The Strategic Importance of Accuracy in the Relative Quality of Conjoint Design

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Abstract

Even when there are no biases in relative partworths, accuracy in conjoint analysis has strategic implications. If firms use lower-quality market research and thus over-estimate uncertainty in prediction they might forego strategic differentiation of product positions and earn less profit in equilibrium. Conversely, if firms evaluate market research predictive ability with calibration data only, rather than external validation tests, they might under-estimate uncertainty and choose differentiated positions that are not as profitable in equilibrium. Over- or under-estimating heterogeneity leads to similar strategic errors. We explore these effects theoretically and empirically. We demonstrate sufficient conditions (uncertainty and heterogeneity) for a unique interior pure-strategy Bertrand-Nash equilibria and we show when uncertainty leads to firms to forego differentiation. We illustrate the phenomena empirically in a market for student apparel. High-design-quality and low-design-quality conjoint studies lead to different uncertainties, different heterogeneity estimates, and different strategic positions. Firms that rely on low-design-quality studies or ignore external-validity uncertainty make strategic errors and choose strategies that leave money on the table.

Keywords: *Conjoint analysis, differentiation, game theory, marketing strategy, product design, strategic positioning, external validation.*

1. Accuracy Has Strategic Implications

Conjoint analysis and other market-research methods help firms design products that meet consumer needs. Intuitively, if a firm is particularly savvy with its market research it will identify new opportunities better than competitors and profit from its competitive advantage. "Savvy" usually means that the firm's estimates of the partworths of feature-levels are unbiased and if there is heterogeneity among consumers the firm can identify and act on that heterogeneity. On the other hand, if all firms in the market are equally savvy, no one has a competitive advantage and common wisdom predicts that any advantage to improvements in market research will be competed away (e.g., Wernerfelt 1984).

In this paper we show that accuracy in conjoint analysis, and the firm's understanding of relative accuracy, have strategic implications as well as the known tactical advantages for firms. Even if all competing firms in the market achieve the same accuracy, the level of accuracy determines their strategic product design decisions. In particular, if true predictive uncertainty is high, firms will eschew differentiation to select the same or similar product designs and, as a result, suffer excessive price competition. If firms use inaccurate methods and believe they reflect true predictive uncertainty, then they might eschew differentiation when the most profitable strategy would have been to differentiate. Alternatively, if they are over confident, e.g., by relying on predictive uncertainty in calibration rather than higher predictive uncertainty from validation data, they might differentiate when the most profitable strategy would have been not to differentiate. Of course, low accuracy can also affect tactical decisions if market research leads to biased partworths or if it under- or over-estimates heterogeneity.

Based on these insights, research to enhance and understand accuracy is important to the structure of competition and to firms' willingness to differentiate. In addition to the greater reliance on validation tests and explicit modeling of validation uncertainty (e.g., Salisbury and Feinberg 2010), improvements in measurement such as incentive compatibility and web-based formats, improvements in estimation such as hierarchical Bayes and machine learning methods, improvements in specification including non-compensatory methods, and adaptive questioning all affect accuracy and hence strategic positioning. (For some of the many examples, see Dahan and Hauser 2002, Ding, Grewal and Liechty 2005; Evgeniou, Pontil and Toubia 2007; Gilbride and Allenby 2004, Kohli and Jedidi 2007; Netzer and Srinivasan 2011; Sawtooth 2008; Toubia, Hauser and Simester 2004; Yee, et al. 2007).

We demonstrate strategic implications both theoretically and empirically. On the theory side we describe a formal game in which firms use conjoint analysis with heterogeneous preferences to select product positions anticipating price equilibria. We show that the price equilibria (given a set of positions) exist and are unique under reasonable conditions. We then argue that accuracy, as related to unobserved variance, affects product positioning decisions. Accuracy that is too low relative to true predictive ability may cause firms to avoid differentiation even if the market is heterogeneous. On the other hand, if firms are over-confident they may make the opposite mistake.

On the empirical side we collect data in which we vary the relatively accuracy of the conjoint analysis design. We show that varying levels of accuracy in that design and/or over-confidence can affect strategic decisions. The empirical examples also illustrate strategic errors when a low-design-quality market-research study over-estimates heterogeneity. In these examples, both low- and high-design-quality studies estimate the same relative (mean) partworths.

2. Prior Research

The analysis of minimum versus maximum differentiation has a rich history in both economics and marketing. Hotelling (1929) proposed a model in which consumers are arrayed along a line and two firms compete by first choosing a position and then a price. Hotelling argued that his model led to minimum differentiation, but d'Aspremont, Gabszewicz and Thisse (1979) demonstrated that Hotelling's price equilibrium did not exist when consumers choose products with no uncertainty. In response, de Palma, et al. (1985) demonstrated that, if there is sufficient uncertainty in consumer choice, the price equilibrium exists and firms choose not to differentiate. Other researchers studied cases in which firms choose to differentiate. For example, using a Lancasterian model, Hauser (1988) shows that the position-then-price-equilibrium game leads to maximum differentiation even if there are more than two firms in the market. Other researchers explored 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, 1986; Graitson 1982; Johnson and Myatt 2006; Novchek 1980; Shaked and Sulton 1982; Shilony 1981). The basic insight from these formal models is that the more heterogeneous consumers preferences, the more likely firms choose to differentiate.

Modern conjoint models enable data-based positioning decisions. With conjoint analysis, product design (positioning) is based directly on measured consumer preferences. Hierarchical

Bayes, latent structure, and machine-learning methods all enable researchers to estimate heterogeneous distributions of preferences (e.g., Andrews, Ansari and Currim 2002; Lenk, et al. 1996; and Evegeniou, Pontil and Toubia 2007).

When conjoint-analysis models allow uncertainty in estimation, but assume homogeneous partworths, Choi, DeSarbo and Harker (1990) demonstrate that the price equilibrium exists as long as consumers are not overly price-sensitive. Their condition (p. 179), like that of de Palma, et al., suggests that the price equilibrium is more likely to exist if there is greater uncertainty in consumer preferences. Choi, DeSarbo and Harker solve the price equilibrium with tantamount iteration and Choi and DeSarbo (1994) solve the positioning problem with exhaustive enumeration. Luo, Kannan and Ratchford (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 they exist.

Caplin and Nalebuff (1991) consider general models of consumer preference in which preferences are linear-in-parameters (as in conjoint analysis and most logit models) and those parameters vary across the population according to a density function that is ρ-concave with $\rho = -(n+1)^{-1}$. (Commonly used density functions, including the normal, uniform, Weibull, and Wishart distributions, are ρ-concave. However, a mixture of normal distributions need not be ρ-concave if the market is sufficiently segmented.) Under these conditions, and reasonable restrictions on price sensitivity, they prove that, for any number of firms and arbitrary product positions, a pure-strategy Bertrand-Nash equilibrium in prices exists. Caplin and Nalebuff establish uniqueness for special cases such as the aggregate logit model of de Palma, et al.

In the following sections we built upon these results. We show that, for price sub-games when preferences are given by heterogeneous partworth models, interior pure-strategy Bertrand-Nash equilibria exist under reasonable restrictions on heterogeneity and uncertainty. We show further that high uncertainty leads firms to choose a strategy of no differentiation.

3. Product Design Game and Notation

We focus on the position-then-price game with *M* consumers and *N* firms. For simplicity of exposition we assume each firm sells one type of product. We do not believe that the central message of the paper would change in sequential games such as those of Lane (1980), Moorthy (1988), or Prescott and Visscher (1977). The game proceeds in three stages:

1. Firms simultaneously choose product designs as defined by a set of levels of features.

2. Firms simultaneously choose prices to maximize profit.
3. Consumers purchase products and payoffs are realized.

Let i index the M consumers and let j and k index the N firms. Without loss of generality we recode all features such that firm j's product design can be represented by a binary vector, X_j, indicating which levels of the features describe product j. Let β_i be a vector of partworths for consumer i and let λ_i be consumer i's price sensitivity in the units of partworth increase for a one-dollar decrease in price. Y is the consumer's income. C_j is firm j's marginal cost of production, which may depend upon the chosen partworths, and P_j is its chosen price. Finally, μ is a parameter, described below, that represents the magnitude in uncertainty in product utility (e.g., Swait and Louviere 1993), and ϵ_{ij} is a noise term drawn from an independent and identically distributed Gumbel distribution. With this notation, we write the net utility, U_{ij}, to consumer i from purchasing product j as:

(1) $$U_{ij} = \beta_i' X_j - \lambda_i P_j + \mu\epsilon_{ij}$$

Because our focus is on the relative positions chosen by the firms rather than market entry or exit, we assume no outside good so that consumers purchase exactly one product from the set. An outside good complicates the exposition, but does not change the basic results. When appropriate in the text, we choose to highlight when the characteristics of an outside good is related to conditions in our propositions. (We need to have some mechanism to prevent infinite prices and mixed strategy equilibria of the type characterized by Varian 1980. This can be done with either an upper bound on income or an outside good.)

Equation 1 implies the standard logit model of consumer choice where the probability, D_{ij}, that the i^{th} consumer chooses the j^{th} product is given by Equation 1. (Our formal results use the logit model because it lends itself to analytical manipulation. However, the basic concepts should apply for other distributions of the error term such as the normal distribution. E.g., see Domencich and McFadden 1975, p. 58.)

(2) $$D_{ij} = \frac{e^{\mu^{-1}(\beta_i' X_j - \lambda_i P_j)}}{\sum_{k=1}^{N} e^{\mu^{-1}(\beta_i' X_k - \lambda_i P_k)}}$$

Assuming fixed costs are sunk, the expected profits for firm j are given by:

(3)
$$\pi_j = (P_j - C_j) \sum_{i=1}^{M} D_{ij}$$

Recall that costs and demand are a function of the product's features. We further assume that marginal costs vary constantly with scale over the demand ranges that are likely to occur based on the positioning-then-price decisions.

4. Existence and Uniqueness

We first establish that equilibria exist and have unique interior equilibrium prices in the price sub-games. Prior research establishes that the equilibrium exists as long as the distribution of partworths combined with the inherent uncertainty (μ) does not lead to a price response that is highly multimodal. Caplin and Nalebuff (1991) state these results with respect to ρ-concavity of the preference function, while Anderson, et al. (1992, 365-366), de Palma, et al. (1985), and Choi, et al. (1990) state these results with respect to sufficient uncertainty in price response for consumers who prefer a given product position. These results apply to our sub-games. Every price sub-game has a pure-strategy equilibrium whenever μ is sufficiently large.

For readers unfamiliar with the earlier results we provide the intuition with a simple example. Suppose there are two types of consumers: a high segment prefers firm j's position and a low segment prefers another firm's position. When heterogeneity is high, the high segment's preferences are very different from the low segment's preferences. If heterogeneity is high and uncertainty in demand is low (low μ) we should not be surprised that a profit as a function of price (holding competitors constant) is bimodal rather than quasi-concave. See Figure 1a. Depending upon competitive positions the firm may either seek to price for both segments or just exploit the more favorable segment as in Figure 1a. In these cases a pure-strategy equilibrium may not exist. On the other hand, if uncertainty increases as in Figure 1b or if preferences are more homogeneous as in Figure 1c, the profit function becomes quasi-concave and the pure-strategy equilibrium exists (e.g., Fudenberg and Tirole 1991, 34). As uncertainty decreases and the consumers become more homogeneous, the profit function becomes concave. (Detailed values of the parameters for these illustrations are available from the authors.)

[Insert Figure 1 about here.]

We formalize the intuition of Figure 1 with the Proposition 1 which builds upon earlier results to establish conditions for a unique interior equilibrium under less restrictive conditions that previous research. (For example, Caplin and Nalebuff require dominant diagonal conditions. We derive conditions that ensure that the Jacobian of the mapping from prices to profit first derivatives is negative quasi-definite.) Proposition 1 is important because our differentiation results assume that the price sub-games have unique interior price equilibria.

Condition 1 states a sufficient criterion for uniqueness. Condition 1 assures that heterogeneity (the variance of the λ_i) is sufficiently low relative to the scale of the λ_i. Condition 1 is a relative condition because the scale of the λ_i is related implicitly to uncertainty (μ) through the logit model in Equation 2. (Utility is unique only to an positive linear transformation; most revealed-preference estimation methods identify λ_i/μ's rather than the λ_i's and μ separately.)

Condition 1
$$\sqrt{\frac{N-2}{N-1}}Stdev[\lambda] < E[\lambda]$$

Proposition 1. *If preferences are not too heterogeneous (Condition 1 holds) and for sufficient uncertainty (μ sufficiently large), then there is a range of prices, [L, Y], such that every pricing sub-game has a unique interior equilibrium within this range.*

The proof of Proposition 1 relies on Condition 1 to establish that the best response mapping is a contraction mapping (Friedman 1990). Sufficiently-large uncertainty enables us to use asymptotic properties to simplify the various derivatives. (Detailed proofs of all propositions are available in a supplemental online appendix.)

Proposition 1 depends upon the technical assumption that prices are restricted to a finite range of values. These bounds are justified formally using upper bounds on consumers' incomes. However, the existence of an outside good could also justify these bounds. We need these bounds to rule out non-local deviations from the equilibria. For example, if one consumer has a price-difference partworth close to zero (or negative), the upper bound on prices prevents the firms from setting extremely high prices to serve just this consumer. In our experience, empirical HB estimates occasionally yield zero or negative price-difference partworths due to random error, however, also in our experience, it is a simple matter to correct for these random empirical variations.

Proposition 1 is limited to cases where the market is not too segmented. If the market is highly segmented relative to any uncertainty in the estimates, then firms might differentiate by each serving a different preference segment. This is a well-known result (e.g., Hauser and Shugan 1983, among others). Our focus is on demonstrating the strategic effect of accuracy under the more common case that preferences are distributed in some reasonable manner over the population of consumers.

5. Insight on the Price and Position Equilibria

We now seek to characterize the price equilibria. In the most general case they depend upon the positions chosen in the first stage of the game. However, we gain insight be temporarily abstracting from general positions and studying a case where preferences are "symmetric." This definition is distinct from an assumption of homogeneity. Preferences can be symmetric when preferences are homogeneous (consumers are indifferent among all firms' products), when preferences are uniformly distributed (positions are spread out equally), or when preferences are heterogeneous (each firm serves a segment, but preferences are not so sharp to violate Condition 1).

> ***Definition 1***. *Preferences are "symmetric across firms" if, when all firms set the same price: (1) demand for all firms is equal and (2) the probability of a consumer buying from any particular firm is uncorrelated with the consumer's price partworth.*

> ***Proposition 2***. *When preferences are symmetric across firms and when all firms have the same marginal costs, then all firms set the same equilibrium prices. The equilibrium price for firm j is increasing in the variance over consumers of the probability of purchasing from firm j. (P_j is increasing in $var_i[D_{ij}]$.)*

There are two implications of Proposition 2 that matter. Firstly, if firms choose not to differentiate in the first stage of the game, then $var_i[D_{ij}]$ will be small. Prices and resulting profits will be lower as expected.

Secondly, intuitively, and consistently with prior research, sub-game prices will be higher when firms can position in the first stage of the game such that they each serve best a subset of the consumers—a local monopoly in product-position-space. The variance of D_{ij} will be high when firm j achieves its demand by serving some consumers extremely well and others poorly. Proposition 2 establishes a force toward maximum differentiation. However, it does not establish maximum differentiation. Other forces might counter this tendency. Both conditions of Proposition 2, symmetry and equal marginal costs, are endogenous. For example, either the preference distribution of the cost of features might be such that each firm chooses positions that are not symmetric or that differ in marginal costs.[1]

Our final proposition establishes that that sufficiently high uncertainly leads to minimum differentiation in the first stage of the game. In Condition 2, the covariance notation is interpreted such that each element of the partworth vector, β_i, is uncorrelated with the marginal utility of income. Condition 2 is sufficient, but not necessary. $\bar{\beta}$ is the mean partworth vector.

Condition 2 $$Cov_i[\lambda_i, \beta_i] = \vec{0}$$

Proposition 3. *When Conditions 1 and 2 hold, and when uncertainty (μ) is sufficiently large, each firm maximizes the same equation, $F(X_j) = \gamma_1 \bar{\beta} X_j - \gamma_2 C(X_j)$, where γ_1 and γ_2 are constant across firms, independent of X_j, but a function of the moments of λ.*

Technically, Proposition 3 allows differentiation if there is more than one maxima for $F(X_j)$, however, for realistic problems this is unlikely to occur. Proposition 3 implies that sufficiently large uncertainty causes all firms to choose the same position and, coupled with Proposition 2, the same price. Low uncertainty may or may not lead to differentiation, depending upon the measured heterogeneity in the market. Our theoretical results establish that uncertainty (and heterogeneity) affect strategic positioning decisions; actual decisions depend upon empirical parameters.

6. Summary of Formal Propositions and Interpretations

In real markets positioning decisions depend upon many variables. For example, if one firm has a patent on popular feature or a particular cost advantage for that feature, the firm will offer products with that feature. If the market is highly segmented, then it may be profitable for firms to offer products each of which serve a unique segment. These phenomena are well-known and we abstract away from them to study situations where varying degrees of accuracy affect strategic decisions. We allow (and model) heterogeneity of preferences as long as it is not so

[1] In most research, first stage decisions in position-the-price games are unique only to label-switching (identifying which firm gets which position). Researchers rely on an external mechanism to break ties. For example, Hauser (1988) assumes that firms cannot "leapfrog" so that order on a given feature is fixed. In practice label-switching ties are broken natural features of the market such as the order of entry or by the fact that some firms have strategic resources that make some positions more favorable to them than other firms.

multimodal that the multimodality swamps the phenomena we are studying.

Accuracy in market research is related to uncertainty in the random utility specification of consumer demand. From a practical perspective, a firm making a position-then-price decision undertakes a market research study to estimate partworths, β_i and λ, but these partworths are confounded with the magnitude of the error term, μ. Instead, the market research returns $\mathrm{B}_i = \beta_i/\mu$ and $\Lambda_\mathrm{i} = \lambda_i/\mu$. The B_i's and Λ_i's clearly have tactical implications. For example, the relative values of the B_i's help determine which features to emphasize, heterogeneity in the B_i's and Λ_i's suggest how the market might be segmented, and the relative values of the B_i's relative to the Λ_i determine prices. The new implication is that uncertainty (μ) matters strategically. Uncertainty must be sufficiently large that the equilibrium exists, but if it gets too large then all firms will chase the same product position (Proposition 3) and this will lead to low prices (Proposition 2).

The converse is possible, but not guaranteed. As uncertainty decreases, either differentiation and no-differentiation can be the positioning equilibrium. The strategy depends upon heterogeneity relative to uncertainty. (We establish this final result with an example in §8.)

To this point we have been ambiguous about the source of uncertainty. This reflects reality. When a firm estimates the B_i's and Λ_i's it knows whether the estimates are high in magnitude ("accurate") or low in magnitude ("inaccurate"), but it does not know why. The uncertainty might come from inherent stochasticity in consumer preferences (e.g., Bass 1974) or from unobserved influences outside the control of the firm. For example, the purchase of a particular washer/dryer may depend upon the space available in a consumer's new apartment. Such uncertainty cannot be resolved through market research, although clearly this uncertainty affects strategic decisions.

However, some uncertainty comes directly from market research. A well-executed study with state-of-the-art estimation, realistic stimuli, and realistic purchase scenarios is likely to yield higher B_i's and Λ_i's than a less-well-executed study. Proposition 3 says that if the firm uses a less-well-executed study and treats the partworths from that study as if they reflect inherent uncertainty in consumer demand, then the firm may falsely choose not to differentiate its products. When competitors respond the equilibrium prices will be lower and the firm will earn lower profit. Alternatively, in some markets the opposite might occur. If the inherent uncertainty is high and the firm under-estimates this uncertainty (perhaps because it does not test the external validity of its models) the firm might choose to differentiate when no differentiation might have been the most profitable strategy. Which cases occur depend upon the actual preferences in the market. The theoretical results show simply that misunderstanding true uncertainty can cause errors in strategic decisions.

We have identified three strategic and tactical implications of low-quality market research. The first two are well known: (1) if the firm estimates the wrong relative $\overline{\mathrm{B}}$ and $\overline{\Lambda}$ it may simply choose to produce a product that does not satisfy customer needs and (2) if the firm estimates the wrong heterogeneity in the B_i's and Λ_{i}'s it may segment the market incorrectly. The third implication is new, but potentially important. If the firm estimates B_i's and Λ_{i}'s and either over- or under-estimates true uncertainty (μ), the firm may choose not to differentiation when differentiation could have been more profitable, or vice versa. We now illustrate that this third implication with a conjoint-analysis study applied to a market for student apparel.

7. Conjoint Study on Student Apparel

To illustrate the strategic implications of accuracy we choose a relatively simple market: student apparel. In this market a second firm was selecting a set of features for apparel to be sold to students at a large university. After interviews with both consumers and producers in this market we selected a relatively small set of relevant features for this market. We then undertook conjoint-analysis studies while varying two characteristics of the study that are known to affect accuracy. The experimental conditions were designed to induce variation is perceived μ. Using the partworths from the studies, we focus on a key binary feature while holding all other features constant. This feature is a surrogate for the product's position. These data demonstrate that varying μ as estimated in the empirical studies affects strategic decisions. These examples provide a proof-of-concept for the theory. If market-research accuracy affects strategic decisions in this simple market, it can also affect strategic decisions when more features, more firms, or more-complex products are involved.

7.1. Market and Respondents

The incumbent firm is a student-run firm that provides casual apparel to their classmates. The apparel is either a hooded sweatshirt, a fleece vest, or a track jacket (three-level feature). It is available with and without a school logo (binary feature) and in one of the two school colors (red or grey). To estimate Λ_i we vary price from its base level ($30 for a sweatshirt; $40 for a fleece vest or track jacket) to its base level plus $10. Thus, we have a 3 x 2 x 2 x 2 conjoint design. Using Sawtooth Software's SSI Web CBC Module we chose a standard design with 16 choice-based questions of five profiles each. We did not include a no-choice option because we sought only to illustrate the relative effects of μ (and heterogeneity).

The respondents are students as is appropriate for this market. They were recruited via e-mail and promised that 1-in-10 respondents would receive an article of apparel. The overall response rate was 50% (53 of 107) and the overall completion rate was 72% (38 of 53). (We examine below whether the response and completion rates varied by experimental condition.) Each respondent completed two preference tasks. The first task was the calibration conjoint task in which we varied the two characteristics known to affect accuracy in conjoint analysis. The second task, which followed a memory-cleansing task, was a validation task.

7.2. Experimental Design

The 2 x 2 experimental design for the calibration task varied incentive compatibility and design quality. In the incentive-compatible calibration condition, the respondents were told that the 1-in-10 respondents would receive the article of apparel that that was based on their answers to the survey (similar to the mechanism used in Ding 2007). In the not-incentive-compatible calibration condition, the article of apparel received by the 1-in-10 respondents was not linked to their survey responses.

In the high-design-quality calibration condition the conjoint questions used careful instructions, training questions, and profiles that included text and pictures. On most respondent machines, the entire question was displayed without scrolling. In the low-design-quality calibration condition the conjoint questions used brief instructions, no training questions, and profiles described by text only. Most respondent machines required scrolling to see all profiles. Figure 2 illustrates the two experimental conditions.

[Insert Figure 2 about here.]

The validation design task was the same for all conditions. Respondents were given twelve new profiles and asked to rank the top five preferred profiles. The task was both incentive compatible and used high design quality. Specifically, in the incentive-compatible condition respondents were told that there was a 50-50 chance that either the calibration task or the validation task would determine the article of apparel received by the 1-in-10 respondents. In the not-incentive-compatible condition only the validation task determined the article of apparel. (The entire survey was in the field sufficiently briefly that respondents were unlikely to speak to one another and anticipate the validation condition. We found no evidence of any inter-respondent discussion.)

7.3. Manipulation Checks

Table 1 reports manipulation checks. As expected and consistent with the manipulations, respondents in the high-design-quality conditions report higher clarity, accuracy, and realism and lower tediousness and randomness than respondents in the low-design-quality conditions. The differences between the incentive compatibility experimental conditions are mixed and not significant <are they>. Because incentive-compatibility did not have the anticipated effect on accuracy, perhaps because of the small sample sizes or perhaps because its impact was overwhelmed by design quality, we pool respondents across the incentive-compatibility conditions leaving us with a two-way manipulation of accuracy. This two-way manipulation is sufficient to illustrate the strategic effects. When pooled, respondents in the high-design-quality condition saw the survey as clearer and easier (6.4 vs. 5.2, p = 0.xx), eliciting more effort to be accurate (6.7 vs. 6.1, p = 0.xx), less tedious (2.5 vs. 4.6, p = 0.xx), less likely to elicit random responses (1.1 vs. 1.7, p = 0.xx), and more like a real purchase decision (5.7 vs. 5.1, $p = 0.11$). All but the last are significantly better in the high-design-quality condition. Completion rates were also higher in the high-design-quality condition, although not significantly so (79% vs. 66%, $p = 0.28$). Overall, it appears that we were successful in manipulating high vs. low accuracy in conjoint-analysis studies.

7.4. Partworth Summary for High and Low Accuracy Conjoint Analysis Studies

Table 2 reports the population means and standard deviations for the partworths in both the high- and low-design-quality studies. First we see that the accuracy manipulation was successful in affecting calibration uncertainty (a component of μ). The high-design-quality partworths are, on average, about 77% greater indicating lower calibration uncertainty. However, both the high- and low-design-quality partworths give roughly the same relative importances – they are highly correlated across features ($r = 0.98$, $p < 0.01$).

The absolute standard deviations of the partworths are roughly equivalent, but heterogeneity is relative to the mean magnitudes. With this measure, the low-design-quality heterogeneity is about 56% larger. For example, there is more agreement among respondents about their preferred color in the high-design-quality condition than in the low-design-quality condition 84% prefer grey in the high-design-quality condition; 58% prefer grey in the low-design-quality condition). Consumers' qualitative comments support an hypothesis that heterogeneity is over-estimated in the low-design-quality condition. For example, after the validation task a respondent in the low-design-quality condition said: "Wish I had seen the pictures before the survey. The grey ones don't look that bad!"

Of the three potential effects of inaccuracy, two occur in our data. Relative to the high-design-quality condition, the low-design-quality condition estimates more calibration uncertainty (related to μ) and greater heterogeneity. Biases in mean partworth values do not seem to occur between conditions: on average both conditions give roughly the same relative partworths and the willingness-to-pay estimates based on Table 2 are roughly the same for the grey color (about \$5.55 in the high-design-quality condition and about \$5.00 in the low-design quality condition).[2]

7.5 External-Validity Uncertainty

Calibration uncertainty is related to μ, but μ is more than calibration uncertainty. As Salisbury and Feinberg (2010) and Sawtooth (2003) suggest, the partworths should also be scaled to account for external uncertainty—the ability of the partworths to predict choices in a real market. To estimate the adjustment to uncertainty, we hold the relative B_i and Λ_i fixed and estimate an adjustment factor based on the validation task such that $\mathrm{B}_i^{adj} = \mathrm{B}_i/\mu^{adj}$ and $\Lambda_i^{adj} = \Lambda_i/\mu^{adj}$. Based on our data, we estimate the adjustment factor (μ^{adj}) to be 1.55 for the high-design-quality condition and 2.08 for the low-design-quality condition. (These estimates are significantly different at the 0.05 level.) These adjustments are consistent with the ability of the conjoint estimates to predict the validation-profile preferences. Validation accuracy is less in the low-design-quality condition (U^2 = 23.6%) than in the high-design-quality condition (U^2 = 45.2%). Consumers' qualitative comments reinforce the quantitative estimates of the μ^{adj}. For example, one respondent in the low-design-quality condition said: "the products that I thought sounded good actually looked really bad in the pictures to me, so the results changed."

Although the validation task was still not the real market it was close to the way these goods were sold. Furthermore, because the validation task was the same for all conditions, the relative uncertainty should not be effected dramatically. For the remainder of the paper we use the high-design-quality-condition partworths as if they were the "true" B_i's and Λ_i's. This is suf-

[2] Consistent with the higher heterogeneity in the low-design-quality condition, the willingness-to-pay (WTP) for grey varies more among consumers in the low condition. If we limit ourselves to those consumers who prefer grey and have correctly signed partworths for price, the medians of the WTPs across consumers in the high- and low-design-quality conditions are, respectively, \$6.34 and \$8.79.

ficient for our illustration.

8. Illustration of the Strategic Impact of Market-Research Accuracy (Apparel Study)

We now use the apparel-market conjoint studies to illustrate the strategic impact of market-research accuracy. To keep the illustration simple, we assume two competing firms, each of which is offering one track jacket with a logo so that they only free decisions are color and price. In this example, "color" serves to illustrate the firms' positioning decisions. "Color" does not affect marginal costs so we choose $40 as the fixed marginal cost. Minimum differentiation occurs if, in equilibrium, both firms choose the same color in the position-then-price game. Maximum differentiation occurs if they choose different colors.

We begin with the "true" market which, in our illustration, is the market predicted by the high-design-quality condition with adjustments in μ to reflect external validity. Once "color" decisions are made, the equilibrium prices result from firms adjusting based on the demand realized in this true market. Recall that we have no outside good, so the total demand is set arbitrarily to 10 million units so that profit is in millions of dollars. The addition of an outside good would make the comparisons even more dramatic. In the empirical conjoint study, the grey color is preferred on average and, not surprisingly, all equilibria include at least one firm offering a grey track jacket. We find no equilibrium in which both firms choose the red color. To make exposition simple and to avoid indeterminacy due to label switching, we allow Firm B to choose the grey color and we focus on the color decision for Firm A.

8.1 Strategic Mistakes Due to Ignoring the Need to Test Predictive Validity

Table 3 reports the true equilibrium prices and profits. Firm A can do better with a grey jacket and so chooses, earning an additional $1.8 M in equilibrium profits. (This is also an equilibrium for Firm B. The Bertrand-Nash equilibrium allows no collusion.)

[Insert Table 3 about here.]

Now assume that Firm A relied entirely on the calibration estimates and did not adjust uncertainty to reflect predictive validity. Table 4 calculates what Firm A would expect if it were to use the calibration partworths blindly. Its strategic positioning decision changes. Differentiation appears to be the best strategy and Firm A chooses the red color. Firm A is pleasantly surprised with higher profit when it launches its product ($55.2 M rather than $40.2 M), but it left money on the table by not choosing the correct strategy. Coincidently, Firm B benefits substantially from Firm A's strategic mistakes.

[Insert Table 4 about here.]

8.2. Strategic Mistakes Due to Relying on Inaccurate Market Research

The equilibrium in the apparel market is minimum differentiation (both firms offer grey track jackets). However, suppose that the "true" market was based on the calibration partworths and the firm incorrectly relied on less accurate market research with higher uncertainty (higher μ). To illustrate this scenario we reverse the examples in Tables 3 and 4. In the reversed example, the realized price, demand, and profits are given by Table 4 and the decisions based on the less-accurate market research are given by Table 3. Based on inaccurate market research the firm would choose not to differentiate expecting \$57 M in profits. It would be surprised to realize only \$36.8 M in profits and would leave \$3.4 M on the table by foregoing differentiation (\$40.2 M vs. \$36.8 M).

8.3. Strategic Mistakes Due to Relying on Estimates of Heterogeneity that are Too Large

Our final illustration uses the partworths from the low-design-quality condition. Recall that that condition estimates uncertainty (μ and μ^{adj}) that is too high (leading toward no differentiation as in §8.2) and heterogeneity that is too high (leading toward differentiation). In general either effect can dominate, but in our empirical illustration it is the errors in estimating heterogeneity that dominate. As Table 5 indicates, the partworths and μ^{adj} from the low-design-quality condition cause Firm A to differentiate and, hence, leave profits on the table relative to its best positioning strategy. In this case, the surprise in realized profits is quite dramatic. Firm A expects over 3.2 times as much profit as it actually obtains.

[Insert Table 5 about here.]

8.4. Summary of Strategic Mistakes Due to Inaccurate Market Research

§7 illustrates that easily-controlled characteristics of a market-research design affect both estimated uncertainty (μ and μ^{adj}) and estimated heterogeneity. (These characteristics can also affect relative partworth values and willingness-to-pay estimates, but did not do so in the apparel studies.) §8 illustrates situations where these inaccuracies lead to strategic positioning decisions that are incorrect. The third phenomena has been explored in prior research; the first two phenomena are the focus of this paper.

- if the firm relies on calibration data and does not correct uncertainty based external validation data, it could choose to differentiate when no differentiation would have been most profitable

- if the firm does not invest in market research accuracy and uses unbiased, but more uncertain, partworths, then it could forego differentiation when differentiation would have been most profitable
- if the firm over-estimates heterogeneity due to low-design-quality in its market research, it could choose to differentiate when no differentiation would have been most profitabl**e**.[3]

9. Summary

Both industry and academia invest considerable time, effort, and expense to improve the quality of market research. Clearly, if inaccurate partworths are biased, firms will make incorrect tactical decisions. But in our examples and in our theory design accuracy does not affect the relative mean partworths nor the estimates of willingness-to-pay.

However, unbiased mean partworths are not sufficient for correct strategic positioning. For strategic positioning decisions the firm must also be able to accurately assess the uncertainty of prediction and the true heterogeneity of the market. Both affect the perceived profitability of differentiation and either can cause the firm to make errors in positioning decisions. To avoid strategic errors, the firm should invest sufficiently so that its market research (1) accurately reflects true uncertainties in predictions and (2) accurately measures the true heterogeneity in consumer preferences. The examples of §8 also caution that firms should not rely only on calibration data only to evaluate models. Validation data is necessary to adjust for predictive-validation uncertainty. This latter insight reinforces the recommendations of Louviere (2001), Salisbury and Feinberg (2010), and others.

[3] Although under-estimation of heterogeneity did not occur in our data, it is easy to demonstrate with synthetic data that under-estimation of heterogeneity could lead a firm to forego differentiation when differentiation would have been more profitable.

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Table 1
Manipulation Checks (answers on 7-point scales)

	High Design Quality		Low Design Quality	
	Incentive Compatible	Not Incentive Compatible	Incentive Compatible	Not Incentive Compatible
Questions are clear and easy	6.5	6.0	5.3	5.0
Tried my best to be accurate	6.7	6.8	5.8	6.3
Survey tedious	2.6	2.4	4.2	5.1
Like real purchase decisions	5.5	6.2	5.0	5.1
I answered randomly	1.1	1.0	1.8	1.7

Table 2
Mean Partworths and Heterogeneity

	High Design Quality			Low Design Quality		
	Population Mean	Relative Mean Importance	Standard Deviation	Population Mean	Relative Mean Importance	Standard Deviation
Fleece Vest	-0.7		3.8	-0.9		3.2
Track Jacket	4.9	39%	5.5	2.7	43%	4.2
Hooded Sweatshirt	0.0 †		–	0.0 †		–
Grey (vs. Red) Color	1.5	10%	2.2	0.6	7%	1.8
School Logo	4.5	31%	2.7	3.0	36%	4.1
Price ($10 difference)	2.7	19%	1.5	1.2	14%	1.0
Goodness of Fit (U^2)		78.2%			69.7%	

† Type of apparel is a three-level feature. The partworth of hooded sweatshirt set to 0.0 for identification.

Table 3
Price and Profit Equilibrium in "True" Market

	Firm A Chooses Grey		Firm A Chooses Red	
	Firm A	Firm B	Firm A	Firm B
Strategic Position (Color)	Grey	Grey	Red	Grey
Equilibrium Price	\$51.40	\$51.40	\$52.63	\$56.31
Demand	5 M	5 M	4.4 M	5.6 M
Profit	\$57 M	\$57 M	\$55.2 M	\$91.9 M

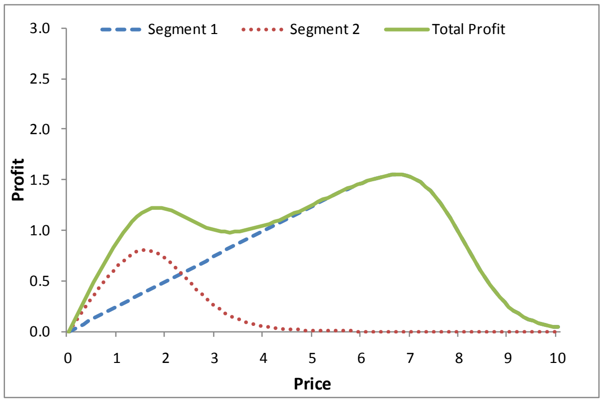
Table 4
Strategic Errors due to Falsely Assuming Calibration Uncertainty is True Uncertainty

	Firm A Chooses Grey		**Firm A Chooses Red**	
	Firm A	Firm B	Firm A	Firm B
Strategic Position (Color)	Grey	Grey	Red	Grey
Predicted Equilibrium Price	\$47.35	\$47.35	\$49.54	\$53.18
Predicted Demand	5.0 M	5.0 M	4.2 M	5.8 M
Predicted Profit	\$36.8 M	\$36.8 M	\$40.2 M	\$76.3 M
Realized Profit (Table 3)	\$57 M	\$57 M	\$55.2 M	91.9 M

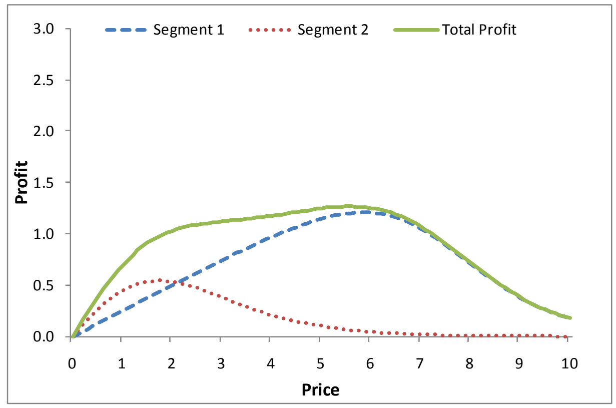
Table 5
Strategic Errors due to Over-estimating Heterogeneity

	Firm A Chooses Grey		**Firm A Chooses Red**	
	Firm A	Firm B	Firm A	Firm B
Strategic Position (Color)	Grey	Grey	Red	Grey
Predicted Equilibrium Price	\$74.45	\$74.35	\$78.53	\$81.50
Predicted Demand	5.0 M	5.0 M	4.8 M	5.2 M
Predicted Profit	\$172.3 M	\$172.3 M	\$184.5 M	\$216.2 M
Realized Profit (Table 3)	\$57 M	\$57 M	\$55.2 M	91.9 M

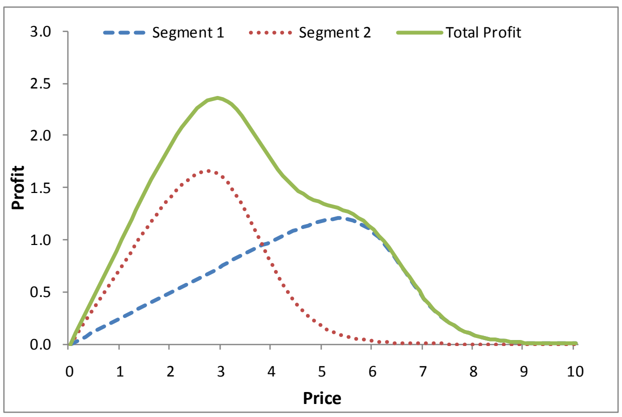
Figure 1
Profit vs. Price as Uncertainty and Heterogeneity Change



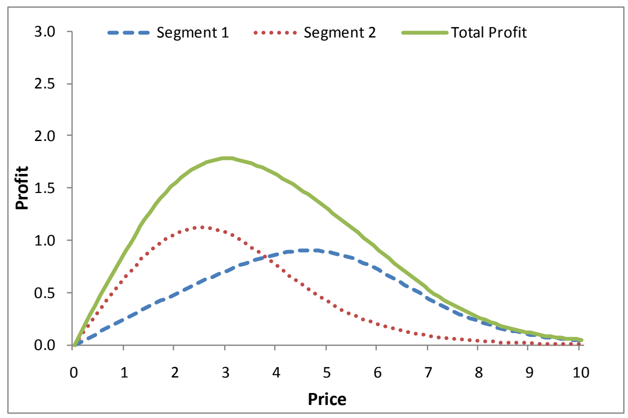
(a) Low μ, high heterogeneity



(b) High μ, high heterogeneity



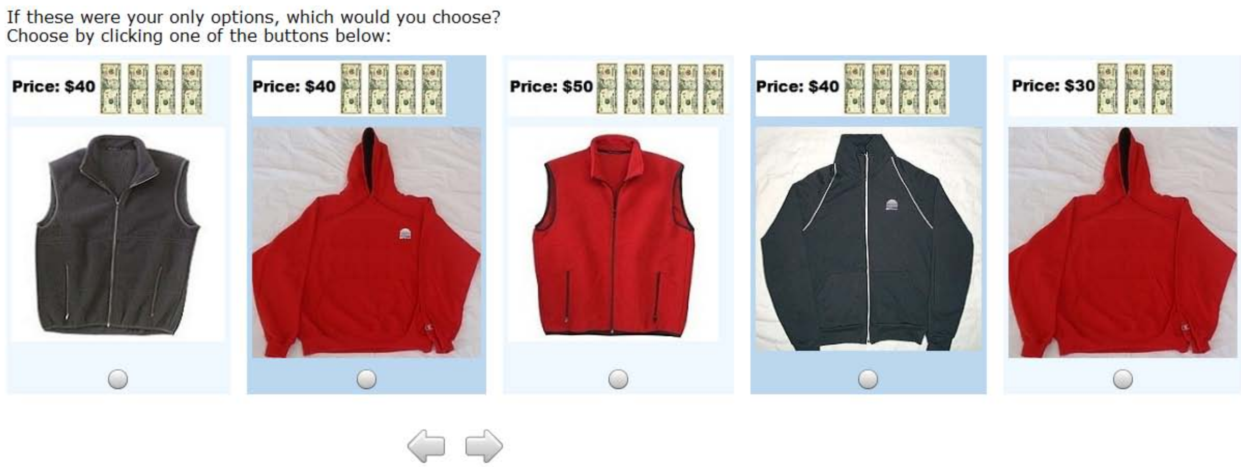
(c) Low μ, more homogeneous



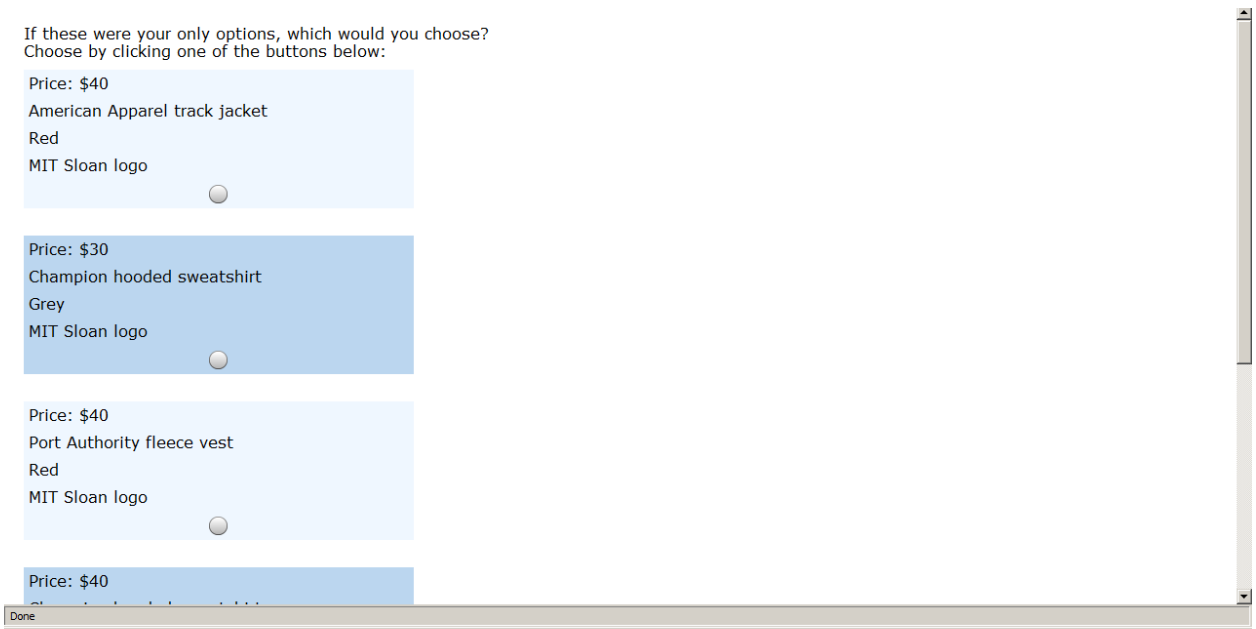
(d) High μ, more homogeneous

Figure 2

Design Quality Experimental Conditions



(a) High Design Quality: Careful Instructions, Training Questions, Text and Pictures, No Scrolling.



(b) Low Design Quality: Brief Instructions, No Training Questions, Text Only, Scrolling Required.