

How Does Incorporating Price Competition into Market Simulators Affect Product Design Decisions?

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1. Strategic Implications of Accuracy in Conjoint Analysis

Market simulators based on conjoint analysis help managers predict the market share and profitability of new product designs. Many simulators assume competitors will not respond to a new product introduction. This assumption can lead managers to make poor decisions. For example, Belloni et al. (2008) show that a simulator that ignores competitive response might indicate that the “optimal” new product is identical to a competing product but priced slightly lower. In a real market this design strategy would provoke a price war that would erode the profits of all firms in the market.

To address this problem, academic researchers have created market simulators that account for price reactions by competitors (Choi, Desarbo, and Harker 1990; Choi and DeSarbo 1994; Luo, Kannan, and Ratchford 2007; Luo 2009). These papers assume that competing firms first set non-price features that depend on manufacturing set-ups that can be changed slowly or at high cost. Firms adjust prices relatively quickly and at low cost until all prices reach a Nash equilibrium conditioned on the non-price features chosen in the first stage. Such competitive market simulators provide insight into how a firm’s product design choices affect price competition in a market and, hence, lead to more profitable strategic decisions.

In this note we summarize results from a recent working paper where we explore how the accuracy of the conjoint-analysis partworths used in market simulators affects firms’ strategic product-design choices (Selove and Hauser 2010). In that paper we address when firms should differentiate their products to soften price competition, and when they offer undifferentiated products. Our key insight is quite relevant to the use of choice-based conjoint analysis: firms acting rationally will make different decisions on differentiation depending upon the amount of noise (or randomness) in customer behavior. This noise is inversely proportional to the logit “scale factor” (Swait and Louviere 1993). We show that when the amount of noise in behavior is small, firms will differentiate their products, but when the amount of noise is sufficiently large, firms will forego differentiation and instead compete for the same customers.

This result has important implications for market researchers. In particular, it implies that firms must accurately estimate the amount of noise in behavior (in other words, accurately estimate the scale factor) in order to develop an optimal product design strategy. If they misjudge the scale factor they will make incorrect strategic decisions and forego potential profit. Many factors contribute to “noise” in real-world choice behavior, including attributes omitted from the conjoint study, changes in behavior across contexts, and inattentiveness or carelessness in customer responses to the survey. If a poorly designed market research study causes respondents to behave more carelessly or randomly than they would in the real world, this will cause a firm to overestimate the amount of noise in choice behavior, causing them to create a product that is too close to competing products, and thus lead to destructive price competition. On the other hand, if a firm fails to account for sources of noise that exist in the real world, this could lead them to focus too much on differentiating their products even though this means providing less utility to customers.

We illustrate the practical relevancy of these results with an application to a conjoint study on student apparel. We first estimate partworths using HB/CBC analysis, and then hold these partworths fixed while adjusting the scale factor to account for differences in behavior between the initial conjoint task and a hold-out task. (This is similar to the approach suggested by Salisbury and Feinberg 2010.) In the illustrative conjoint-analysis study, accounting for noise across settings implies that a firm should choose the most popular color for its product, even if a competitor also chooses that color. On the other hand, failure to account for this additional noise leads a firm to differentiate its product by choosing a less popular color. This incorrect decision reduces profits for the firm.

2. Intuition for Why Uncertainty Affects Strategic Decisions

Selove and Hauser (2010) provide detailed proofs to illustrate how noise affects product design choices. Although we do not repeat that formal proof here, the intuition can be seen from the following simple example. Suppose a product is available in two colors: grey or red. Most consumers prefer grey, but there is also a segment of consumers who prefer red. Two firms compete in this market, and each firm sells a single type of product. The strategic question is

whether, in equilibrium, both firms will choose to produce a grey product (the more popular color), or whether one firm will produce a grey product while the other firm produces a red product to soften price competition. For this example, color and price are the only product features.

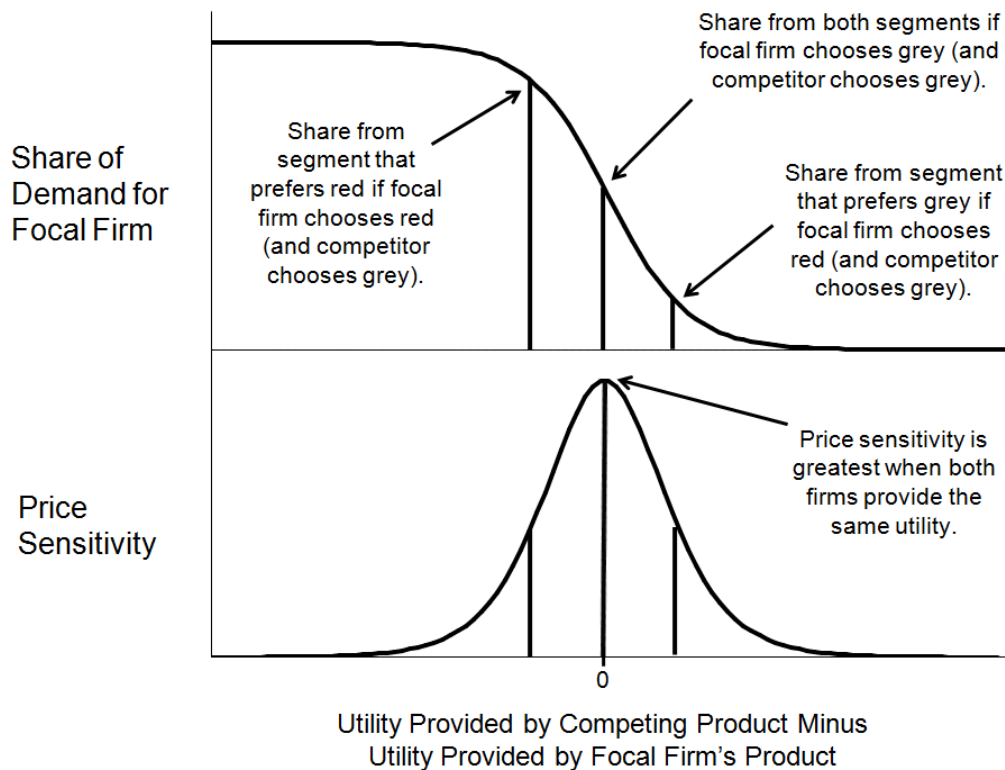
Assume that consumers are described by random utility models where the observed utility component is the standard partworth model (for color and price) and the random component follows a double-exponential extreme-value distribution. In other words, demand follows a logit function. The presence of the random component to utility implies, for example, that some consumers who prefer the color the competitor's product may still choose the focal firm's product (even if prices for both products are the same).

Figure 1 shows how color choice affects competition in the market when there is relatively low utility randomness. This figure assumes (for simplicity of exposition and intuition) that both firms have set the same price and that the competitor has chosen a grey product. The proofs do not require these latter assumptions.

The top half of this figure shows the focal firm's share of demand as a function of the difference between utility provided by the competing firm's product and utility provided by the focal firm's product. The inner bar is for both segments and assumes the focal firm chooses grey; the outer bars are for the two different segments and assume the focal firm chooses red. The bottom half of the figure shows the sensitivity of each segment's demand to changes in price, where "price sensitivity" is the negative of the first derivative of demand with respect to price. Note that the horizontal axis is (for each given segment) utility provided by the competing firm's product minus utility provided by the focal firm's product.¹ The two firms provide equal utility at the "bar" in the center of the figure.

¹ To be precise, this axis reflects the difference in *observed* utility, based on color and price.

Figure 1. How Differentiation Affects Demand and Price Sensitivity
(For **Low** Randomness in Product Utility)



If the focal firm chooses grey, then each firm receives half of the demand from each segment. Because the derivative of the logit function is highest when the focal firm has one-half of demand, price sensitivity is at its highest at this point. On the other hand, if the focal firm chooses a red product, its share of demand increases for the segment that prefers red, but decreases for the segment that prefers grey. Both customer segments are now less price-sensitive (as is indicated by the two outer bars on the bottom half of the figure, showing lower price sensitivity for both segments). Intuitively, customers who have strong preferences for one color or another are less likely to be swayed by small price differences. Differentiation softens price competition. It is not hard to show that, in equilibrium, prices in the market will be higher. Figure 1 illustrates the basic trade-off faced by a firm choosing red or grey: higher average prices result from each firm choosing a different color, but for the firm that chooses the less-popular color, that color reduces share of demand in the larger segment (while increasing share of demand from the smaller segment). The size of the smaller segment determines whether the net

of this tradeoff is profitable for the firm choosing the less-popular color.² (We ignore for the purposes of this example, which firm gets to be grey and which red. We assume that the focal firm, if it differentiates, is the red firm.)

Figure 2. How Differentiation Affects Demand and Price Sensitivity
(For *High* Randomness in Product Utility)

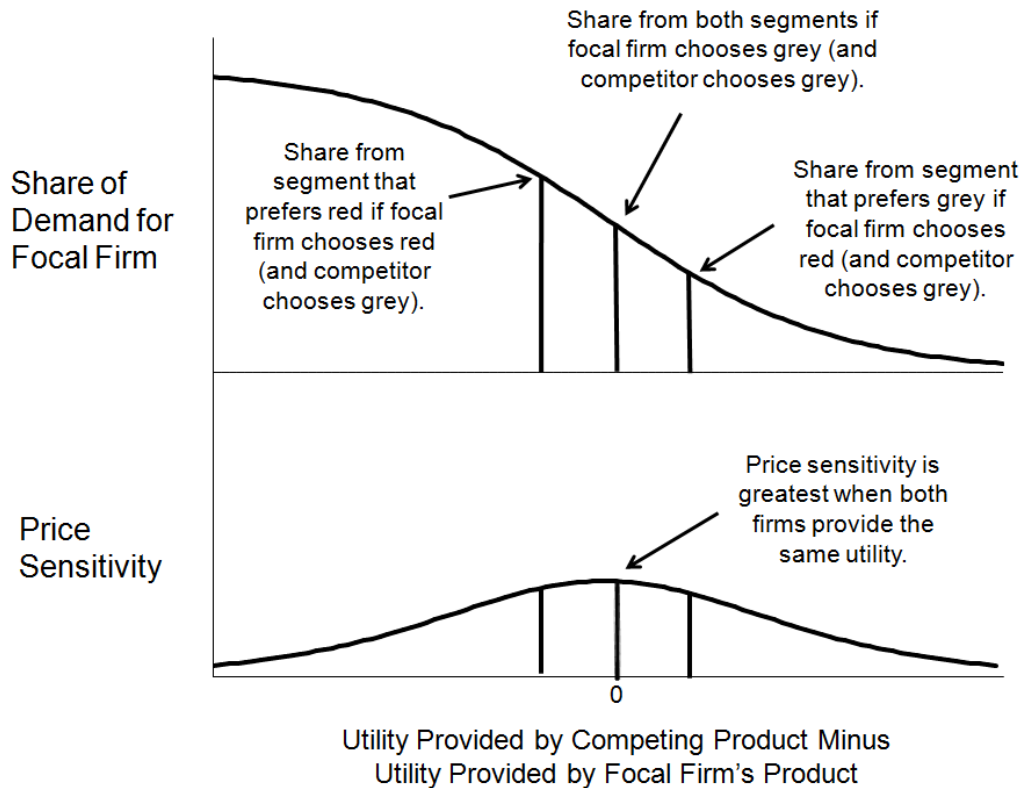


Figure 2 presents the same analysis with one key change: we increase the error term on product utility (that is, decrease the logit scale factor). The demand curve is now flatter, and the first derivative of demand is now smaller. Increasing the amount of noise in customer behavior implies that customers are less sensitive to all product features (including price). In Figure 2 if the focal firm chooses grey, then each firm still receives half of the demand from each segment.

² Although the proofs in Selove and Hauser (2010) assume a logit demand model, the intuition behind these results would hold for any demand function with the property that customers who strongly prefer one firm or another are less price-sensitive. This seems like a reasonable property for demand functions, and it is also consistent with the standard strategic advice that differentiating from competitors helps avoid price wars.

As before, if the focal firm chooses a red product, this increases its demand in the segment that prefers red and decreases its demand in the segment that prefers grey. It also reduces price sensitivity for both segments. However, these effects are now smaller. As randomness in behavior becomes greater, a company's color choice has a smaller effect on both demand in each segment and the sensitivity of demand to price.

The arguments so far suggest that the net effect of greater randomness is ambiguous. The reduction in demand due to differentiation (choosing a red product) is less when randomness increases, but so is the softening of price competition. However, the additional randomness makes customers less sensitive to changes in price, hence equilibrium prices (and profit margins) are higher, all else equal. This implies that even a small decrease in demand has a substantial effect on profits, since this small change is multiplied by larger profit margins. Therefore, although the net benefit from differentiation (softening price competition) becomes trivial as randomness increases, the cost of choosing a less popular color is still substantial. When randomness becomes sufficiently high, this confluence of effects leads all firms to choose the most popular color (grey) in equilibrium.

To summarize, two firms face the standard differentiate-or-not dilemma – greater differentiation reduces price competition but less differentiation allows both firms to focus on the highest-demand segments. The key new insight is that inherent uncertainty in consumers' choice behaviors affects how firms resolve the dilemma. Greater uncertainty leads to less differentiation.

This insight has roots in prior research that suggests similar results for a demand model in which preferences are uniformly distributed, all products have the same marginal cost, and all customers have the same price sensitivity (de Palma et al. 1985; Irmen and Thisse 1998). One contribution of our paper is that it extends this result so that it is connected to the means by which firms measure consumer preferences—choice-based conjoint analysis. This connection is critically important because it allows us to demonstrate that the accuracy of market research, not

just the relative partworths or the distribution of relative partworths, will determine how firms make strategic decisions on differentiation.

Specifically, the “scale factor” in choice-based conjoint analysis (the logit model) is a function of inherent uncertainty and uncertainty due to measurement. By inherent uncertainty we mean residual uncertainty (stochasticity) in consumer decisions, stochasticity that might be due to actions beyond the firm’s control. Uncertainty in measurement is a function of the quality of the questionnaire, the completeness of the set of product features, and the ability of an estimation method to uncover accurate parameters from the data.

3. Illustrative Example: Conjoint Study on Student Apparel

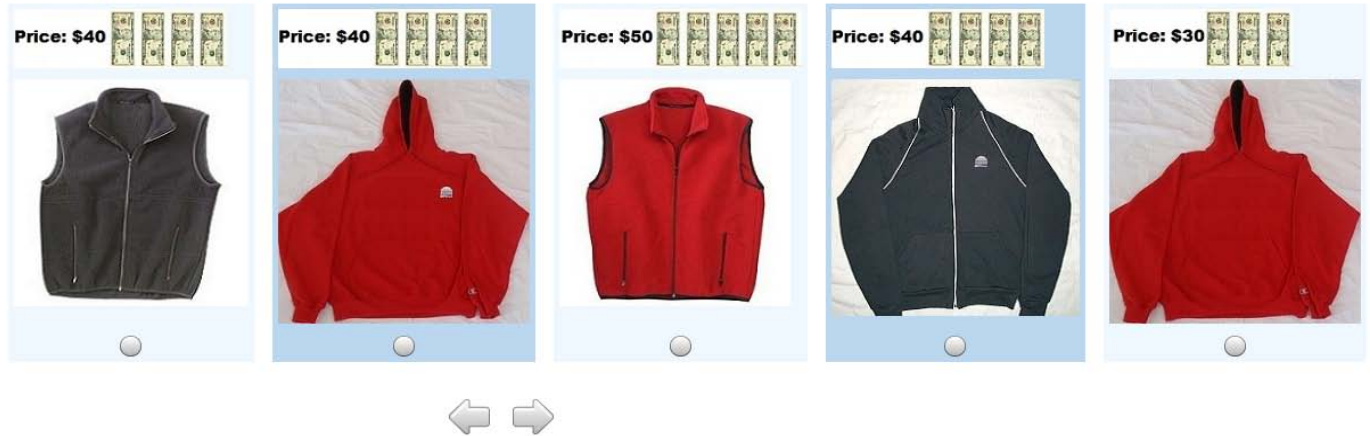
Selove and Hauser (2010) illustrate the practical impact of the theoretical result with an example drawn from a conjoint study on student apparel. Thirty-eight students completed a CBC study with the following features. The study had four cells that varied in a 2×2 design of {careful design and graphics vs. less careful design, words only} \times {incentive compatible vs. not incentive compatible}. For the purposes of this illustration we focus on the nineteen students in the careful-design-and-graphics cells. The product features and levels were:

- Type of clothing: track jacket, sweatshirt, or fleece vest
- Color: grey or red
- Logo: School logo or no logo
- Price: Base level (\$30 for the sweatshirt; \$40 for the other two); or Base level plus \$10

Figure 3 presents a sample choice set. To keep the illustration simple, we have foregone a “no choice” option.

Figure 3. Sample Conjoint Question

If these were your only options, which would you choose?
Choose by clicking one of the buttons below:



Each respondent answered 16 conjoint questions, then, after several memory-cleansing tasks, completed a hold-out task in which they ranked their top 5 out of 12 products. (Asking respondents to rank five products instead of choosing one increases the statistical power of our validity tasks.)

Table 1 reports average partworths computed using Sawtooth's HB/CBC software. The data are from the initial conjoint task. On average, respondents prefer the track jacket, the color grey, the school logo, and lower prices.

Table 1. Average part-worth for each feature level

Sweatshirt	0.0
Fleece vest	-0.7
Track jacket	4.9
Red	0.0
Grey	1.5
No logo	0.0
School logo	4.5
Base price	0.0
Plus \$10	-2.7

Following Salisbury and Feinberg (2010), we adjust the scale factor to account for variance in behavior between the original conjoint task and the hold-out task. This enables us to parse the random component of consumers' utility functions into components: (1) randomness in the ability of the conjoint model to predict behavior in the calibration choice setting and (2) randomness that accounts for changes in behavior across settings. The scale factors estimated by the original HB partworths account for the first type of randomness. Comparison of predictions to the validation task account for the second type of randomness.

To estimate the second component of randomness, we hold fixed the partworths estimated from the calibration data and then estimate an adjustment to the scale factor using the hold-out data. Our estimates suggest that the scale factor needs to be adjusted downward by 0.65 to account for the second type of uncertainty.

We next compute equilibria in a simple product-design game. Two firms each produce a track jacket with a school logo. Firms simultaneously choose colors, then simultaneously set prices. Firms make their color decisions based on (possibly inaccurate) market research, and cannot later change the color of their product once they observe demand. However, prices can be easily adjusted and will reach a Nash equilibrium based on the "true" model of customer behavior. In this game scenario, firms that conduct inaccurate research might make sub-optimal color choices due to inaccurate predictions of demand and of equilibrium prices. In light of our earlier theoretical arguments, firms with inaccurate market research might make erroneous decisions to differentiate and then face a "world" in which differentiation might not have been the better strategic solution, or vice versa.

To demonstrate why market research has strategic implications, we assume that the "true" model of customer behavior is represented by the partworths as estimated on the calibration data, but adjusted by a factor 0.65 to represent the second form of uncertainty. If both firms know the true model of behavior, the best equilibrium strategy is for both to produce a grey jacket. Equilibrium mark-ups are \$11.40 per jacket, and each firm captures one-half of the potential customers. They each have equilibrium profits of \$108.30 among the nineteen students.

Now assume one firm believes that its market research is more accurate than it really is. We represent these delusional beliefs by assuming the firm fails to adjust the scale factor to account for the uncertainty between calibration and validation. Under these conditions the delusional firm (incorrectly) predicts that differentiating its product will increase its equilibrium earnings. It does so but is surprised when true demand is at variance with its predictions. Its actual earnings are lower than they would have been by 3.4%. (The magnitude is not important; this example is illustrative. Different assumptions on factor costs could make this percentage much larger.)

Table 2 provides more detail on equilibrium prices and profits assuming that market research accounts for both forms of uncertainty accurately. Although Firm B would prefer a differentiated market, this is not an equilibrium. Firm A is faced with the differentiation dilemma and should resolve it toward no differentiation (because uncertainty is high). The only equilibrium is the undifferentiated market where both firms offer grey jackets.

Table 2. Equilibrium Prices and Profits in the “True” Market

	Firm A	Firm B			Firm A	Firm B
Color	Grey	Grey		Color	Red	Grey
Marginal Cost	\$40.00	\$40.00		Marginal Cost	\$40.00	\$40.00
Equilibrium Price	\$51.40	\$51.40		Equilibrium Price	\$52.63	\$56.31
Profit Margins	\$11.40	\$11.40		Profit Margins	\$12.63	\$16.31
Demand	9.5	9.5		Demand	8.3	10.7
Profits	\$108.30	\$108.30		Profits	\$104.64	\$174.73

Table 3 provides detail on a simulator that Firm A would use if it did not recognize the need to adjust the scale factor. Firm A underestimates the true uncertainty in the market and resolves the differentiation dilemma in favor of differentiation. It predicts that both firms are better off differentiating and, thus, produces a red jacket.

Table 3. Firm A's Simulator Based on Inaccurate Market Research

	Firm A	Firm B			Firm A	Firm B
Color	Grey	Grey		Color	Red	Grey
Marginal Cost	\$40.00	\$40.00		Marginal Cost	\$40.00	\$40.00
Equilibrium Price	\$47.35	\$47.35		Equilibrium Price	\$49.54	\$53.18
Profit Margins	\$7.35	\$7.35		Profit Margins	\$9.54	\$13.18
Demand	9.5	9.5		Demand	8.0	11.0
Profits	\$69.86	\$69.80		Profits	\$76.08	\$145.32

In this example, Firm A is pleasantly surprised when it launches its product because it actually earns \$104.64 rather than \$76.08. The market research firm is probably rewarded and rehired. However, Firm A does not observe the opportunity loss because its “but-for” world is not accurate. Firm A never knows that it could have earned even greater profits by launching a grey jacket. (However, there are some hints. If Firm A knew that uncertainty implied lack of differentiation, it should be suspicious because its simulator under-forecast profits by 27%.)

We find this example compelling. Firm A makes the wrong strategic decision because it is unaware that its market research is inaccurate. More importantly Firm A never gets to observe its opportunity cost and is pleasantly surprised by the market outcome. Firm A will continue to rely on inaccurate market research and continue to make incorrect strategic decisions. This example illustrates why it is imperative that a firm adopt best practices in market research. The example also motivates academic research for improved measurement and estimation. Even small improvements might tip the scales in the differentiation dilemma.

This example also illustrates the pitfall of relying on internal validation only. It is not hard to image a “quick-and-dirty” CBC study that has good internal validity but poor external validity. For example, the stimuli might make a feature unnecessarily salient, key features may be left out of the mix, or the questions might be worded incorrectly.

Our example is illustrative. Our “validation task” is a within-respondent holdout task and, hence, may not capture all type-2 uncertainty. Nonetheless, by extension of our arguments, firms are advised to undertake true external validity studies. Such studies may pay off by assuring that the firm makes the right strategic decisions.

4. Conclusion

Recent academic research has developed tools that enable managers to predict how product-design decisions affect price competition in a market. Selove and Hauser (2010) show that a firm's strategic behavior can depend upon the accuracy with which it predicts consumer behavior. As true noise in behavior becomes greater, firms shift their emphasis away from product differentiation and focus on the largest segment of demand. Incorrect estimates of the logit scale parameter lead to costly strategic errors.

It is important to conduct market research studies that accurately represent the level of care and thought involved in real-world decision-making, for example, by providing incentives for truthful responses (Ding, Grewal, and Liechty 2005; Ding and Huber 2009), by making sure respondents are familiar with the attributes and the task (Johnson and Orme 1996), and – as was the focus in the current paper – by adjusting for variance in behavior across settings (Salisbury and Feinberg 2010). Such procedures help ensure that managers neither overestimate nor underestimate the true amount of noise in behavior and, hence, make the correct strategic decisions.

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