we used 10,000 burn-in iterations and a subsequent 10,000 iterations to draw partworths, from which we kept every 10th draw. The iteration time series show that the process converged after the burn-in phase for all specifications (see Figure OA5.1 for log-likelihood statistics). See Appendix_5_Supplement_Iteration_Statistics.xlsx. All summaries, profits, and other reported quantities are based on the posterior distributions.

Figure OA5.1. Iteration time series of the three CBC HB Specifications



Online Appendix 6
Specifications of the Bayesian Methods to Estimate the Scale-Adjustment Factors

The model that we estimate is given in the text as Equation 4 and repeated here as Equation OA6.1.

(OA6.1)
$$u_{ij} = \gamma^{QV}\gamma_i\left(\sum_{k=1}^{K}\beta_{ki}a_{jk} - p_j\right) + \epsilon_{ij}$$

That means we allow the scale adjustment factor to vary according to the experimental cell, λ_{Q^h}, between estimation and validation tasks, λ_V, and the interaction thereof, λ_{Q^hV}:[1]

(OA6.2)
$$\ln\left(\gamma^{QV}\right) = \lambda_{Q^h}Q_i^h + \lambda_V V_i + \lambda_{Q^hV}Q_i^h V_i$$

where (as per the text):

- $Q_i^h = 1$ if respondent i was exposed to the realistic-image-incentive-aligned condition (0, otherwise),
- $V_i = 1$ for respondent i's validation task (0 for the estimation tasks),
- γ_i reflecting unobserved heterogeneity in scale.

Accordingly, we identify three scale adjustments—all relative to text-only-no-incentive-aligned no-validation-adjustment experimental cell, which is normalized to 1.0.

This specification is equivalent to and was estimated as a random-effects model within a hierarchical Bayes framework that assumes a normal distribution for $\ln(\gamma_i)$ with means according to the experimental condition and validation task, such that $\ln(\gamma_i) \sim N(\lambda_{Q^h}Q_i^h + \lambda_V V_i + \lambda_{Q^hV}Q_i^h V_i, V)$. The prior settings were otherwise as in Online Appendix 5.

The model in hierarchical notation is:

$$y_i | a_j, p_j, \beta_i, \gamma_i$$

[1] We also estimated a similar random-effects model with preference heterogeneity between estimation and validation task. Results are available upon request.

$$\gamma_i | \lambda_{Q^h}, \lambda_V, \lambda_{Q^h V}, Q_i^h, V_i, V$$

$$\beta_i \sim N(0, V)$$

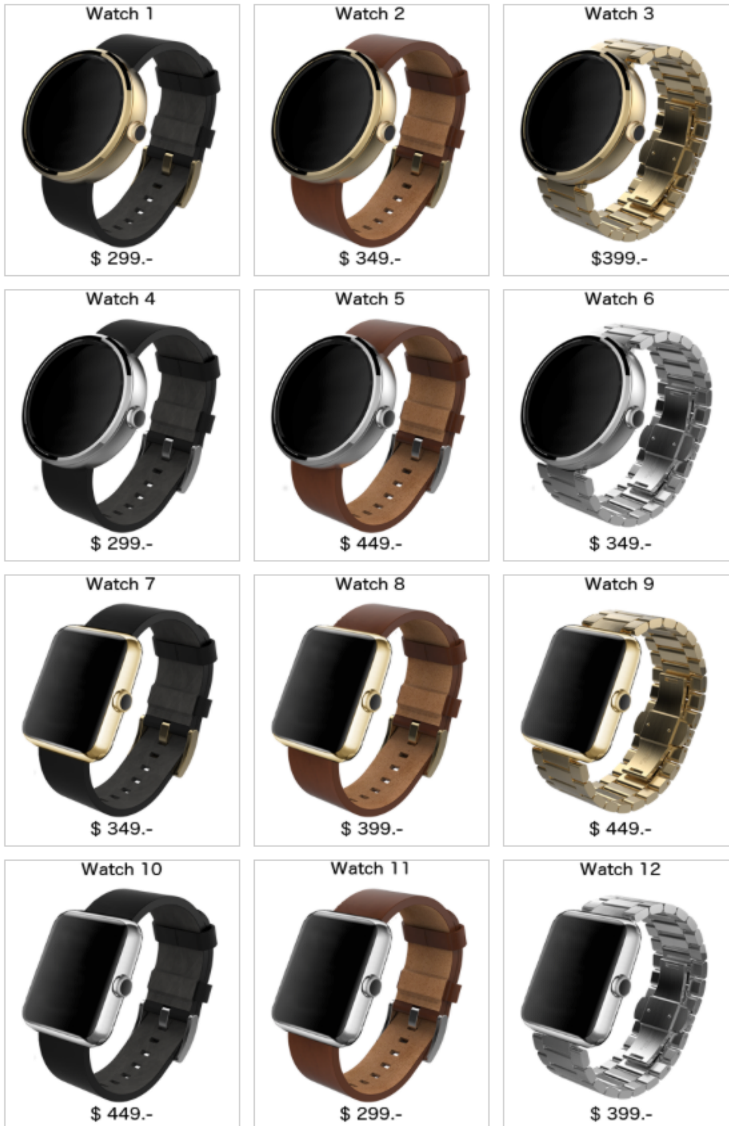
$$\ln(\gamma_i) \sim N(\lambda_{Q^h} Q_i^h + \lambda_V V_i + \lambda_{Q^h V} Q_i^h V_i, V)$$

$$V \sim IW(\nu, \nu V_0)$$

The validations task itself is given in Figure OA7.1. The twelve watches represent all design combinations. The prices were chosen randomly (without replacement) according to minimal overlap regarding the design attributes. The resulting prices are almost orthogonal to the design attributes. The validation task used a different selection process (dropdown menu) was delayed three weeks to avoid habitual behavior and to cleanse memory. We abused notation slightly for clarity on what is varied. For greater details we can provide R programs upon request.

Figure OA7.1. Validation Task

Final decision: If these are the available smartwatches which one do you like best?
You can click on each image to get a larger view.



Please assume that all watches are from your preferred brand Apple and are compatible with your smartphone so that they can show incoming messages or calls. Assume that all of these watches have a battery that lasts a day or more, a heart rate monitor, Bluetooth, high definition color LED touchscreen, 1.2 GHz processor, 4 GB storage, and 512 MB RAM.

Would you consider buying your preferred option if it was available?

- Yes
- No

Online Appendix 7
Comparison Of Estimates for Scale Adjustment Factors from the Three Normalizations

The detailed estimates are contained in a companion spreadsheet,

Appendix_7_Comparison_of_Posterior_Scale_Adjustment Estimates.xlsx.

Online Appendix 8
Alternative Estimations Accounting for Gender, for Split-Sample, for Split Choice Task, and for a Mixtures of Normal Distributions

The detailed estimates are contained in a companion spreadsheet,

Appendix_8_Alteernative_Scale_Adjustment Estimates.xlsx.

Online Appendix 9
Posterior Distributions for Scale Adjustment Factors and Attribute Importances

The full posterior distributions and summaries for the scale adjustment factors, attribute importances, and individual posterior means are contained in a companion spreadsheet, Appendix_9_Table_3_Scale_Adjustments.xlsx and Appendix_9_Table_4_Relative_Importances.xlsx. See also Appendix_9_Individual_Posterior_Means_of_Random_Parameters.xlsx.

Online Appendix 10
Posterior WTP Estimates from the Three Normalizations

The detailed estimates are contained in a companion spreadsheet,

Appendix_10_Posterior_WTP_ratio_method.xlsx.

Online Appendix 11

Hit Rates and Uncertainty Explained ($\mathbf{U^2}$) for Holdout Tests and Validation Tests

Table OA11. Sample Size, Time to Complete, and Predictive Statistics

(values in parentheses indicate posterior standard deviations)

	Higher-Cost Study	Lower-Cost Study
Sample size	270	275
Median time to complete choice tasks (seconds)	217	206
Holdout hit rate (two choice tasks) [a]	0.77	0.64
	(0.02)	(0.02)
Holdout uncertainty explained [b]	0.53	0.34
	(0.03)	(0.04)
Validation hit rate [c, d]	0.39	0.24
	(0.02)	(0.02)
Validation uncertainty explained (unadjusted partworths) [b]	0.32	-0.02
	(0.02)	(0.03)
Validation uncertainty explained (adjusted partworths) [b, e]	0.33	0.16
	(0.02)	(0.01)

[a] Average rate of correct predictions among four alternatives in the two internal holdout tasks (chance is 0.25). Predicted choice is alternative with highest utility within the task (invariant to scale).

[b] Percent of uncertainty explained by model relative to that explainable by perfect prediction (Hauser 1978). Uncertainty explained is equivalent to relative Kullback-Leibler divergence (Ding, et al. 2011) for continuous probability predictions.

[c] Rate of correctly predicted validation choices among 13 alternatives (chance is 0.08).

[d] Validation hit rates are not affected by scale-adjustment factors.

[e] Adjustment according to scale-adjustment factors.

Online Appendix 12
Empirical Post-Test for Validation Task

Our goals in designing the validation task were (1) to demonstrate that a validation task could impact a firm's estimate of (true) scale and (2) to explore whether the change in estimated scale was sufficient to impact strategic decisions. In the text, we argue that our validation task was a sufficient proof of concept. Validation-task adjustments impact estimated scale and the adjustments change strategic decisions. This online appendix provides further support for the validation task as a proof of concept.

Characteristics of a validation task. To achieve our goals, we sought a validation task that was more likely to be perceived by respondents as representative of marketplace choice than the CBC choice tasks. We wanted to avoid confounds with internal consistency, thus we wanted the task to rely on a format that was different than the choice tasks. We wanted to avoid respondents' tendency to answer consistently due to spurious demand artifacts. To achieve this goal we wanted the task to be delayed sufficiently so that respondents would need to rely on their preferences among attribute levels rather than a desire to reproduce their choice-task decisions.

Design of the validation task. To make it more likely that the validation task represented the marketplace better than a choice-task, we designed the validation task so that it asked respondents to choose among more than three options and so that the validation task allowed an outside option. (Each choice task had three options plus the outside option.) For example, online marketplaces often have a large number of options available. To have the most options available, our validation task asked respondents to choose among all of the attribute-level combinations possible within the experimental design.

For our initial validation task, we targeted online shopping because, unlike for offline shopping, we did not need to model store layout and other unrelated marketing issues. We wanted the layout and formatting of the choice task to have a different look and feel than the choice task, so we chose a look and feel not unlike an online marketplace layout. To cleanse memory and minimize demand artifacts that might drive spurious internal consistency, we designed the validation task so that it was delayed three weeks. It was positioned to respondents as a follow-up market research study. To assure that respondents took the task seriously and answered as they would for marketplace choices, we used incentive alignment for the validation task.

We recognize that our validation task is a proof of concept. We encourage researchers to explore other validation tasks and, perhaps, to compare various validation tasks to marketplace choice, if the latter can be measured feasibly. With experience, we hope that researchers improve validation tasks so that the validation tasks provide the best possible adjustment to γ^{true}. At minimum, our proof of concept suggests that such validation-task development will have substantial managerial impact.

Post-test of the validation task. As a proof of concept, we wanted the validation task to be perceived as more representative of the marketplace than the choice tasks. Furthermore, we hypothesized that the realistic-image-incentive-aligned choice tasks would be more representative of the marketplace than the text-only-no-incentive-aligned choice tasks. Thus, we hoped that the percentage of respondents who perceived the validation task as more representative would be higher for the realistic-image-incentive-aligned choice tasks than for the text-only-no-incentive-aligned choice tasks.

We piggy-backed on an unrelated Peanut Lab study that allowed us to ask respondents to complete two choice tasks according to the experimental condition and the validation task. Four hundred and five (405) respondents completed the post-test—186 in the realistic-image-incentive-aligned experimental cell and 219 in the text-only-no-incentive-aligned experimental cell. The results were as expected. For both experimental cells, more respondents than not perceived the validation task to be more similar to online shopping than the choice task and the differences were substantially higher for the experimental cell that we believed to be less similar to online shopping—the text-only-no-incentive-aligned experimental cell. In particular, 72% of the respondents perceived the validation task as more similar to online shopping than the text-only-no-incentive-aligned choice tasks and 69% perceived the selection of options to be more realistic. The realistic-image-incentive-aligned choice tasks were much more like real online shopping—53% of the respondents perceived the validation task as more similar to online shopping than the realistic-image-incentive-aligned choice tasks and 56% of the respondents perceived the selection of options to be more realistic in the validation task than the realistic-image-incentive-aligned task. We believe the post-test supports the validation task as a reasonable proof of concept, but allows for further improvement as motivated by the theory developed in the text.

Online Appendix 13
Relationship of the Minimum vs. Maximum Differentiation Literature to the Stylized Model

The study of minimum versus maximum differentiation has a rich history in both economics and marketing. Hotelling (1929) proposed a model of minimum differentiation in which consumers are uniformly distributed along a line and two firms compete by first choosing a position (attribute level) and then a price. After demonstrating that the price equilibrium did not exist in Hotelling's model, d'Aspremont, Gabszewicz, and Thisse (1979) proposed quadratic transport costs and obtained an equilibrium of maximum differentiation—firms choose strategic positions at opposite ends of the line. We extend and modify their model to model heterogeneity explicitly in order to study the practical implications of market research quality.

Many other researchers explore Hotelling-like models to derive conditions when differentiation is likely and when it is not (e.g., Eaton and Lipsey 1975; Eaton and Wooders 1985; Economides 1984; Graitson 1982; Johnson and Myatt 2006; Novshek 1980; Sajeesh and Raju 2010; Shaked and Sutton 1982; Shilony 1981). In these formal models, differentiation is driven by the heterogeneity of consumer preferences—something we hold constant.

In marketing, Thomadsen (2007) shows how asymmetries in attribute levels lead one firm to favor maximum differentiation in physical location while another favors minimum differentiation. Gal-or and Dukes (2003) show that a two-sided market (commercial media serving consumers and advertisers) reverses the differentiation found in d'Aspremont, Gabszewicz, and Thisse (1979). Guo (2006) extends an attribute-based analysis to forward looking consumers who observe one of two product attributes. In Guo's model, consumers anticipate probabilistically future valuations for the other product attribute. In these models, heterogeneity in preferences (partworths) drives strategic behavior with respect to prices and profits.

In the language of CBC, all of these papers focus on the distribution of relative partworths or on the partworths of unobserved or uncertain attributes. Although many models include error terms, none analyze the effect of imperfect market research or inherent stochasticity. The stylized model in the text shows that these phenomena alone can drive firms' decisions on differentiation.

Additional References for Online Appendix 13

d'Aspremont C, Gabszewicz JJ, Thisse JF (1979) On Hotelling's stability in competition. *Econometrica* 47(5), (September):1145-1150.

Eaton B, Lipsey RG (1975) The principle of minimum differentiation reconsidered: Some new developments in the theory of spatial competition. *Review of Economic Studies* 42(129):27-50.

Eaton B, Wooders MH (1985) Sophisticated entry in a model of spatial competition. *Rand Journal of Economics* 16(2)(Summer):282-297.

Economides N (1984) The principle of minimum differentiation revisited. *European Econ Review* 24:1-24.

Graitson D (1982) Spatial competition a la Hotelling: A selective survey. *The Journal of Industrial Economics* 31(1-2)(September-December):13-25.

Guo L (2006) Consumption flexibility, product configuration, and market competition. *Marketing Science* 25(2):116-130.

Hotelling H (1929) Stability in competition. *The Economic Journal* 39:41-57.

Johnson JP, Myatt DP (2006) On the simple economics of advertising, marketing, and product design. *American Economic Review* 96(3):756-784.

Novshek W (1980) Equilibrium in simple spatial (or differentiated product) models. *Journal of Economic Theory* 22:313-326.

Sajeesh S, Raju JS (2010) Positioning and pricing in a variety seeking market. *Management Science* 56(6):949-61.

Shaked A, Sutton J (1982) Relaxing price competition through product differentiation. *Review of*

Economic Studies 49:3-13.

Shilony Y (1981) Hotelling's competition with general customer distribution. *Economic Letters* 8:39-45.

Thomadsen R (2007). Product positioning and competition: The role of location in the fast food industry. *Marketing Science* 26(6):792-804.

Online Appendix 14
Comments on a Simultaneous Positioning Game

The stylized model in the text analyzes a two-stage game in which the innovator chooses its strategic position (r or s) first anticipating the follower's optimal strategic position (r or s for a market of rs or rr) if the innovator chooses r and a market of sr or ss if the innovator chooses s. After both the innovator and the follower choose their strategic positions, both launch their products to the marketplace. The marketplace then determines the equilibria prices and, by implication, the equilibrium profits.

We selected the innovator-follower game for multiple reasons. First, this game is typically used in the strategic positioning literature reviewed in Online Appendix 13. Second, the game is more realistic than a simultaneous game. It is rare that two firms innovate simultaneously. More often, one firm has a lead due to either technological or marketing know-how. Third, because r is the favored position relative to s, all else equal, there is only one positioning equilibrium in the sequential game. The innovator gets to choose r.

However, for completeness, it is worth considering a simultaneous game. If γ^{true} is small, then the first-stage positioning equilibrium will be rr, just as in the sequential game. However, if γ^{true} is large, there is an indeterminacy in the sense that both firms prefer r if the other firm were to choose s. Post hoc both rs and sr are Nash equilibria in the sense that, once these positions are chosen, there are no unilateral incentives to change position. We broke this indeterminacy by formulating entry as a sequential game. All other results apply. For example, the equilibrium prices and profits are a function of

rs, rr, sr, or ss and are computed in the same manner for both the sequential and the simultaneous game. Furthermore, if the firms enter simultaneously (and we have some mechanism to resolve the indeterminacy), then both firms can make strategic positioning mistakes if they shirk on CBC craft and misestimate γ^{true}. The results are driven by the relationships of $\gamma^{market\ research}$, γ^{cutoff}, and γ^{true}, just as in the sequential game.

Online Appendix 15
Additional Citations: Six Marketing Science Papers that Discuss Scale Explicitly

Fiebig DG, Keane MP, Louviere J, Wasi N (2010) The generalized multinomial logit model: Accounting for scale and coefficient heterogeneity. *Marketing Science* 29(3):393-421.

Gilbride TJ, Lenk PJ, Brazell JD (2008) Market share constraints and the loss function in choice-based conjoint analysis. *Marketing Science* 27(6):995-1011.

Narayan V, Rao VR, Saunders C (2011) How peer influence affects attribute preferences: A Bayesian Updating Mechanism, *Marketing Science* 30(2):368-384.

Ofek E, Srinivasan V (2002) How much does the market value an improvement in a product attribute? *Marketing Science* 21(4):398-411.

Salisbury LC, Feinberg FM (2010) Alleviating the constant stochastic variance assumption in decision research: Theory, measurement, and experimental test. *Marketing Science* 29(1):1-17.

Swait J, Erdem T (2007) Brand effect on choice and choice set formation under uncertainty. *Marketing Science* 26(5): 679-697.