The Strategic Importance of Predictive Uncertainty in Conjoint Design

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Abstract

Even if firms have precise partworth estimates, predictive uncertainty (which arises due to randomness in customer behavior and attributes not included in the conjoint study) has strategic implications. Firms make strategic errors that reduce profits if they overestimate or underestimate predictive uncertainty. If firms use low-quality market research and thus overestimate uncertainty in prediction, they might forego strategic differentiation of product positions and earn less profit in equilibrium. Conversely, if firms evaluate predictive uncertainty with calibration data only, rather than external validation tests, they might underestimate uncertainty and choose differentiated positions that are not as profitable in equilibrium. We demonstrate these effects theoretically and empirically, with applications to simulated partworths and a real conjoint study on student apparel. In an apparel application, we find that 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 makes accurate estimates of average customer partworths, and if there is heterogeneity among consumers (as is typically the case), the firm can accurately estimate the distribution of partworths. 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).

This paper shows that accuracy in conjoint analysis has strategic implications, in addition to the well-known tactical implications. We demonstrate this point using a framework that incorporates game-theoretic price competition into simulators based on market research (see Choi, DeSarbo and Harker 1990; Choi and DeSarbo 1994; Luo, Kannan, and Ratchford 2007). Even if all competing firms in the market achieve the same accuracy, the level of accuracy determines their strategic product positioning decisions. In particular, if true predictive uncertainty (which exists due to randomness in customer behavior and attributes not included in the conjoint study) is high, firms should all choose the same design. Instead of trying to differentiate, they should all try to provide as much average utility as possible to customers for a given level of marginal production cost.

One implication is that firms will make strategic errors that reduce their profits if they overestimate or underestimate predictive uncertainty. If firms use inaccurate methods that cause them to overestimate uncertainty, then they might all choose the same design when the most profitable strategy would have been to differentiate. Alternatively, if they are overconfident, for example, by relying on predictive uncertainty as estimated from calibration data rather than
(true) 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. However, our results show that accurate estimates of average preferences and heterogeneity in preferences are not sufficient. In order to make correct strategic decisions, firms also need an accurate estimate of predictive uncertainty.

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; Toubia, et al. 2011).

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 predictive uncertainty, as related to unobserved variance in the utility customers derive from products, affects product positioning decisions. When predictive uncertainty is sufficiently high,
there is an equilibrium with minimum differentiation (all firms choose the same design). On the other hand, if preference heterogeneity is sufficiently large, then there is an equilibrium with maximum differentiation (firms differentiate along all features).

On the empirical side we first illustrate our theoretical results with simulated partworths. We then collect real conjoint data in which we vary the quality of the conjoint study design. We find that varying the study design does not significantly affect estimates of average relative partworths, but it does affect estimates of predictive uncertainty and heterogeneity, which leads to different strategic positioning decisions. The empirical examples also illustrate strategic errors when firms fail to account for additional predictive uncertainty in a validation task that is more complex (and in this respect, more realistic) than the original conjoint task.

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 uniformly distributed along a line and two firms compete by first choosing a position and then a price. Assuming quadratic transportation costs and no predictive uncertainty, firms locate at opposite ends of the line in equilibrium (d’Aspremont, Gabszewicz and Thisse 1979). On the other hand, if there is sufficient predictive uncertainty in consumer choice, both firms locate in the middle of the line (de Palma, et al. 1985; Rhee, et al. 1992). In this context, uncertainty takes the form of an error term in product utility, which is interpreted as representing differentiation along dimensions other than the Hotelling line. Similarly, if customers are uniformly distributed along a multi-dimensional space, firms are maximally different along the “dominant” dimension, but choose the same location on all other dimensions (Irmen and Thisse 1998).

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; Novshek 1980; Shaked and Sutton 1982; Shilony 1981; Sajeesh and Raju 2010; Zeithammer and Thomadsen 2010). One insight from these formal models is that the more heterogeneous consumers preferences, the more likely firms choose to differentiate.

Whereas these earlier theoretical papers use stylized models in which all products have the same marginal cost, all customers have the same marginal utility of income, and the distribution of preferences is uniform, the current paper uses the more realistic assumptions typical of conjoint simulators, with marginal costs that vary across feature levels, heterogeneity in the marginal utility of income (i.e., the partworth of price), and a flexible, non-parametric distribution of customer preferences. Generalizing prior game-theoretic results, we derive results that apply to the more realistic and flexible demand model that is common in applied market research studies.

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 Evgeniou, Pontil and Toubia 2007).

However, many conjoint simulators assume competitors will not respond to a new product introduction. This can generate unreasonable results. For example, Belloni, Freund, Selove, and Simester (2008) show that a simulator that assumes no competitive response and no predictive uncertainty can generate recommendations that the “optimal” design is to mimic competitive
products while undercutting their price. By contrast, the current paper shows that simulators that account for competitive price response imply that firms should differentiate their products as long as predictive uncertainty is low enough.

Our paper also builds on previous research that studied price competition in conjoint market simulators. 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) 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 $\rho$-concave with $\rho = -(n + 1)^{-1}$. (Commonly used density functions, including the normal, uniform, Weibull, and Wishart distributions, are $\rho$-concave. However, a mixture of normal distributions need not be $\rho$-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 subgames
when preferences are given by heterogeneous partworth models, interior pure-strategy Bertrand-Nash equilibria exist under reasonable restrictions on heterogeneity and uncertainty. Furthermore, we prove that, using a realistic demand model based on conjoint analysis, high predictive uncertainty leads firms to choose a strategy of no differentiation, whereas high heterogeneity leads firms to differentiate along all available attributes.

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 $\beta_i$ be a vector of partworths for consumer $i$ and let $\lambda_i$ 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, $\mu$ is a parameter, described below, that represents the magnitude in uncertainty in product utility (e.g., Swait and Louviere 1993), and $\epsilon_{ij}$ 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:
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.

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 2. (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.)

$$D_{ij} = \frac{e^{\mu^{-1}(\beta'_jX_j - \lambda_i P_j)}}{\sum_{k=1}^{N} e^{\mu^{-1}(\beta'_kX_k - \lambda_i P_k)}}$$

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

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

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 subgames. Prior research establishes that the equilibrium exists as long as the distribution of partworths combined with the inherent uncertainty ($\mu$) does not lead to a price response that is
highly multimodal. Caplin and Nalebuff (1991) state these results with respect to \( \rho \)-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 customers’ utility
functions. These results apply to our subgames. Every price subgame has a pure-strategy equilib-
rium whenever \( \mu \) is sufficiently large.

For readers unfamiliar with the earlier results we provide the intuition with a simple ex-
ample. 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 \( \mu \)) we should not be surprised that 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
(there may only be a mixed strategy equilibria of the type characterized by Varian 1980). 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). (Detailed values of the parameters for these illustrations
are available from the authors.)
We formalize the intuition of Figure 1 with 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; we find that this makes it possible to prove uniqueness under less restrictive conditions.) Proposition 1 is important because our differentiation results assume that the price subgames have unique interior price equilibria.

Condition 1 states a sufficient criterion for uniqueness. Condition 1 assures that hetero-
geneity in price sensitivity (the standard deviation of the $\lambda_i$) is sufficiently low relative to the expected value of the $\lambda_i$. (Most revealed-preference estimation methods identify $\lambda_i/\mu$’s rather than the $\lambda_i$’s and $\mu$ separately. Note that dividing by $\mu$ would simply scale both sides of Condition 1 by the same factor.)

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

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

Sufficiently-large uncertainty enables us to use asymptotic properties (as each customer’s demand for each product approaches $1/N$) to guarantee that profit functions are quasi-concave in price. Condition 1 ensures that optimal prices are sufficiently insensitive to competing prices that the equilibrium is unique. Together these conditions ensure existence of a unique equilibrium on the interior of some range of prices. (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. 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 with logical constraints.

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 by 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 (all consumers are indifferent among all firms’ products), or when preferences are heterogeneous (for example, if each firm has a different segment that prefers its product).

**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 $\text{var}_i[D_{ij}]$.)

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

Secondly, intuitively, and consistently with prior research, subgame 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. 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. In fact, Proposition 2 guarantees maximum differentiation in the special case in which there are two firms, all products have the same marginal cost, and heterogeneity in preferences is sufficiently large. Under these conditions, if we hold average partworths constant but increase heterogeneity (the standard deviation) of partworths, preferences eventually become arbitrarily close to being symmetric for all possible product design decisions, and therefore Proposition 2 guarantees that the firms differentiate along all available features in order to maximize equilibrium prices.¹

Our final proposition establishes that sufficiently high uncertainty 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, $\beta_i$, is uncorrelated with the marginal utility of income. Condition 2 is sufficient, but not necessary.

**Condition 2**

$$\text{Cov}_l[\lambda_i, \beta_i] = 0$$

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

Proposition 3 states that sufficiently large uncertainty causes all firms to maximize a function that increases in the average utility provided to customers, and decreases with marginal cost. Because all firms maximize the same function, there is no force compelling them to become different, and there is an equilibrium in which they all choose the same design.

¹ On the other hand, if marginal costs vary depending on feature choices, or if preferences are not very heterogeneous (for example, if all customers prefer the same level for one feature), firms may choose positions in which preferences are not symmetric, and maximum differentiation may not hold.
The formal proof (available in the online appendix) is technically complicated. However, the intuition for Proposition 3 can be seen as follows. As $\mu$ becomes sufficiently large:

1. Equilibrium prices are high even if all firms choose the same design. This is because a high value of $\mu$ implies that consumers are relatively insensitive to changes in price.
2. Differentiation has a negligible effect on equilibrium prices. This is because differentiation does not create a group of strongly loyal customers, as each customer always has a relatively high chance of choosing any given product when $\mu$ is high.
3. Even a small increase in demand (resulting from an increase in the average utility provided by a product) has a significant effect on profits, since this small increase in demand is multiplied by the large profit margins that result from a high value of $\mu$.

Due to the combination of these forces, when $\mu$ is sufficiently high, firms do not try to differentiate. Instead, they focus on providing as much average utility as possible to customers for a given level of marginal costs.

6. Application to Simulated Partworths

The theoretical results in the previous section imply that for sufficiently large heterogeneity (variance in partworths), firms are maximally different in equilibrium; on the other hand, for sufficiently large predictive uncertainty ($\mu$), firms are minimally different in equilibrium. We now illustrate these theoretical results with an application to simulated partworths.

We assume two firms each produce a product that has 4 binary features. For each feature, we normalize the partworth for level “zero” to zero. Let $\beta_{i,n}$ denote respondent $i$’s partworth.

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2 Sufficiently high values of $\mu$ allow us to use asymptotic approximations of the demand and profit functions. When $\mu$ is large enough, first-order Taylor approximations of these functions become arbitrarily close to the actual function over the range of possible feature choices. This allows us to explicitly solve for the sensitivity of equilibrium demand, prices, and profits with respect to each firm’s feature choices, and thus to show how a firm’s feature choices affect its equilibrium profits. Technically, $F(X_f)$ can have multiple optima, in which case there are multiple equilibria.
for level one of feature \( n \). We create 500 simulated respondents. For each respondent, part-
worths for the four features are drawn independently from the following distributions:

\[
\beta_{i,1} \sim N(2, \sigma^2) \\
\beta_{i,2} \sim N(4, \sigma^2) \\
\beta_{i,3} \sim N(6, \sigma^2) \\
\beta_{i,4} \sim N(8, \sigma^2)
\]

Note that on average, customers prefer level one of each feature. The strength of this preference
for the average consumer is lowest for attribute one, and highest for attribute four.

Letting \( \lambda_i \) denote consumer \( i \)'s partworth for a one dollar decrease in price, we assume:

\[
\bar{\lambda}_i \sim N(1, [0.2\sigma]^2)
\]

To avoid price partworths with the wrong sign, we restrict them to the range \([0.5, 1.5]\), by trun-
cating values that fall outside this range.

Firms first choose levels for each of the four attributes, and then set prices. For each pos-
sible pair of attribute choices, we compute a corresponding price equilibrium using an algorithm
similar to the one developed by Choi et al. (1990). We assume that firms are forward-looking in
that they anticipate how their choice of attributes in the first stage of the game will affect the
price equilibrium in the second stage of the game. In all of our examples, we find that there is an
equilibrium in which one firm chooses level one for every feature, while the other firm chooses a
mixture of zeroes and ones. The second firm’s choice ranges from all ones (minimum differen-
tiation) to all zeroes (maximum differentiation). By varying the standard deviation of partworths ($\sigma$) and the noise in product utility ($\mu$), we explore how these parameters affect the degree of differentiation in equilibrium.

Figure 2

**Number of Features on which Firms Differentiate in Equilibrium**

![Bar graph showing the number of features on which firms differentiate in equilibrium.](image)

Figure 2 presents the results for values of $\sigma$ and $\mu$ ranging from 2 to 8. Maximum differentiation (along all four features) only occurs when $\sigma$ is large and $\mu$ is small. Minimum differen-

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3 As in most analyses of this type, there is a label-switching issue: who gets to be “firm 1”? For example, one firm might be the incumbent or have a first-mover advantage. The label-switching issue does not change the basic insight from the illustration.
tiation occurs when the opposite is true. Figure 2 illustrates the theoretical results from the previous section.

7. Implications for Market Research

The results in Figure 2 assume both firms know precisely the distribution of partworths and also know precisely the magnitude of predictive uncertainty ($\mu$). In fact, to make optimal decisions firms only need to know the ratios, $B_i = \beta_i/\mu$ and $\Lambda_i = \lambda_i/\mu$, because the logit demand model depends on the relative values of these parameters (the magnitude of partworths and noise cannot be separately identified). From a practical perspective, a firm making a position-then-price decision undertakes a market research study to estimate the $B_i$’s and $\Lambda_i$’s. These estimates 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 suggest how the market might be segmented, and the relative values of the $B_i$’s relative to the $\Lambda_i$ determine prices. The new implication of our paper is that uncertainty ($\mu$) matters strategically. Sufficiently high levels of uncertainty (which corresponds to low values of the $B_i$’s and $\Lambda_i$’s) imply that all firms choose the same product position (Proposition 3).

In the real world, uncertainty might come from inherent stochasticity in consumer preferences (e.g., Bass 1974) or from unobserved influences. For example, airlines might use conjoint analysis to determine their flight schedule, entertainment options, and seat sizes, but customers’ purchase decisions also depend on other factors such as previously accumulated frequent flier miles. Predictive uncertainty almost always exists because market research cannot typically include all factors that matter to customers.

In addition, predictive 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 $\Lambda_i$’s (implying lower values of $\mu$) 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 incorrectly choose not to differentiate its products. When products are actually released on the market, equilibrium prices will be lower than the firm expected, and it will earn lower profits than it would have with a more differentiated position.

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.

Our theoretical analyses identify three strategic and tactical implications of low-quality market research. The first two are well known: (1) if the firm estimates the wrong relative $\overline{B}$ 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 $\Lambda_i$’s it may segment the market incorrectly. The third implication is new, but potentially important. If the firm estimates $B_i$’s and $\Lambda_i$’s and either over- or under-estimates true uncertainty ($\mu$), the firm may choose not to differentiation when differentiation could have been more profitable, or vice versa. We illustrate this third implication with a conjoint-analysis study applied to a market for student apparel.

8. 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 (in addition to the incumbent) 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 in measured $\mu$. 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 $\mu$ 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.

8.1. 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 $\Lambda_i$ 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 $3 \times 2 \times 2 \times 2$ 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 $\mu$ (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 re-
spondent 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.

8.2. Experimental Design

The $2 \times 2$ 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. While the low-quality design uses (for the most part) the default settings in the Sawtooth Software package we used, the high quality design represents what a market researcher can create using the same software by investing additional time and effort in study design. Figure 3 illustrates the two experimental conditions.
Figure 3

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.
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 the 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. (When respondents completed the calibration task, they did not know about the validation task. 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.)

8.3. Manipulation Checks

Table 1 reports manipulation checks. As expected and consistent with the manipulations, respondents in the high-design-quality conditions report significantly 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 not significant. Because incentive-compatibility did not have the anticipated effect on accuracy, perhaps because a 1-in-10 chance of winning did not provide sufficient incentives or perhaps because the respondents took the task seriously even in the absence of incentives, 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, \( p = 0.01 \)), eliciting more effort to be accurate (6.7 vs. 6.1, \( p = 0.01 \)), less tedious (2.5 vs. 4.6, \( p < 0.01 \)), less likely to elicit random responses (1.1 vs. 1.7, \( p = 0.02 \)), 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.

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

<table>
<thead>
<tr>
<th></th>
<th>High Design Quality</th>
<th>Low Design Quality</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Incentive Compatible</td>
<td>Not Incentive Compatible</td>
</tr>
<tr>
<td>Questions are clear and easy</td>
<td>6.5</td>
<td>6.0</td>
</tr>
<tr>
<td>Tried my best to be accurate</td>
<td>6.7</td>
<td>6.8</td>
</tr>
<tr>
<td>Survey tedious</td>
<td>2.6</td>
<td>2.4</td>
</tr>
<tr>
<td>Like real purchase decisions</td>
<td>5.5</td>
<td>6.2</td>
</tr>
<tr>
<td>I answered randomly</td>
<td>1.1</td>
<td>1.0</td>
</tr>
</tbody>
</table>

8.4. **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 manipulation of accuracy was successful in affecting calibration uncertainty (a component of \( \mu \)). The high-design-quality partworths are, on average, about 77\% greater indicating lower calibration uncertainty. However, both the high- and low-design-quality designs give roughly the same relative feature importances: they are highly correlated across features \( r = 0.98, p < 0.01 \).
Table 2
Mean Partworths and Heterogeneity

<table>
<thead>
<tr>
<th></th>
<th>High Design Quality</th>
<th>Low Design Quality</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Population Mean</td>
<td>Relative Mean</td>
</tr>
<tr>
<td>Fleece Vest</td>
<td>-0.7</td>
<td>3.8</td>
</tr>
<tr>
<td>Track Jacket</td>
<td>4.9</td>
<td>39%</td>
</tr>
<tr>
<td>Hooded Sweatshirt</td>
<td>0.0 † †</td>
<td>–</td>
</tr>
<tr>
<td>Grey (vs. Red) Color</td>
<td>1.5</td>
<td>10%</td>
</tr>
<tr>
<td>School Logo</td>
<td>4.5</td>
<td>31%</td>
</tr>
<tr>
<td>Price ($10 difference)</td>
<td>2.7</td>
<td>19%</td>
</tr>
<tr>
<td>Goodness of Fit ($U^2$)</td>
<td>78.2%</td>
<td></td>
</tr>
</tbody>
</table>

† Feature importance is defined as the difference between the highest and lowest mean partworths of different levels of a feature.

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

The absolute standard deviations of the partworths are roughly equivalent, but heterogeneity should be measured 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.

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 (higher $\mu$) 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).  

8.5 External-Validity Uncertainty

Calibration uncertainty is related to $\mu$, but $\mu$ 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 illustrate how external-validity scaling affects firms’ product strategies, we adjust the uncertainty parameter to fit the results of the validation task. Although the validation task was not the real market, it was more complex than the original conjoint task, and in this respect more similar to real-world choice decisions.

To estimate the adjustment to uncertainty, we hold the relative $\beta_i$ and $\Lambda_i$ fixed and estimate an adjustment factor based on the validation task such that $\beta_i^{adj} = \beta_i / \mu^{adj}$ and $\Lambda_i^{adj} = \Lambda_i / \mu^{adj}$ using maximum likelihood estimation. Based on our data, we estimate the adjustment factor ($\mu^{adj}$) 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.) Validation accuracy is less in the low-design-quality condition ($U^2 = 23.6\%$) than in the high-design-quality condition ($U^2 = 45.2\%$). In addition to a worse internal accuracy in the calibration task, the low-quality design also leads to worse external accuracy in predicting results of the validation task. In §9.1 we show how these adjustments to the uncertainty parameter affect firms’ product design choices.

9. 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

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4 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-design-quality condition.
which is offering one track jacket with a logo so that the 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.

For illustrative purposes, we assume the “true” market prices and profits are predicted by the high-design-quality condition with adjustments in $\mu$ to reflect external validity. Once “color” decisions are made (based on market research that can either be accurate or inaccurate), firms set equilibrium prices after observing the true market demand function. 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. In the empirical conjoint study, the grey color is preferred on average and, not surprisingly, all equilibria include at least one firm (the incumbent) offering a grey track jacket. Our main focus is on illustrating how inaccurate market research by firm A (the entrant) can cause it to make strategic errors in its product positioning decision (choosing a sub-optimal color).

The timing of the game is as follows:

1. The incumbent conducts accurate market research. It then chooses a color, under the assumption that the entrant will also use accurate market research.
2. The entrant conducts its own market research (we study what happens when its research is either accurate or inaccurate). It then chooses its own color.
3. Both firms launch their products and observe the true market demand. In other words, they learn implicitly the true distribution of partworths and the value of noise ($\mu$).
4. Both firms simultaneously set prices, given their color decisions and the true market demand.
To summarize, we assume firms make color decisions sequentially, each using its own research, and that firms are able to observe the true demand function before setting prices. The motivation for these assumptions is that changing color is relatively expensive and difficult, whereas firms can easily adjust prices based on new information. The assumptions used here are one approach for illustrating that firms need accurate estimates of the noise term ($\mu$) to make correct strategic positioning decisions. This point could also be illustrated under other assumptions, for example, if firms choose colors simultaneously, if the incumbent anticipates that the entrant will use inaccurate market research, if both firms use inaccurate research, or if firms set prices based on market research instead of based on the true demand function. For any of these alternative assumptions, inaccurate estimates of the noise term could also cause strategic errors.

9.1 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.

<table>
<thead>
<tr>
<th>Strategic Position (Color)</th>
<th>Firm A Chooses Grey</th>
<th>Firm A Chooses Red</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Firm A</td>
<td>Firm B</td>
</tr>
<tr>
<td>Equilibrium Price</td>
<td>$51.40</td>
<td>$51.40</td>
</tr>
<tr>
<td>Demand</td>
<td>5 M</td>
<td>5 M</td>
</tr>
<tr>
<td>Profit</td>
<td>$57 M</td>
<td>$57 M</td>
</tr>
</tbody>
</table>

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.

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

<table>
<thead>
<tr>
<th></th>
<th>Firm A Chooses Grey</th>
<th>Firm A Chooses Red</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Firm A</td>
<td>Firm B</td>
</tr>
<tr>
<td>Strategic Position</td>
<td>Grey</td>
<td>Grey</td>
</tr>
<tr>
<td>(Color)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Predicted Equilibrium Price</td>
<td>$47.35</td>
<td>$47.35</td>
</tr>
<tr>
<td>Predicted Demand</td>
<td>5.0 M</td>
<td>5.0 M</td>
</tr>
<tr>
<td>Predicted Profit</td>
<td>$36.8 M</td>
<td>$36.8 M</td>
</tr>
<tr>
<td>Realized Profit (Table 3)</td>
<td>$57 M</td>
<td>$57 M</td>
</tr>
</tbody>
</table>

9.2. 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 $\mu$). 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).
9.3. 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 ($\mu$ and $\mu^\text{adj}$) that is too high (leading toward no differentiation as in §9.2) 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 $\mu^\text{adj}$ 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.

<table>
<thead>
<tr>
<th>Table 5</th>
<th>Strategic Errors due to Over-estimating Heterogeneity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Firm A Chooses Grey</td>
<td>Firm A Chooses Red</td>
</tr>
<tr>
<td>Strategic Position (Color)</td>
<td>Grey</td>
</tr>
<tr>
<td>Predicted Equilibrium Price</td>
<td>$74.45</td>
</tr>
<tr>
<td>Predicted Demand</td>
<td>5.0 M</td>
</tr>
<tr>
<td>Predicted Profit</td>
<td>$172.3 M</td>
</tr>
<tr>
<td>Realized Profit (Table 3)</td>
<td>$57 M</td>
</tr>
</tbody>
</table>

9.4. Summary of Strategic Mistakes Due to Inaccurate Market Research

§8 illustrates that easily-controlled characteristics of a market-research design affect both estimated uncertainty ($\mu$ and $\mu^\text{adj}$) 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.)
§9 illustrates three situations where these inaccuracies lead to strategic positioning decisions that are incorrect. The third of these 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 on external validation data, it could choose to differentiate when no differentiation would have been more profitable.
- If the firm does not invest in market research accuracy, and still makes accurate estimates of partworths, but it overestimates predictive uncertainty, then it could forego differentiation when differentiation would have been more 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 more profitable.⁵

10. Conclusion

Both industry and academia invest considerable time, effort, and expense to improve the quality of market research. Clearly, if firms inaccurately estimate mean partworths or heterogeneity in partworths, they will make incorrect tactical decisions.

However, accurate estimates of the partworth distribution are not sufficient. Firms must also be able to accurately assess the true predictive uncertainty of the market to make correct strategic positioning decisions. Our results in §5 prove this theoretically, and the simulations in §6 show how changes to the uncertainty parameter affect optimal strategic positioning in a simple four-attribute example. The application to a real conjoint study in §9 shows that inaccurate estimates of uncertainty affect the expected profitability of differentiation and can cause the firm to make errors in positioning decisions.

⁵ 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.
In many cases, firms’ capacity for investment is limited, and managers face trade-offs between investing in marketing and other activities. For example, Hess and Lucas (2004) study the optimal allocation of scarce resources between marketing (to estimate the distribution of customer preferences) and manufacturing (to improve production efficiency). Our results demonstrate another important factor that firms should consider when deciding how much money, time, and effort to allocate to market research. To avoid strategic errors, the firm should invest sufficiently in the quality of its study design so that its results do not overestimate predictive uncertainty. Our results also caution that firms should not rely only on calibration data only when evaluating models. It is necessary to account for predictive-validation uncertainty, so firms do not underestimate uncertainty. This latter insight reinforces the recommendations of Louviere (2001), Salisbury and Feinberg (2010), and others. Future research could study the optimal amount firms should invest in marketing research once they account for these additional factors.
References


Sawtooth Software (2003), “Advanced Simulation Module (ASM) for Product Optimization v1.5,” (Sequim WA; Sawtooth Software, Inc.).


