Game Theory and Conjoint Analysis: Using Choice Data for Strategic Decisions

Christopher N. Chapman, Google[1], cchapman@google.com
Edwin Love, Western Washington University, ed.love@wwu.edu

Chapman, CN, Love, E (2012). Game Theory and Conjoint Analysis: Using Choice Data for Strategic Decisions. From B. Orme, ed. *Proceedings of the 2012 Sawtooth Software Conference*, Orlando, Florida, March 2012.

Abstract
We demonstrate an approach to combine choice-based conjoint (CBC) market simulations with strategic analysis using game theory (GT) models. This extensive and applied case example builds on the limited prior research that has explored the use of game theory and conjoint in combination. We argue that this approach helps to clarify strategic decisions, serves to communicate CBC results more effectively, and focuses research outcomes more clearly on business goals. We present two cases of CBC+GT in a retail product line, and discuss considerations to conduct such analysis properly. Our goal in this paper is to provide an introduction to GT for strategic marketing applications and to demonstrate how it was used successfully in two industry cases.

Introduction

In practitioner settings, presenting the results of choice-based conjoint analysis (CBC) is complex due to the large number of possible analyses and the mass of data available. Although an analyst may wish to represent the breadth and depth of results, stakeholders and decision makers may be distracted or led astray when they focus on details. For instance, in our experience stakeholders often inspect granular effects, such as "Is feature 3 really preferred over feature 5?" As experienced practitioners know, in random utility models, details such as point estimates may be unreliable and do not present the complete information at hand. This means that inspection of such estimates can be misleading.

More importantly, such details of a CBC model are often distant from the actual decisions at hand. We propose that executive stakeholders generally should pay little attention to the specifics of CBC analyses, and instead should spend time considering evidence that more directly informs the strategic decisions at hand. Those may be questions such as: "Should we invest in feature X? What will happen to our brand if we undertake action Y?"

Game theory (GT) presents an approach to address such decision making in the face of uncertainty. If one is able to model possible decisions (business actions), the potential competitive and market responses to those actions, and to assign outcome metrics, then GT potentially can assess likelihood of those outcomes and the forecasted effect of the decisions (Myerson, 1991). Prior research on GT with conjoint has been limited (cf. Choi and Desarbo 1993; Smith 2000) and not yet widely known. We hope that the cases presented here will advance game theory in marketing research generally, and especially in relation to current developments in CBC.

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1 Current affiliation. The research described here was performed while the first author was affiliated with Microsoft Hardware, and is presented with permission.

The quality of a GT analysis is dependent on the accuracy of the strategic model and the data that informs it. However, it is possible to model uncertainty in assumptions and to examine the estimated outcome of a decision under various assumed conditions. Thus, even in cases where outcomes are unclear, one may use GT to examine the likelihood across multiple sets of assumptions.

Consider one possibility: across a range of possible conditions and models, GT indicates that the same decision is warranted. In such a case, one will feel substantially more confident in recommending a strategy thanks to the strategic simulation. A contrary possibility would be if GT indicates that outcomes diverge on the basis of minor differences in assumptions and actions; yet this is also valuable to know because it suggests that a decision is highly uncertain or that we need more information to inform it. In either case, GT is a valuable adjunct to sensitivity analysis.

We outline here an approach to presenting CBC results when specific decisions are needed in the context of market competition: to combine CBC market simulation with game theory (GT) models. We argue that focusing on a strategic decision (when appropriate) may help to make CBC results more useful in a business context. We do not present GT models in depth because the literature on such models is too extensive to review in this paper. However, we hope that the cases here are illustrative for CBC practitioners and will inspire consideration of GT models.

Pairing Game Theory with CBC

There are seven steps required to create a game theory model informed by CBC. First, one must identify the business decision(s) under consideration and the associated outcome metrics of interest. For example, one might consider the decision of whether to enter a new foreign market, with an outcome metric of expected profit over some period of time.

Second, one must identify potential competitive responses to the decision point. In the case of new market entry, a competitive response might be that existing participants in the market would cut their prices in an attempt to retain share and make entry unprofitable.

Third, one must consider responses "by nature" that occur according to outside forces or chance and are not determinable by any participants. An example of this would be refusal of consumers in the new market to purchase goods coming from a foreign entrant. In game theory jargon, such possibilities are likely to involve "information sets" that are not known in advance but become known at some later point.

Fourth, one must assess the various outcomes of other participants and the data needed to inform all of those. For instance, in the foreign market scenario, although the new entrant might be interested in profit, a current participant may be primarily interested in retaining share. It is not required that players have identical goals; but it is necessary to determine the reasonable competitive decisions that could influence outcomes for the focal player.

Fifth, it is necessary to represent these decision points, inputs, naturalistic paths, and final outcomes as a strategic game, and to ensure that the structure and outcomes are complete. In principle, this is easy to do; however, that belies two points: (a) the game must be plausibly correct so that the relevant factors are modeled; and (b) the stakeholders must be convinced of the structural correctness.

Sixth, one must then collect the data required to calculate each of the outcome metrics. In the present example, one might collect data from a CBC study to estimate preference share in the new market using a market simulator, which is then matched with the expected cost of goods to determine profit. It is often the case that some information is unknown, especially as regards other players' intentions and the likelihood of natural outcomes. In those cases, one may substitute expert guesses where better estimates are unavailable. It is advisable to run multiple simulations using both optimistic and pessimistic estimates to determine a likely range of results.

Seventh, the game may then be subjected to estimation using various methods. The most common way to analyze a game is to search for Nash equilibria, which are points where players' strategies are stable given the strategies of other players. In a Nash equilibrium (NE), there is no decision that any single player could take to obtain a better result, given the strategy adopted by other players, and this is true for all players; thus, these are particularly plausible outcomes if players are informed and rational. A particular game may have no NE, or it might have one, or many.

Importantly, an NE does *not* imply a global optimal outcome for any single player or for all players. It merely implies a likely and stable outcome, even if suboptimal. A well-known example is the “prisoners' dilemma,” in which two assumed criminal partners are separately offered a deal to testify against the other: testify and you'll receive between zero to two years in jail; but if you refuse and the other person testifies against you, you'll receive 10 years. Assume that the payoff for each participant looks like the following (for grammatical convenience, we'll assume both players are men):

You testify, he testifies:	2 year in jail for you	(2 for him)
You don't testify, he testifies:	10 years in jail for you	(0 for him)
You testify, he doesn't:	0 years in jail for you	(10 for him)
You don't testify, he doesn't:	1 year in jail for you	(1 for him)

This may be shown as a “strategic form” matrix as shown in Figure 1, where the numbers in parentheses indicate the outcomes for (Player 1, Player 2).

Figure 1: Years in Jail as a Result of Testifying or Not
(Prisoners' Dilemma, Strategic Form Payoff Matrix)

		Player 2	
		Testify	Not testify
Player 1	Testify	(2, 2)	(0, 10)
	Not testify	(10. 0)	(1, 1)

Assume that you are Player 1 and the other person is Player 2. If Player 2 testifies (the first column above), then you are better off testifying as well (receiving 2 year instead 10 years). If he doesn't testify (the second column above),then you are still better off testifying (0 years vs. 1 year). Thus, regardless of what the other player decides, your best strategy is to testify. Because the payoffs are symmetric, the same analysis applies to Player 2.

In this case, testifying is a stable strategy and NE, because given the other player's decision, there is no way to achieve a better outcome. The expected outcome, then, is for both of you to testify and serve 2 years in jail. Although this is a stable and rational strategy under the assumptions here, it is globally suboptimal to the case in which both players refuse to testify and therefore end up with only one year in jail. The problem with the cooperative strategy is that neither player has an incentive to follow it: if you truly believe that the other person is *not* going to testify, then it is in your interest to testify, and walk away with no jail time.

There are various ways to solve for NE. For simple games, as above and in Case 1 below, it may be possible to evaluate them by hand by considering the dominant outcomes. For somewhat more complex games, as in Case 2 below, it may be possible to find an analytic solution through computational processes such as solving simultaneous equations (McKelvey, McLennan, and Turocy, 2007). In other complex cases, solutions expressed as long-run expected outcomes might be approximated through repeated simulations (Gintis, 2000).

It is important to realize that there is no general assurance of finding a solution or being able to estimate stable outcomes; an attempt to create a game that models a complex situation very well may lead to a non-tractable model. To increase the odds of finding a solution, one should strive to keep a game model as simple as is possible and useful in a given circumstance.

The primary results of finding equilibria are estimates of the probabilities that the game concludes at each outcome state. In the prisoners' game above, there is one NE with an outcome node with probability 1.0: that both players testify. In more complex cases, a successful solution will yield the probability for each outcome state. This may be interpreted as the frequency that one would expect to end up in that state, if the game were played an infinite number of times with the same assumptions.

An overall expected value for the game may be computed by vector multiplication of probabilities by outcome value; a confidence interval may be constructed by ranking the values weighted by probability. For instance, suppose a game has three outcomes with (value, probability) = (1, 0.02), (100, 0.96), (10000, 0.02). The expected value is 1*0.02 + 100*0.96 + 10000*0.02 = 200.96, while the 95% confidence interval is [100, 100].

A few other notes are in order. Estimation approaches other than evaluating NE are available and can be useful in situations in which equilibria do not exist or are doubted to be applicable. In general, we recommend evaluating for NE first, and considering other methods after NE feasibility is determined. Repeated games and cooperative games in particular may lead to strategies that are quite different from NE. In the game above, if the players above are 100% cooperative, then the dominant strategy would be *not* to testify.

In this paper, we consider non-cooperative games because those are more often typical of competitors in a market. Additionally, our cases concern two-player, non-repeated games; for more complex situations than those described here, one will wish to review the GT literature to determine which models may apply. An extensive GT literature exists in economics, psychology, and evolutionary biology.

Case 1: Whether to Develop a New Feature

The manufacturer of a PC accessory hardware device was considering the question of whether to add a feature (feature X) to its product line, after learning that Feature X was going to be available from component suppliers in the near future.

For purposes here, the category and feature are disguised. However, the feature X component was somewhat analogous to a higher-speed processor in a computer: it would bring a higher "spec" to the products and was seen as desirable by consumers. On the other hand, it would add cost and might not make much, if any, difference in users' actual experience.

Importantly from a GT modeling perspective, this product category had two dominant players (the manufacturer in question and one other firm), and feature X would be available to both.

Various business stakeholders had differing opinions about whether feature X should be included. Some thought it would appeal to customers and grow category share, while others argued that it would simply add cost and make the category less profitable. The latter group was, in effect, arguing that this was a variety of the prisoner's dilemma described above: adding the feature (e.g., "testifying") would benefit either player in isolation because it appealed to consumers and would take market share from the other player; yet if both players added it, they would simply be dividing the same market at a higher cost, and thus both would be worse off.

The authors realized that this was an almost canonical case of a two-player strategic game: two players faced a single and identical business question, and they had to act simultaneously without knowledge of the other's intent. Additionally, the authors could model the various possible outcomes of the game: because they had fielded more than a dozen conjoint analysis studies in this category, they had the data needed to model a likely market outcome. As shown in Chapman et al (2009), conjoint analysis had proven to be a robust and useful indicator of market outcomes in this product category.

Game 1

We modeled Case 1 as a two-player, simultaneous, one-step game with identical goals for the two players. Since each player had two options, to include feature X or not, the game had four possible outcomes – four "strategies" in GT jargon – for (us, them) respectively: (not include, not include), (not include, include), (include, not include), and (include, include). This game is shown schematically in Figure 2.

Product executives identified the division's strategic goal as maximization of market share, specifically to gain share from the other dominant player. This led us to compute the four sets of outcomes for each player as preference share for likely product lines, with and without feature X, according to the scenario. We then computed share for the players in each of the four outcome scenarios using a comprehensive set of CBC data, using Sawtooth Software Randomized First Choice market simulation.

Figure 2: The Game for Case 1
(Preference Share in Strategic Form Payoff Matrix)

		Player 2 (them)	
		Do not include	Include feature
Player 1 (us)	Do not include	(X11, Y11)	(X12, Y21)
	Include feature	(X21, Y12)	(X22, Y22)

Nothing is Crucial: Why Outside Good Must be Modeled

So far the situation seems simple: for the game we just need the decision points, and the outcomes measured by CBC market simulation. Right? Not quite; there's one fundamental problem that must be resolved: correctly estimating the contribution of outside good (often known in CBC models as the contribution from the "none part worth").

Here's the problem: if both players add feature X, and product lines stay exactly the same otherwise, then the relative preference on an individual by individual basis should not change. In that case, the strategy (include, include) would be identical to the strategy (don't include, don't include). If the latter has share of (40, 60) then the former should also have share (40, 60). Under a strict first choice market simulation model, that is exactly what we would see. Suppose that for an individual, the utilities for player 1 and player 2, without feature X, are *U1* and *U2*; and that the utility of feature X is *X*. Since conjoint assumes that utilities are additive, then for a n arithmetic, binary comparative operator *R* (e.g., *less than*, *greater than*, *equal to*), *U1 R U2* implies *(U1+X) R (U2+X)*. For example, if *U1>U2*, then *(U1+X) > (U2+X)*. Both players have made the same move at the same time, so their relative positions are unchanged.[2] In the strategic game shown in Figure 2, this would imply X11 = X22 and Y11 = Y22. In other words, it says that it makes no difference what the two players do, as long as they both do the same thing. This is obviously not a useful or correct model.

The key to addressing this problem is to have a reasonable baseline from which one can determine whole-market change and not simply relative preference. This is the problem of reference to outside good, in economic jargon, or the "none" choice in conjoint, and is a complex area with ongoing research (cf. Dotson et al, 2012; Howell and Allenby, 2012; and Karty, 2012; all in this volume). Here, we note several ways possibly to address it in routine conjoint models: (1) use first choice preference models in market simulation that are resilient to some foundational issues with logit-model preference estimation (cf. Footnote 2) ; (2) include a dual-response none option in CBC surveys; (2) when estimating part-worths and running simulations, model common or expected interaction effects (such as brand*price interaction, which is common in many categories); (4) in product line simulations, include some fixed products that have or do not have the feature across all scenarios.

In the present case we adopted all four of those strategies to account for the outside good in simulation and ensure that results were not predetermined to be identical. As a general rule, one should have confidence in such choices on the basis of prior research experience (as we noted above, e.g., Chapman, et al, 2009).

Another option we did not employ, but may be considered on other grounds, is using a set of hierarchical Bayes (HB) draws instead of respondent mean betas. Any single draw would have the same issue of preference that is intransitive to feature addition as does any other single-point preference estimate. However, by using multiple draws, such as 1000 estimates per respondent, one would obtain a more accurate picture of the per-respondent distribution of utility overall. By having a more accurate overall estimate, one might expect that concerns about other sources of estimation bias would be partially mitigated. Also, HB draws may be especially valuable for parameters that are more difficult to estimate reliably, such as interaction effects.

A final issue concerns source of volume modeling: feature X may have different effects on the share of other products according to how similar or dissimilar they already are, compared to feature X. For instance, adding a 50 MPG engine to an automotive line should have a different

2 For completeness, we should mention the Red Bus/Blue Bus problem where multinomial logit share models *would* show a change when the same utility is added to both sides of a relation – but that change is inappropriate and an artifact of those models, not a reasonable market expectation. A full discussion of that phenomenon is available in a variety of papers from previous Sawtooth Software Conferences and the AMA ART Forum – e.g., Dotson et al, 2010 – so we leave it aside here except to note it.

effect if the line currently has no car above 30 MPG than it would if the line already includes a car with 45 MPG or 60 MPG; and likewise with respect to competition. Similarity between products ought to inform market simulation, but that is the case in all simulation methods, such as simple logit model estimation. A strategy that at least partially mitigates the problem is a randomized first-choice model (which we employed); more complex models are available when this is a crucial issue for the category and features in question (cf. Dotson et al, 2010).

Case 1 Result

Existing CBC data was used to estimate preference shares as noted above. The CBC exercise comprised 8 attributes with 30 total levels, 12 tasks with no holdouts, collected from N=359 respondents, and utilities estimated with Sawtooth Software CBC/HB. Figure 3 shows the result of four market simulations required for the game and performed with Sawtooth Software SMRT randomized first choice simulation. Each outcome listed in Figure 3 shows the estimated sum preference of the modeled product lines for (Player 1, Player 2), including the "none" option in simulation.

Figure 3: Estimated Market Results for Case 1
(Preference Share in Strategic Form Payoff Matrix)

		Player 2 (them)	
		Do not include	Include feature
Player 1 (us)	Do not include	(23, 44)	(10, 72)
	Include feature	(61, 20)	(29, 54)

In this game, there is one NE that shows strict dominance: both players should include Feature X. We can find this as follows. First, look at the outcomes for Player 2 in Figure 3. In both rows, the outcome for Player 2 is better if they include the feature (72 > 44, and 54 > 20). Thus, Player 2 should include the feature no matter what Player 1 does, and Player 1 only needs to consider the alternatives shown in column 2 (i.e., where Player 2 includes feature X). Looking at that column, Player 1 is better choosing to include feature X (29 > 10). Thus, the strategy of (Include, Include) is a stable strategy and reflects the rational choice for each player given the game assumptions. The same conclusion would be reached by starting with Player 1 instead.

We note also in Figure 3 that both players see an increase in preference share by following the (Include, Include) strategy. In other words, by including feature X, it is possible that the overall market will grow, with both players taking share from the "none" option. This indicates that the game as modeled with its assumptions may not be a prisoners' dilemma with regard to profit, and certainly is not with regards to preference share.

We shared this analysis with executive management, along with the following discussion: (1) we should expect Player 2 to include feature X; (2) if in fact they do not include feature X, that is not a reason for us not to, but rather it is an even stronger reason to include it because of the share we would gain; (3) there is reason to hypothesize that feature X might grow the overall category, which would mitigate concern about increased per-unit cost.

Management was convinced by this analysis and ultimately included feature X in the product line. It turned out that Player 2 had not anticipated this, but belatedly added X to their product line, and that sluggishness appeared to be somewhat detrimental to their brand image. Three years later, Player 1 and Player 2 were the only makers with products in the top 10 by unit sames in this category, and 8 of those 10 products included feature X.

In short, the analysis here appears to have been correct for determining the market demand for feature X, helped management to make that choice, and let the product team advance its brand in the face of a sluggish competitor.

Without the game model that convinced business stakeholders, it is likely that neither Player 1 nor Player 2 would have introduced feature X for one or more years, and would have lost this opportunity to advance their product lines and to meet consumer demand. In a worst-case scenario, this might even have risked incursion in the category by another brand if it discovered the unmet need through such research, which might have caused serious setbacks to the position of both players 1 and 2. Instead, the category was improved by players 1 and 2 strengthening their positions and delivering better, more highly desired products.

Case 2

Following the success described in Case 1, we tackled a more complex problem: what would we expect to occur if an entire product line attempted to redefine its brand position? This would include actions such as redesigning products in terms of features and industrial design, adding and dropping products from the line, producing new packaging and brand materials, advocating different retail presentation, and adopting a new messaging strategy, all in order to change the line's perception and positioning vis-a-vis competitors in the category.

There are many variables in such a question, so we worked with stakeholders to identify a narrower set of questions: (1) if we repositioned as planned, what would be the best-guess outcome for full-line preference share? (2) how much potential downside risk would there be? (3) how would our primary competitor be most likely to respond? (Due to the sensitive nature of the decisions in this case, we disguise the product and refer to the category and issues using only general terms.)

Important background information for this case is that the category had two dominant players (players 1 and 2) along with several smaller players. There was no question of *how* to reposition; the possible direction had been established by other work, and the question was whether it was likely to succeed. Further, it was known that players 1 and 2 had very similar brand perceptions at the present time.

Unfortunately, circumstances required us to produce an answer quickly, without time to collect new data: executives asked for a best-guess assessment with existing data. Luckily, we had data on hand from a recent study in which the category assessed using a CBC with attributes reflecting the full product line scope, along with scale-based adjectival ratings of key brands in the space (e.g., rating of each brand on attributes such as value for the money, trendy design, high performance, and so forth). That data had already been processed to yield three key sets of measures: (a) CBC/HB utilities for brand and other attributes; (b) segmentation of respondents into two segments that differed substantially in both adjectival ratings and CBC utilities; (c) perceptual dimensions (aka composite product mapping, CPM; Sawtooth Software, 2004) for the brands as reflected by adjectival ratings, for each of the two segments.

To make use of that data, we proceeded under the following assumption: brand value as measured in CBC brand utility should be related to a brand's position in perceptual space as measured by CPM. In short, with several brands, it would be plausible to regress their CBC brand utilities on CPM product dimensions. If a brand repositioned in the perceptual space, that regression line might be used to determine its best-guess new value in CBC utility. We assumed that the two segments would have different models according to their differing perceptual and utility measures.

To express that model schematically, we postulated the following:

1. *Brand dimensions ~ adjectival ratings* (CPM model, multiple discriminant analysis; cf. Sawtooth Software, 2004)
2. *Brand utility ~ stated choice observations* (standard CBC model)
3. *Preference share ~ brand utility* (and other CBC utilities, in a standard market simulation model)
4. *Updated brand utilities ~ new position on brand dimensions* (linear model regressing utility on principal brand dimensions)
5. *Updated preference share ~ updated brand utilities* (market simulation with new brand utilities estimated from the regression model)
6. *Full preference model* would express the model above as performed separately for two attitudinal segments, and weighted according to estimated segment prevalence

There are several questionable assumptions in that model; perhaps the most dubious concerns modeling brand utility as a function of perception. Among the objections to such a model are that different brands might each be highly valued exactly because of their perceptual differences (i.e., not fit a regression model); that measurement error in both metrics could make it difficult to find any relationship; and that a relationship would in any case be expected to change precisely because of brand repositioning, invalidating conclusions based on previous positioning.

We agree that those are serious concerns. As researchers in this case we confronted a game theoretic choice of our own: do nothing because of admittedly imperfect data, or try to extract what information we could. In the given context – confronting an imminent decision and request for analysis – we decided there was more value if we informed the executive decision as best we could. In other contexts and with more time, we might prefer to conduct the research differently with another model and freshly collected data.

The Game Model for Case 2

Case 2 poses a simple strategic question: should Player 1 adopt the repositioning strategy or not? Likewise, we were interested whether Player 2 would be likely to adopt the same strategy. We also considered the case that Player 1 might initially stay, but then decide to reposition later, depending on what player 2 did. Thus, the game was:

Time 1:	Player 1 repositions or not, in a specified direction
Time 1:	Player 2 repositions or not, in the same direction
Time 2:	If Player 1 did not reposition at time 1, but Player 2 does, then Player 1 repositions or not at time 2

Despite that simplicity, there is another complication: an attempt to reposition might succeed fully, succeed to a partial extent, or fail altogether. Thus, attempting to reposition does not lead to single predictable outcome, but rather opens the possibility of multiple different outcomes which occur (in game theory parlance) “by nature,” i.e., which occur beyond the control of the player.

Such divergences in possible outcomes should be modeled in the game. In the present case, we modeled four possible outcomes:

1. *Full success*: reposition achieves 100% of the regression model change in brand utility
2. *Partial success*: reposition achieves 25% of the regression model outcome
3. *No change*: reposition results in no change in brand value
4. *Backfire*: reposition results in loss of brand value, -25% of the regression model

Note that the levels of possible outcome (100%, 25%, etc.) are not determinable from data but must be specified by expert opinion. This is a strength of GT models, that they are able to use expert opinion to model multiple scenarios when better information is not available.

The full game model had 41 outcome nodes, as follow:

Player 1 choice	**Player 2 choice**	**Outcome nodes**
Do nothing	Do nothing	1
Do nothing	Reposition (4 outcomes)	4
Reposition (4 outcomes)	Do nothing	4
Reposition (4 outcomes)	Reposition (4 outcomes)	16
Do nothing at Time 1 + Reposition Time 2 (4 outcomes)	Reposition (4 outcomes)	16
Total scenarios (ignoring duplicates)		41

Some of those scenarios are effective duplicates (e.g., “do nothing, do nothing” has the same effective outcome as “attempt reposition with no change, attempt reposition with no change”). However, the odds of the branches occurring could be different and they might occur at different times in the game when different information is available top the players (e.g., if a decision occurs at Time 2 in the game). We shall skip a detailed exegesis of those combinations, except to say that they should be reflected in the game model with careful attention to timing and the appropriate “information sets” available to the players.

We then specified a range of likelihoods for each of those outcomes, again, based on expert assumption. For instance, one set of likelihoods we assigned was the following:

Full success:	10% chance
Partial success:	50% chance
No change:	30% chance
Backfire:	10% chance

We constructed multiple sets of such outcomes likelihoods, using a conservative set of assumptions that regarded full success as unlikely.

To recap, the model comprised the following elements:

- Predicted change in brand utility based on movement on a perceptual map
- Estimated change in preference share based on those brand utilities (market simulation)
- A game reflecting player strategic decisions and subsequent natural outcomes
- Multiple sets of assumptions about the likelihood of those natural outcomes

With those elements in place, we were then able to run the game multiple times, under the various sets of assumptions about natural outcome likelihood. Unlike Case 1 above, the GT model for Case 2 requires estimation software; we used the open source Gambit program (McKelvey, McLennan, and Turocy, 2007).

Case 2 Result

The model results in two components: (1) preference share for each outcome node, as determined by the market simulation using adjusted brand utilities, and (2) the result of the game model, which specifies the likelihood for that outcome node. Given the values and their likelihood estimates, simple descriptive statistics can be used to determine a median outcome, 80% likelihood intervals, or other distribution characteristics.

Across runs with varying sets of parameters as noted above, the Case 2 model yielded the following overall result:

1. If we repositioned, and given the model assumptions, the likely outcome would be a gain in preference share of 6 to 12 points vs. the primary competitor in the category.
2. Downside risk from attempting repositioning appeared to be no more than -1 point change in preference share.
3. The competitor was unlikely to respond with a similar repositioning strategy.

On the basis of this analysis, stakeholders felt more confident in the repositioning strategy, and we did not find any reason to object to it. The outcome appeared unlikely to be worse that the current position, while it offered substantial opportunity for differential and advantageous positioning with respect to the competitor and consumer perception.

The repositioning strategy was adopted soon after this analysis, which was approximately two years before the time of this writing. Market results are unavailable due to confidentiality and employment change for the first author, but there is no reason to suspect that the choice was mistaken, and the product line continues to follow the repositioned strategy.

Potential Pitfalls of Game Theory with CBC Data

The validity of a game model depends, of course, on the quality of the outcome estimates for the various strategic branches. There are several generally well-known issues in CBC modeling that are especially problematic for GT models. Indeed, one of the advantages of GT modeling is that it forces an analyst to confront those issues with CBC deliberately, whereas in other circumstances it would be possible to ignore them and perhaps reach erroneous conclusions.

<u>Problem 1: Market simulation</u>. To have confidence in the GT mode, the underlying market simulations must be strongly reliable. It is best to do this modeling in an area where there

is enough history to know that the proper attributes/levels are being tested with conjoint, and that market simulations are giving reasonably accurate results. An analyst will need to decide case by case when it is better to do some GT modeling in the face of imperfect data than to do nothing. In any case, it is strongly recommended to use more advanced market simulation models such as RFC or bootstrapping over HB draws instead of logit share models.

Problem 2: None. As we described above, an especially important part of a GT model with market simulations concerns the question of outside good. The "None part worth" may be used to get an estimate of that (as described in Case 1 above), but it must be noted that there are many conceptual, methodological, and empirical problems with None. When None is used, an outcome may be more attractive because of its potential to attract new interest. However, when this involves a new feature, it may also simply reflect error in the None distribution that makes anything new appear erroneously to be attractive (cf. Karty, 2011). Recommendation: if your game requires an estimate of outside good – as any or even most interesting marketing cases do – review the issues and options carefully.

Problem 3: Main effects vs. interaction. For many CBC+GT models, it is important to add an interaction effect between key decision components (such as brand and price). Consider the following situation: Brand A and Brand B could each add feature X, which costs the same for both brands. Assume that utility outcome was estimated from CBC using only main effects. If there is a brand*price interaction – for instance, because one brand customarily has had higher price points – then adding the same price utility for feature X in both brands would likely be inappropriate. This does not imply one should estimate all possible interaction terms in CBC, but rather the ones most important for market simulation stability and the GT decision points. Quite often that may be one specific attribute (price, design, or a feature) that interacts with brand.

Problem 4: Similarity and source of volume. There are well-known problems with portfolio comparisons when products are similar (Huber, et al, 1999; Dotson, et al, 2010). If the market simulation model has several products that are closely related or functionally interchangeable, the analyst should consider correction for product similarity. Without correction for similarity, and especially if simple logit models are used, then the market simulation estimates may be substantially in error. At a minimum, we recommend to use randomized first choice (RFC) models; there are other procedures available for cases where similarity is high (Dotson, et al, 2010).

Other Notes about Game Theory

There are a few other important concepts in game theory that are likely to come up in marketing applications. We note them here primarily for awareness of GT options.

Payoff imbalance. Businesses typically view active mistakes as much worse than a passive loss, so utilities may need to be adjusted to account for risk avoidance and other mis-estimation behavior (cf. Gourville, 2004). For instance, the outcome metric in a game (such as *share* in the games presented here) might be weighted such that negative change is calculated on an altered scale that reflects the imbalance as viewed by stakeholders, such as 3x, $-(x^2)$ or some other multiple of its actual value.

Iterated or sequenced games. In actual situations, strategic decisions may be iterated, rather than adopting a simple "simultaneous decision" model. Thus, GT models may need to be iterated, and likely will need to model multiple information sets rather than perfect knowledge (cf. Myerson, 1991). A particularly interesting family of games involves those that are iterated indefinitely. These are often used in evolutionary models, and also provide alternative methods to find equilibria and stable points in some classes of games that defy analytic solution (cf. Gintis, 2000).

Multi-player games. Game models can be extended in a straightforward way to situations where there are multiple players (multiple brands, etc.). However, the stability of market simulation results is likely to decline, and very close attention should be paid to brand effects, the impact of distribution, channel, and availability, and so forth. Those effects may not be necessary to model formally as part of the market simulation, but should be considered and included in the interpretation.

Conclusion

Game theory has great potential for analyzing strategic marketing situations. We believe that the examples presented here are illustrative of its power to inform business decisions. In particular, game theory is a valuable adjunct to conjoint analysis for three primary reasons: (1) it directly models strategic decisions, which is intrinsically of interest for businesses; (2) it provides a concise way to frame questions, assumptions, and results, allowing for direct focus on the decisions at hand; (3) it can incorporate uncertainty and assumptions, making it a valuable adjunct to sensitivity analysis and situations where data such as conjoint analysis informs only one part of a complex picture.

It seems that game theory has been little used to date in marketing science, but with the growth of available data and computing power to simulate complex models, there is great potential for the application of game theory to marketing problems in the future.

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