Note on Conjoint Analysis

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Suppose that you are working for one of the primary brands of global positioning systems (GPSs). A GPS device receives signals from satellites and, based on those signals, it can calculate its location and altitude. This information is displayed either as text (latitude, longitude, and altitude), as a position relative to a known object (waypoint), or a position on a map or navigational chart. GPSs are particularly useful when you are out of range of cell phone towers and cannot rely on the mapping function in your smartphone. (Although smartphones are now more ubiquitous, this example nicely illustrates conjoint analysis. We'll see other more-recent examples in class.) Last year there were 20,000 documented applications of conjoint analysis involving products and services in almost all industries.)

GPSs come in many versions. We will consider handheld devices that are useful for hiking, camping, canoeing, kayaking, or just walking around remote areas. Suppose that it is your responsibility to decide which attributes (and prices) the new handheld GPS will have. Each attribute is costly to include. Including the attribute is likely to be profitable if the consumers' willingness to pay (WTP) for that attribute exceeds the cost of including that attribute by a comfortable margin.

Simplified Conjoint Analysis Illustration

We simplify the problem for illustration. First, let's assume that all consumers have the same preferences – the same WTP for each attribute. In real markets we do not need this assumption because we analyze preferences by segment or by individual consumers. Second, let's assume that there are no engineering constraints. The GPS can have all of the attributes, some of the attributes, or none of the attributes and the costs are additive. Finally, we focus only on three binary attributes of interest, plus price:

- Accuracy – the GPS can locate your position within 5 feet or within 50 feet
- Display – the screen either displays objects in 3D with a resolution so good that you cannot discern pixels or the screen displays only 2D maps with resolution sufficient for almost all uses
- Battery life – the battery lasts either 12 hours or 32 hours
- Price – the price is either $150 and $250

With four things varying (3 attributes plus price), at two levels each, there are $2\ x\ 2\ x\ 2\ x\ 2 = 2^4 = 16$ possible combinations. Suppose that we create realistic pictures of each of the sixteen handheld GPSs and have consumers evaluate all sixteen GPS "profiles." We might also include animations so that consumers understand the attributes accurately. A simple conjoint analysis task asks consumers to rate each potential GPS on a 100-point scale where 100 means most preferred. Naturally, great care would be taken to make sure that consumers understood the attributes and that the task is realistic. (We show examples later in this note.)

The data, for a single consumer, might look like that in Table 1. The first column indicates the consumer's preference for a particular combination of attributes and price. (These data are indicated by *italics* in the first column.) The next four columns describe the experimental design. Each entry indicates whether or not the rated handheld GPS has that attribute-price combination. An entry of '1' indicates the attribute is at its "high" level, e.g., 5 feet rather than 50 feet, and an entry of '0' indicates a attribute is at its "low" level, e.g., 50 feet rather than 5 feet. In Table 1, the consumer gives a low rating ('*4*') to indicate that consumer prefers least an inaccurate GPS, with low battery life, a 2D adequate screen, and priced at $250. This row is highlighted in red. The same consumer might give a high rating ('*99*') to indicate that the consumer prefers most an accurate GPS, with a long battery life, a 3D high-resolution screen, and priced at $150. This row is highlighted in green.

The goal of conjoint analysis is to determine how much each level of each attribute contributes to the consumer's overall preference. This contribution is called the "partworth" of the attribute level. (One level of accuracy is 5 feet; the other level is 50 feet. Because all partworths are relative to the low level of a attribute, we need only report the partworth of the best level, (5 feet) relative the worse level (50 feet). There are other ways to scale the partworths., for ex-

ample, we can use "mean-centered differences" in which the partworths add to zero. For mean-centered differences, the partworth of 50 feet would be minus the partworth of 5 feet. You will see "mean-centered differences" in the dormitory design exercise.

Table 1. Illustrative Preference Ratings for 16 Handheld GPSs

Data	***Experimental Design (Coding of Attribute Levels)***			
Preference Rating by Consumer	**Accuracy** within 5 feet vs. within 50 feet	**Battery** 32 hours vs. 12 hours	**Display** 3D high vs. 2D adequate	**Price** $150 vs. $250
4	0	0	0	0
41	0	0	0	1
18	0	0	1	0
60	0	0	1	1
33	0	1	0	0
74	0	1	0	1
49	0	1	1	0
86	0	1	1	1
11	1	0	0	0
55	1	0	0	1
27	1	0	1	0
66	1	0	1	1
41	1	1	0	0
85	1	1	0	1
58	1	1	1	0
99	1	1	1	1

In this illustration, we can use ordinary least-squares (OLS) regression as taught in DMD. The analysis is easy to run in Excel as will be demonstrated in class. An abridged output is shown below. The partworths are the regression coefficients. For example, the partworth of 5 feet (vs. 50 feet) is 9.6 indicating that the consumer gets 9.6 "utils" if the accuracy of the GPS is improved. Similarly, the regression estimates that the consumer gets 40.6 "utils" if the price is reduced from $250 to $150.[1]

We use the output of the regression to compute the consumer's willingness to pay (WTP) for each change in the level of a attribute. Because the consumer gets 40.6 "utils" when the price is reduced by $100 ($250 → $150), the value of each "util" is about $2.46/util, that is ($250 – $150)/40.6 utils. We now compute the WTP for accuracy. It is approximately $23.65, which we as obtained by (9.6 utils)*($2.46/util). Similarly, the WTP for increased battery life is $74.88 and the WTP for a the improved display is $36.70. All partworths are relative, that is,

they measure the value of changing a attribute of the GPS from its low level to a higher level.

Table 2. Regression to Estimate Partworths for Attributes and Price

	Coefficients	*Standard Error*	*t-statistic*
Intercept	2.7	1.0	2.7
Within 5 feet vs. within 50 feet	9.6	0.9	10.9
Battery life: 32 hours vs. 12 hours	30.4	0.9	34.5
3D high-res vs. 2D adequate	14.9	0.9	16.9
Price of $150 vs. $250	40.6	0.9	46.1

These partworths are approximate rather than exact numbers because there is measurement error when the consumer provides his or her preferences on the questionnaire. This measurement error translates into uncertainty in the estimates of the partworths as indicated by the standard errors that are reported in the regression (not shown in Table 2). Nonetheless, if we asked enough consumers to complete a conjoint analysis exercise, we gain greater statistical power and obtain estimates of the partworths that are more accurate. The more accurate partworths give more accurate estimates of WTP.

Stimuli shown to consumers are usually more than simple lists of attributes. Figure 1 illustrates a stimulus from an actual GPS study. The application used more attributes than our simple example and some of the attributes are different than in our example. Figure 1 illustrates the care that is often used so that consumers can respond to stimuli that accurately depict potential products that are to be sold in the market. Researchers often use animations to describe the attributes and describe the tasks that the respondents should complete.

We provide software that enables you to develop conjoint-analysis questionnaires. If you obtain responses to your questionnaires, the software automatically computes the partworths (using a more sophisticated method than OLS regression). The software also displays average partworths and partworths for each segment. The software also provides a file that enables you to examine partworths for each respondent.

Figure 1: GPS Stimulus with 16 attributes

Another Example with a Different Format – Laptop Computer Bags

The figure on the right asks consumers to compare two laptop computer bags that differ on two attributes plus price. Consumers are asked to assume that all other attributes of the two bags are identical. This format is known as a "partial profile" method. In this particular study there were ten attributes that were varied in combinations of three attributes at a time. The set of questions asked of each consumer, was adaptive in the sense that the computer chose the next set of comparison attributes based on the consumer's previous answers. In this way, roughly 16 questions were enough to provide sufficient accuracy.

Suppose that, after the consumer answered all 16 questions, we use an estimation method that takes the adaptive nature of questions into account.[2] Suppose further that all estimates are of sufficient accuracy. Then, the partworths might be the following. (I've chosen simple numbers to illustrate WTP calculations.)

- price: partworth = 5
- handle: partworth = 2
- mesh pocket: partworth = 1

The consumer "pays" 5 utils to reduce the price from $100 to $75, thus each util is worth $5 to the consumer ($25/5 utils). This implies that the mesh pocket is worth $5 [$25*(1 util/5 utils]and the handle is worth $10 [$25*(2 utils/5 utils)]. In other words, consumers would be willing to pay $5 more for a laptop bag with a mesh pocket and $10 more for a laptop bag with a handle. If, when selling direct (with a unique brand so that there is no price competition), the manufacturer could produce a laptop bag with a handle for less than $10, it should do so because there is profit to be made. If the bags are not sold direct, then retail margins have to be taken into account. If the firm has competition, then competition must be taken into account. (We would need a simulator as in the dormitory design exercise.)

We cover segmentation, targeting , and positioning (STP) elsewhere in the course and it applies here. Conjoint analysis tells us about the demand curve as based on the consumers' WTPs. The market price will depend upon the ability of the firm to differentiate its product and upon competition in the market place. Nonetheless, conjoint analysis tells us what attributes are important to consumers and gives us ideas about differentiation.

An advantage of modern estimation methods for conjoint analysis is that they handle differences among consumers. This enables conjoint analysis to be used for segmentation and targeting. For example, one segment of consumers might be willing to pay substantially more for a handle than $10 while another segment of consumers might not be willing to pay even $1. If you are selling online, you can promote the handle to the first segment of consumers, but not the second segment. (We address the prediction of market share or sales later in this note.)

Choice-Based Conjoint Analysis

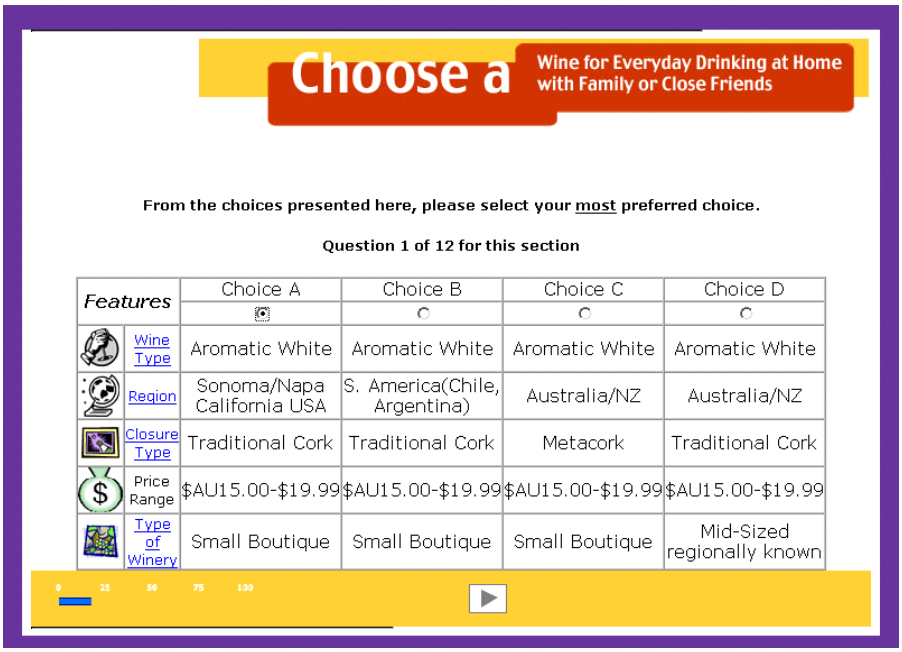
The GPS and laptop bag examples illustrate two data-collection formats that are well-

suited to analysis with OLS regression. Modern estimation methods are more-sophisticated and "borrow" information from the consumer population as a whole. We describe two such estimation procedures later in this note.

With the advent of web-based interviewing and improved computational methods, conjoint analysis evolved to a "choice-based" format. Although other formats are still in use, the choice-based format is now used in the vast majority of applications. The basic idea is that, rather than asking consumers to rate product profiles in terms of utility, we simply ask consumers to choose among alternative product profiles. Most researchers believe that the choice-based format is more realistic, although there is evidence that other formats work well if they are implemented carefully.

Figure 2 illustrates a conjoint analysis that was used to evaluate consumers' preferences for various wine-closures. Notice that some of the attributes of the profiles in Figure 2 have more than two levels. For example, the region of origin for the wine can be the US, South America, Australia/New Zealand, or France. (France was in the study but not shown in Figure 2). As with two-level attributes, conjoint analysis measures relative preferences, such as the relative preference for a wine from France relative to a wine from the US. Only differences in part-worths matter.

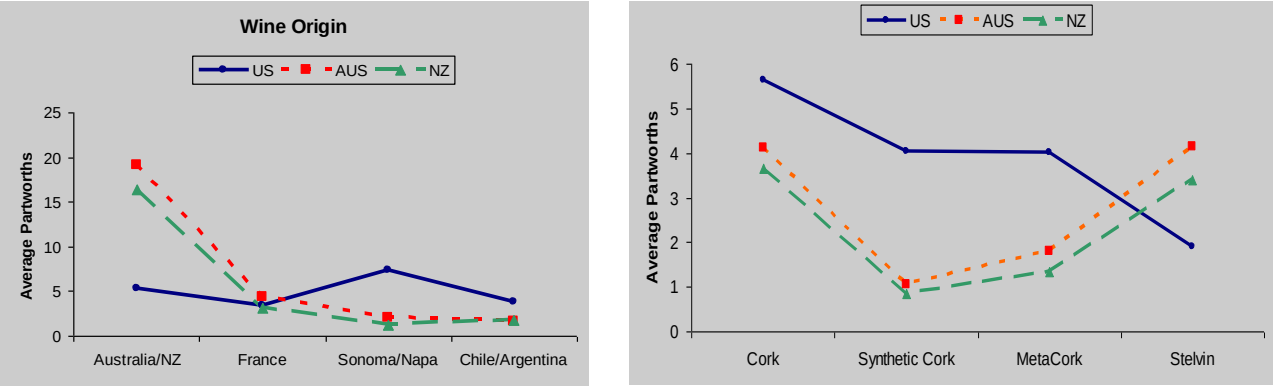
Figure 2. Choice-based Conjoint Task for Premium Wines



The particular closure of interest in the study was a screw-top cap called a Stelvin. Stelvins are a superior closure to prevent wines from being "corked." A wine becomes corked when it is spoiled by rapid aging, discoloration, and/or loss of fruit flavors due to contamination by trichloroanisole. Stelvins are also favored by hotels, restaurants and other functions, because they can be opened rapidly during table service. In the US there is a perception that screw-top caps connote lower quality wines. In Australia and New Zealand, where Stelvins have been in common use since the early 2000s, many wineries sell their best wines sealed with Stelvins. (Fifteen wineries in Australian and 27 wineries in New Zealand simultaneously introduced Stelvins in a campaign known as "Riesling with a twist.")

After being introduced to the various attributes of wines, consumers were given a choice among four wine-profiles where each profile was described by its attributes.[3] The task was repeated for twelve sets of four alternative wines. By making these choices, consumers revealed the tradeoffs that they were making among the attributes. Recall that the underlying data provide partworths for every consumer in the sample, thus enabling both segmentation and targeting. Figure 3 indicates the average partworths of US consumers, Australian consumers, and New Zealand consumers for wine closures and for country of origin.

Figure 3. Partworths for Country of Origin and for Wine Closures



As expected each country's consumers tend to favor wines from their own regions. More interestingly, both the Australian and New Zealand consumers prefer Stelvins as much as traditional corks. On the other hand, US consumers have a very low preference for Stelvins—much lower than for traditional corks and well below even synthetic corks and metacorks. Clearly, US consumers are not yet ready to accept Stelvins for premium wines, but there is

hope. Australia and New Zealand changed the image of Stelvins with a coordinated marketing effort. If the US wineries were to repeat that effort, they might successfully introduce Stelvins. Alternatively, US wineries might lower the price of Stelvin-closed wines for a few premium wines. If the US wineries could get US consumers to be comfortable with Stelvins and experience the benefits of Stelvins, then the US wineries could move US consumer preferences toward the preferences that are observed in Australia and New Zealand. Willingness to pay analyses based on the conjoint analysis data suggested that a minimal price reduction would be sufficient to seed the market.

How Choice-Based Conjoint Analysis Works – the Conceptual Idea

Although the software we provide you for your action-learning projects computes partworths automatically, we recommend that you read the following to understand how those estimates were obtained. For the dormitory design exercise, we provide a file with pre-estimated partworths.

The choice-based format does not measure utility directly, so OLS regression (as in DMD) cannot be used. The secret to the analysis of choice-based data is that each question reveals constraints on the partworths. With enough constraints we can identify partworths quite well. We begin with a conceptual example that is designed to be very simple. In a real study we would describe the attributes more realistically.

Figure 4. A Consumer Reveals a Constraint on Partworths by Answering a Choice Question

Satellite Television Service

	Profile 1	Profile 2
Network	Dish	Dish
Number of Channels	120	120
Premium Channels	3	3
Includes DVR	NO	YES
Price	$35	$40
Which product do you choose between the two?	○	✓

Suppose that we are using conjoint analysis to determine the willingness to pay for attributes of a satellite television service and describe two satellite-television-service profiles to a consumer. These profiles are shown in Figure 4. Both are available from the same provider, the Dish Network. They are identical except that one has a DVR and the other does not and that the DVR-less service is priced at $35 per month rather than $40 per month – that is, $5 less expensive.

Now suppose that the consumer checks the satellite television service on the left indicating that he or she prefers a satellite television service without a DVR if he or she can get it for $5 less per month. The consumer's answer to this question tells us that the consumer values the DVR by <u>less than</u> $5 per month. This gives us one constraint: the partworth of a DVR (vs. no DVR) is less than the partworth of $35 (vs. $40). We call the datum a constraint because the consumer's choice tells us that "value of DVR" $\leq$ $5, where $5 = $40 – $35. The datum does not provide an number for the "value of DVR."

On the other hand, if the consumer had checked the satellite television service on the right, then he or she would be telling us that he or she values the DVR by <u>more than</u> $5 per month ("value of DVR" $\geq$ $5, where $5 = $40 – $35). If the consumer checked the DVR on the right, we would know that the partworth of a DVR (vs. no DVR) is more than the partworth of $35 (vs. $40).

A single constraint tells us something about the partworths. More constraints tell us more. Suppose that each choice question has four alternatives, then we observe three constraints. The chosen profile is preferred to the second, third, and fourth profile. If we ask sixteen choice questions with four alternatives in each question, then we have 48 constraints for each consumer. [48 = $(4-1)\ x\ 16 = 3\ x\ 1$]

But we also gain information from an economic theory of rationality. We know that the partworth of $35 is larger than the partworth of $40 because consumers prefer a price of $35 to $40. We also know that the partworth of a DVR (all else equal – the inherent assumption in conjoint analysis) is greater than or equal to the partworth of no DVR, etc. For the five two-level attributes in Figure 4, we gain five additional constraints.[4] We have a total of 53 (= 48 + 5) constraints.

If we were only interested in population averages, we might merge data from a sample of 300 consumers. A sample of 300 consumers would provide $300\ x\ 53 = 15{,}900$ constraints – more than enough to get good population-level estimates of the relative partworths. More advanced estimation methods, some based on machine-learning, "borrow" information from the population estimates and modify those estimates for each respondent. The software we provide for your action-learning projects uses such modern methods.[5]

Handling More than Just a Few Attributes

In Table 1 we obtained preference ratings for each combination of the three attributes and price. There were 16 possible profiles representing every possible attribute-price combinations. ($16 = 2\ x\ 2\ x\ 2\ x\ 2$). Suppose we add a GPS attribute such as weight (4 oz. vs. 7 oz.). We would now require 32 profiles to represent all combinations ($2\ x\ 2\ x\ 2\ x\ 2\ x\ 2 = 32$). If the consumer were to rate all 32 profiles the task would be twice as hard, but still feasible. Each time we add a binary attribute we double the number of profiles in a "full factorial" design. As the number of attributes gets large, the consumer's task becomes difficult, if not impossible. For example, the real GPS example in Figure 1 has sixteen binary attributes. If we were to simply continue doubling the number of profiles every time we added another binary attribute, we would need $2^{16} = 65{,}546$ profiles – a burdensome task for even the most patient consumer. If the attributes had three levels each, we would require $3^{16} = 43{,}046{,}721$ profiles.

When using choice-based conjoint analysis, we can use a simple "trick" if we have enough respondents. We choose profiles randomly subject to what is know as level balance. For example, if there are four alternatives in a choice task and we have four levels of an attribute, say US, France, New Zealand, and Australia as country of origin (wine study), then each alternative in a choice set has a different country of origin. Such designs tend to be highly "efficient" such that, when we consider the entire data set, each attribute is either uncorrelated or weakly correlated with every other attribute in the experimental design. The software package made available for you action-learning projects chooses questions automatically using a random design.

High-Realism Stimuli are Critical

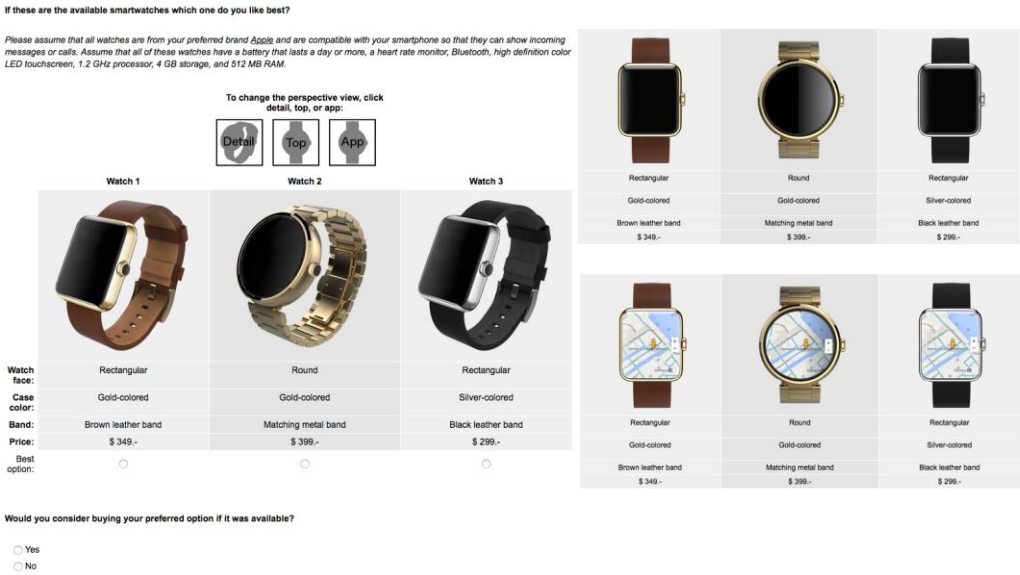
Conjoint analysis asks respondents to choose among product (or service) profiles that

are described by attributes and price. To obtain accurate partworths and to be able to predict how respondents will behave in real markets, we want the respondent to react to the questions in the same way the respondent would react in real markets. It stands to reason that if the attributes or the profiles are not described well, neither the partworths nor the predictions will be accurate. Choosing high-realism images is important.

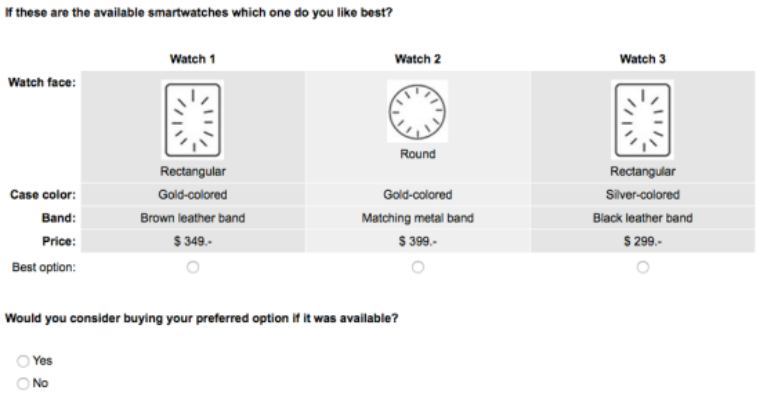
Most software uses a standard format. It is tempting to use only that format and describe each attribute by text only. You are jeopardizing your career if you do so, because price and positioning decisions based on poorly-estimated partworths could lead to unprofitable decisions. For stimuli used in conjoint-analysis profiles, text is not always sufficient. For example, when the iPhone was first introduced, pinch to zoom was relatively new. (It's hard to image now that pinch to zoom was once new and had to be explained to consumers.) If Apple had used only the words, "pinch to zoom," respondents likely would have underestimated the relative importance of this attribute. WTP estimates would have been low and Apple may not have introduced this attribute that changed the way we communicate. Instead, when Apple sought to determine how much consumers valued pinch to zoom, they used realistic animations to illustrate the pinch-to-zoom attribute and to compare it to a touchscreen that could not use pinch to zoom.

Figure 5 illustrates two conjoint profiles for smart watches. The first uses images and allows the respondent to toggle among alternative views. The second uses rudimentary images and text. This is a simplified example, but, even here, which do you find more realistic? To further enhance realism, respondents were shown an animation that described the attributes and gave instructions on how to answer the questions. See https://youtu.be/oji_bw_oxTU.

Figure 5. Higher-Realism And Lower-Realism Profiles



(a) Higher-realism stimuli (left). Respondent could toggle the view



(b) Lower-realism stimuli. Toggling was not available in this condition.

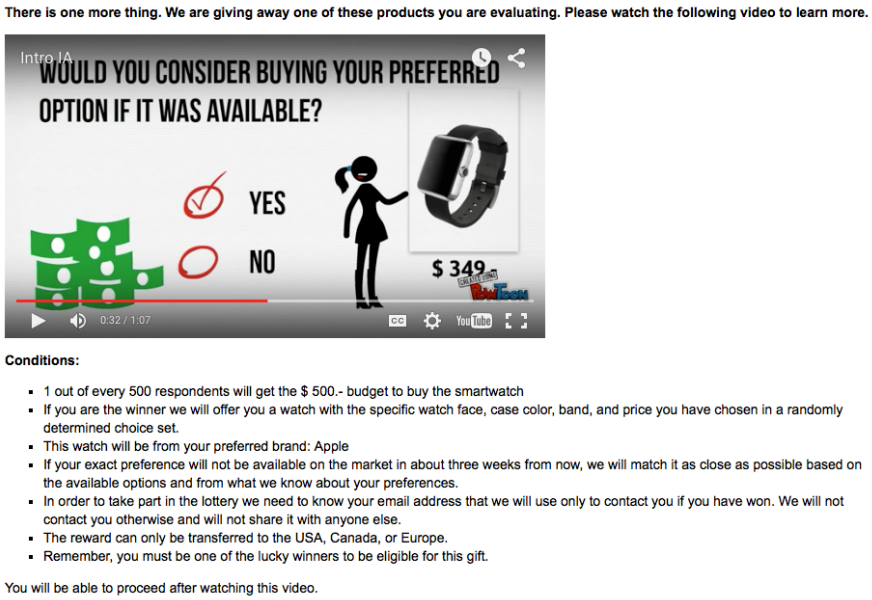
Incentive Alignment

In addition to high-realism profiles, conjoint analysis often uses incentive alignment. The goal of incentive alignment is to make the choice task meaningful to the respondent so that the resulting partworths best describe how the respondent will act in a real marketplace. A task is incentive aligned if (1) each consumers believes it is in his or her interests to think hard and tell the truth, (2) it is, as much as feasible, in each consumer's interests to do so, and (3) there is no way, that is obvious to the a consumers, by which a consumer can improve his or her welfare by "cheating."[6]

The simplest way to align incentives for conjoint analysis is to tell respondents, who complete the conjoint analysis task, that one or more consumers will be chosen by a lottery to win a prize. The prize will be chosen from a secret set of products. The secret set will be revealed at the end of the study and will consist of products described by the attributes in the study. For example, in the GPS study (Figure 1), one out of every one hundred consumers who completed the questionnaire received a GPS. The respondents were told truthfully that the researcher would choose the product that the respondent received based on the respondent's answers to the conjoint analysis questions. To avoid incentives to choose the most expensive product, the winning respondents received a predetermined value, say $300. If a respondent's answers indicated that the respondent's most preferred GPS was priced at less than $300, the respondent received the indicated GPS plus enough cash to equal $300.

Figure 6 illustrates incentive-alignment instructions for the conjoint analysis profiles in Figure 5. See https://youtu.be/DBLPfRJo2Ho for a video describing incentive alignment for this study. All respondents saw this video. The data on which the dormitory design exercise is based used incentive alignment. Respondents had a reasonable chance of winning free rent for a year, plus any cash remainder.

Figure 6. Incentive Alignment Screenshot from the Higher-Quality Study



Incentives can be aligned even for expensive durable goods. For example, we used in-

centive alignment for a study of automotive attributes. The lottery winner received a chance to win an automobile worth $40,000. The winner chose two out of twenty envelopes. If both had said "automobile," then the lottery winner would have received the $40,000 prize. If at least one envelope did not say "automobile," the winner received a consolation prize of $200.[7] Because most researchers cannot afford to risk $40,000 in a conjoint analysis study, researchers purchase prize-indemnity insurance to cover the risk. (In the automotive study, prize indemnity insurance cost approximately $1,200 and was obtained from a bonded firm specializing in lotteries for media—Million Dollar Media.)

Do High-Realism Images and Incentive Alignment Matter?

High-realism images and incentive alignment are aspects of "craft," that is the care and effort put into the conjoint analysis study. Other aspects of craft include the instructions to respondents, how carefully the "all else equal" aspect of the study is described to respondents, and the overall format of the questions. The selection and definitions of attributes is an aspect of craft that is often overlooked. For high accuracy, craft should be a consideration is all aspects of the conjoint analysis study. Do not just use software defaults!

We recently completed one study based on Figures 5 and 6. Conjoint studies were completed (for respondents drawn from the same sample population) in which some respondents saw high-realism images and other respondents saw low-realism images. Likewise, some respondents received incentive alignment instructions and some respondents did not. Table 3 summarizes the average willingness-to-pay estimates. (For comparative purposes, we averaged over high- and low-realism stimuli in the incentive columns and we averaged over both incentives and no incentives in the images columns. When we compare high-quality-image-incentive-aligned with low-quality-image-not-incentive-aligned, the results are even more dramatic.

Clearly, craft matters. The effect is not large for some attributes (gold- vs. silver), but huge for other attributes (metal vs. leather). It is your product and you want to make the best decisions. You shirk on craft at your peril. Suppose that you used low realism images. You would have underpriced all attributes of the smart watches and left substantial profit on the table. If your competitor bases its decisions on high-craft studies, it will introduce more profitable and higher-market-share products.

Table 3. Craft Affects Willingness To Pay (Price Premium, Consumer Demand)

	High-realism images	Low- realism images	Incentive alignment	No incentive alignment
Round to rectangular watch face	$103	$39	$89	$47
Gold-colored to silver-colored case	$65	$59	$71	$55
Brown leather to black leather band	$130	$42	$97	$62
Metal to black leather band	$132	$4	$71	$42

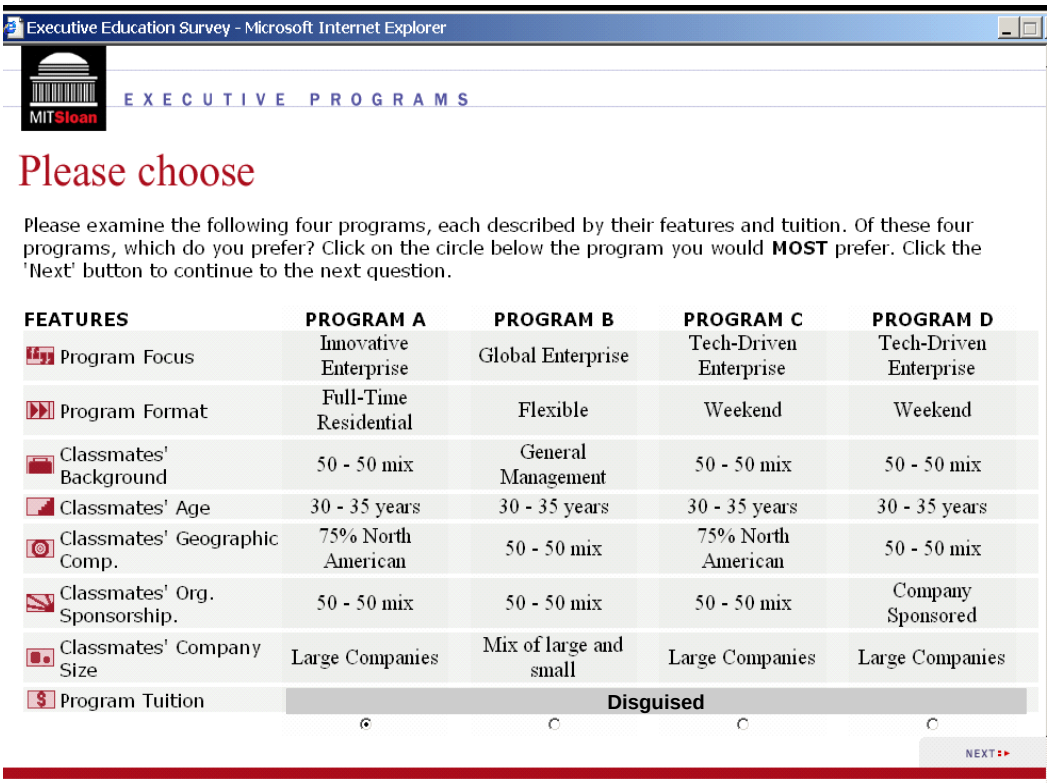
We cannot assume that low-realism or no-incentives will always underestimate WTP. In this study, we used attributes that the respondent valued more when they understood the attributes better. In other instances, respondents might value attributes less after they see them. In those cases the use of low-realism images or the lack of incentive alignment would cause you to overestimate WTP and demand—you could launch a new product that fails or set too high a price for a attribute that would have been profitable at a lower price.

Conjoint Analysis Simulators

Summaries, such as in Tables 2 and 3 or Figure 3, provide valuable insight for selecting product attributes and setting price. But conjoint analysis can do even more. Conjoint-analysis partworths represent "virtual customers." We use those partworths to build a market simulator. With the partworths and with a list of the competitive products that are on the market or will be on the market, we predict sales for the combination of attribute levels and prices that describe the products in the market (assuming competition does not change its attributes and price). If we are designing a product line, we can predict sales for a portfolio of products that we might launch to the market. If we have good intelligence (or good guesses) about how competition will respond, we can simulate markets that take competitive response into account.

For example in 2003, the MIT Management School already had world-class MBA, Ph.D., and undergraduate programs. MIT Management also had two flagship executive education programs: the Sloan Fellows and the Management of Technology Program.

Figure 7. Choice-based Conjoint for MIT Sloan Executive Education



Executive Education Survey - Microsoft Internet Explorer

MITSloan EXECUTIVE PROGRAMS

Please choose

Please examine the following four programs, each described by their features and tuition. Of these four programs, which do you prefer? Click on the circle below the program you would **MOST** prefer. Click the 'Next' button to continue to the next question.

FEATURES	PROGRAM A	PROGRAM B	PROGRAM C	PROGRAM D
Program Focus	Innovative Enterprise	Global Enterprise	Tech-Driven Enterprise	Tech-Driven Enterprise
Program Format	Full-Time Residential	Flexible	Weekend	Weekend
Classmates' Background	50 - 50 mix	General Management	50 - 50 mix	50 - 50 mix
Classmates' Age	30 - 35 years	30 - 35 years	30 - 35 years	30 - 35 years
Classmates' Geographic Comp.	75% North American	50 - 50 mix	75% North American	50 - 50 mix
Classmates' Org. Sponsorship.	50 - 50 mix	50 - 50 mix	50 - 50 mix	Company Sponsored
Classmates' Company Size	Large Companies	Mix of large and small	Large Companies	Large Companies
Program Tuition	Disguised			

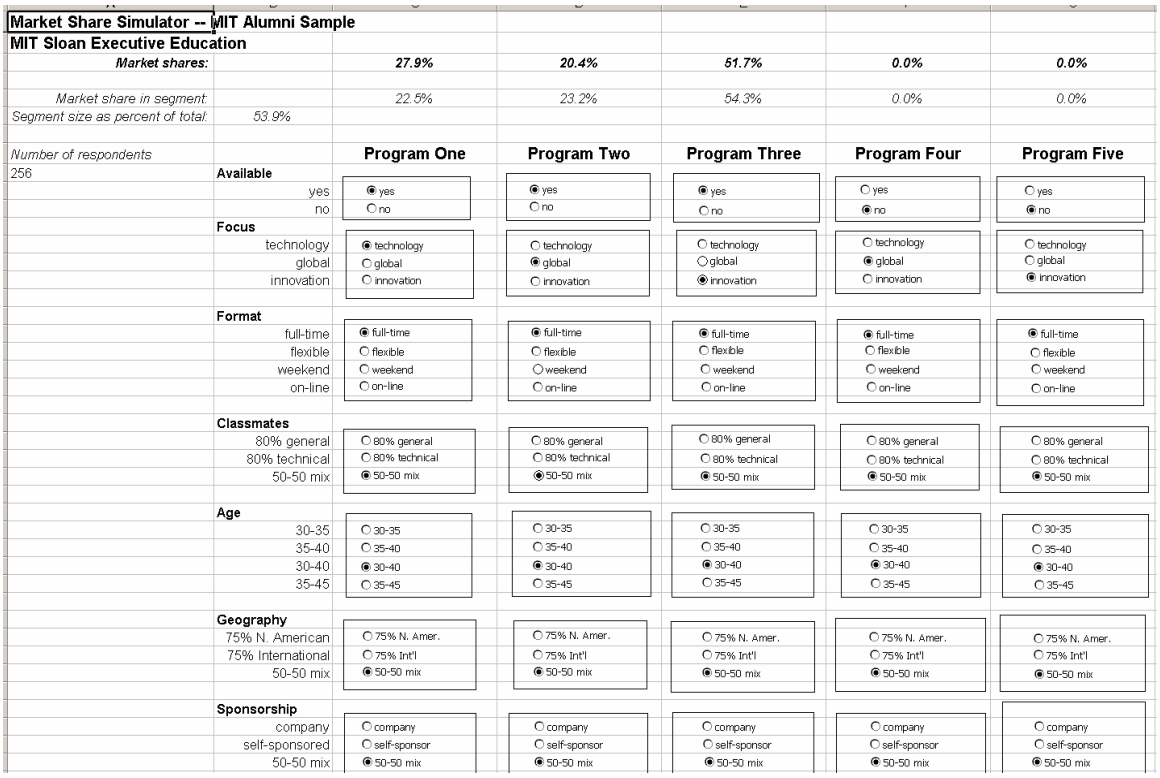
NEXT

However, the market was changing. Mid-career executives (Sloan Fellows) wanted more education about the management of technology and technology professionals wanted more education about general management. In addition, it was becoming increasingly difficult for executives to come to MIT Management for a full year. Markets were becoming global and changing rapidly, hence, the costs of staying away from the firm for a full year were becoming larger. MIT Management wanted to test two aspects of executive education. First, they wanted to test whether or not it would be feasible to combine the Sloan Fellows and Management-of-Technology Programs so that students in each program could learn from students in the other program. Second, MIT Management wanted to test whether there was a market for a flexible program. The planning committee also faced sub-decisions on class composition and program focus. To address these questions, MIT Management sampled potential mid-career students who had GMAT scores above a target level and who otherwise fit the profile for the new executive programs. Each consumer answered 16 choice-based questions, one of which is illustrated in Figure 7. (In 2003, we had not yet understood the critical impact of realistic images and in-

centive alignment. However, both would have been difficult for this particular study.)

The partworths for 354 potential mid-career students (with target GMATs), combined with their demographic information, were summarized in a spreadsheet. MIT Management then created a simulator that enabled the committee to "test the waters" for different types of programs. The goal was to provide a program that would best serve potential students in the target market. The design was tricky because the attractiveness of the program depended upon who it would attract.

Figure 8. Conjoint Analysis Market Simulator for MIT Executive Education



Market Share Simulator -- MIT Alumni Sample						
MIT Sloan Executive Education						
Market shares:		*27.9%*	*20.4%*	*51.7%*	*0.0%*	*0.0%*
Market share in segment:		*22.5%*	*23.2%*	*54.3%*	*0.0%*	*0.0%*
Segment size as percent of total:	*53.9%*					
Number of respondents		**Program One**	**Program Two**	**Program Three**	**Program Four**	**Program Five**
256	**Available**					
	yes	◉ yes	◉ yes	◉ yes	○ yes	○ yes
	no	○ no	○ no	○ no	◉ no	◉ no
	Focus					
	technology	◉ technology	○ technology	○ technology	○ technology	○ technology
	global	○ global	◉ global	○ global	◉ global	○ global
	innovation	○ innovation	○ innovation	◉ innovation	○ innovation	◉ innovation
	Format					
	full-time	◉ full-time	◉ full-time	◉ full-time	◉ full-time	◉ full-time
	flexible	○ flexible	○ flexible	○ flexible	○ flexible	○ flexible
	weekend	○ weekend	○ weekend	○ weekend	○ weekend	○ weekend
	on-line	○ on-line	○ on-line	○ on-line	○ on-line	○ on-line
	Classmates					
	80% general	○ 80% general	○ 80% general	○ 80% general	○ 80% general	○ 80% general
	80% technical	○ 80% technical	○ 80% technical	○ 80% technical	○ 80% technical	○ 80% technical
	50-50 mix	◉ 50-50 mix	◉ 50-50 mix	◉ 50-50 mix	◉ 50-50 mix	◉ 50-50 mix
	Age					
	30-35	○ 30-35	○ 30-35	○ 30-35	○ 30-35	○ 30-35
	35-40	○ 35-40	○ 35-40	○ 35-40	○ 35-40	○ 35-40
	30-40	◉ 30-40	◉ 30-40	◉ 30-40	◉ 30-40	◉ 30-40
	35-45	○ 35-45	○ 35-45	○ 35-45	○ 35-45	○ 35-45
	Geography					
	75% N. American	○ 75% N. Amer.	○ 75% N. Amer.	○ 75% N. Amer.	○ 75% N. Amer.	○ 75% N. Amer.
	75% International	○ 75% Int'l	○ 75% Int'l	○ 75% Int'l	○ 75% Int'l	○ 75% Int'l
	50-50 mix	◉ 50-50 mix	◉ 50-50 mix	◉ 50-50 mix	◉ 50-50 mix	◉ 50-50 mix
	Sponsorship					
	company	○ company	○ company	○ company	○ company	○ company
	self-sponsored	○ self-sponsor	○ self-sponsor	○ self-sponsor	○ self-sponsor	○ self-sponsor
	50-50 mix	◉ 50-50 mix	◉ 50-50 mix	◉ 50-50 mix	◉ 50-50 mix	◉ 50-50 mix

Figure 8 provides a screen-shot from the simulator. By selecting aspects of the program, the program design committee could determine the share of applications that the program would achieve from the target market. For example, in Figure 8, the new program might be similar to "Program Three" in an environment where "Program One" and "Program Two" were offered by competitors. On a separate worksheet, the committee could choose target demographics and determine what share the new program would achieve among those demographics. (The segment shown in Figure 8 is students within driving distance of Cambridge,

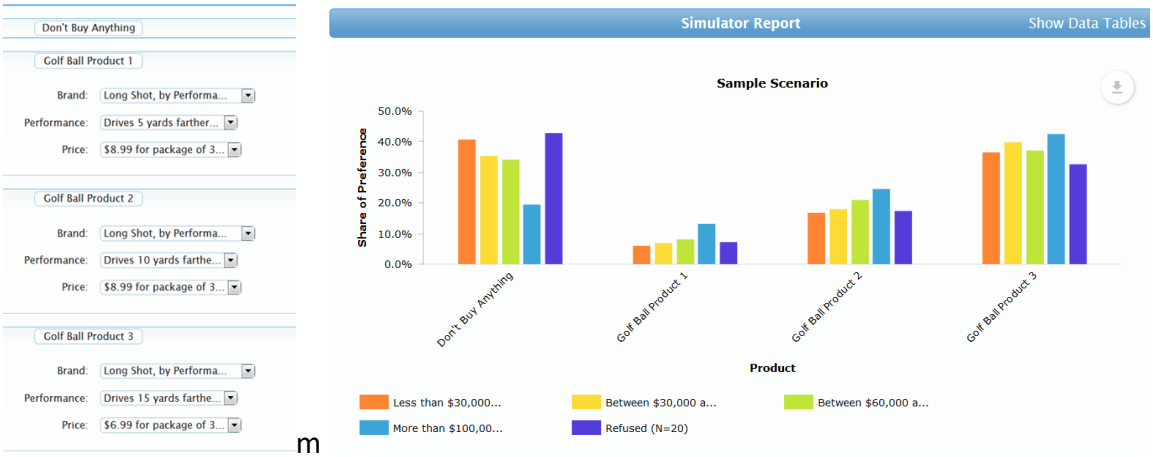
MA.) The net result was the MIT Sloan Fellows Program in Innovation and Global Leadership which was launched in June 2003 and the Executive MBA program that was launched soon thereafter. Of course, the conjoint analysis was just one input. There were many other factors in the decision, such as the fit with the school's mission and its impact on other programs.

Today's conjoint-analysis simulators are easy to use. For the dormitory design exercise, you will use the Online Simulator. The Online Simulator allows you to run simulations for any set of partworths that you upload to the simulator. (We provide the data files for the dormitory design exercise based on a study of students' preferences for dormitories.)

For example, Sawtooth Software provides an example set of partworths for 250 respondents who evaluated three attributes of golf balls—brand, performance and price. (We will post that data.) Figure 9 illustrates the importances for the three attributes and does so for each of five income segments. Using the software we define three products as shown in Figure 10. The Online Simulator predicts the market shares for each income segment.

Figure 9. Importances From Sawtooth Software's Online Simulator (Example Data).

Figure 10. Using Sawtooth Software's Online Simulator



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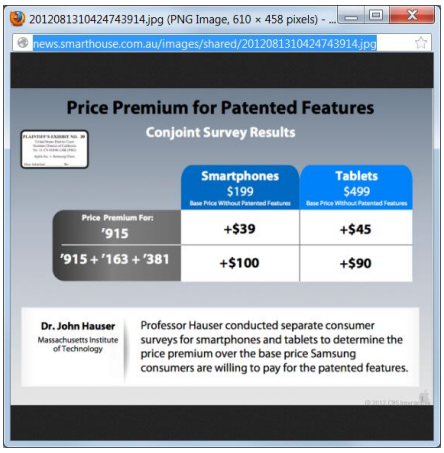
Conjoint Analysis in Litigation

Within the last five years, conjoint analysis has become a key tool to value patents and copyrights. If done carefully, conjoint analysis provides reliable estimates of the price premium that consumers would have paid for product attributes. (A price premium is another word for willingness to pay.) The WTP estimates provide an indication of the value that consumers place on attributes that were enabled by patents or copyrights and provide insight about any profits that the patent or copyright holder might have lost due to an infringement. For example, conjoint analysis was used in the Apple v. Samsung trials to estimate the price premiums for Apple's touchscreen patents. (The following figure was obtained from the open web and is not proprietary.)

Figure 11. Price Premiums for Apple's Touchscreen Attributes



It is important to note that the price premium is not a market price. The market for smartphones is competitive. The prices of the smartphones are set by many considerations including prices set by other manufacturers and the cost of the materials that go into producing the smartphones. Prices must also cover advertising and distribution. In litigation, just as in the managerial use of conjoint analysis, testifying experts should apply the highest feasible craft to get the most accurate estimates of price premiums. We used high-realism images and animations and paid careful attention to all aspects of the study. When feasible we provided aligned incentives. In one study, 1 in 20 respondents received a smartphone (plus change) based on their answers to the survey. (Estimates of lost profits were provided by another expert. The conjoint analysis provided a means to argue that the lost-profit estimates were reasonable.)

Getting More Information

The purpose of this note is to provide you with a basic understanding of conjoint analysis including how to obtain data and how to use conjoint analysis in marketing management, pricing, and product development.

If you are interested in more information, there are literally hundreds, if not thousands, of papers written about conjoint analysis. Appendix 2 provides a few references to get you started. Many scientific articles are available through the MIT Libraries.

Appendix 1
State-of-the-Art Estimation of Partworths

Because conjoint analysis is used widely for marketing, pricing, and product development, researchers have developed advanced methods to estimate partworths. Such methods became feasible in the 1990s when computers became sufficiently powerful. Today, these advanced methods are available widely through advanced software. For those students with advanced programming skills, there are also open-source programs in R that implement advanced estimation and question-selection methods.

Advanced methods make it possible to obtain partworth estimates for each respondent in the sample. We'll get to caveats in a minute, but such respondent-by-respondent partworth estimates are extremely valuable. Respondent-by-respondent partworth enable you to segment the population for targeting and positioning. In addition, they greatly enhance the predictive ability of the conjoint-analysis simulations. With greater predictive ability you can be more confident in your decisions about which attributes to offer to which segments and about how to price your products.

The advanced methods come in two flavors, machine learning and Bayesian statistics. Both flavors are highly accurate when used carefully. The selection of methods often depends on the researcher's experience and the availability of software. In this note, we cover a purely Bayesian method, hierarchical Bayes (HB), and a hybrid method, empirical Bayes (EB). The Discover software that is available for use in your action-learning project is based on empirical Bayes (EB). EB is relatively new, but early indications suggest that it is as accurate as HB. (You also have access to professional-level software that uses advanced HB methods). We'll begin by describing HB because it is the most-widely-used method to obtain conjoint-analysis partworth.

Logit Model. Both HB and EB are based on the "logit model." The underlying model of choice-based data must recognize that we only observe choices, not utilities. In an analogy to regression analysis, the utility of a profile is the sum of the partworths of its attributes—more specifically, the sum of the partworths of the levels of the attributes that describe the profile. If we assume the measurement error is given by an "extreme-value distribution," we get a model known as the logit model.[8] (The logit model was instrumental in the Nobel prize awarded to

Daniel McFadden, who did much of that research while at MIT.)

We can the write down an equation for the probability that a profile is chosen from a set of J profiles. The equation assumes that the "utility of profile j" is equal to the sum of the partworths for the levels of the attributes that are in profile j.[9, 10]

We relate the choices made by the consumers to the expression for the probability of choice and use various statistical methods to estimate the partworths of the levels of the attributes. (For students familiar with advanced statistics, the methods are either maximum-likelihood methods or Bayesian statistics.)

Hierarchical Bayes (used in dormitory design exercise). Hierarchical Bayes estimation (HB) is the best known method and often called the "gold standard." HB software is based on the concept of a statistical hierarchy. Using the data from all consumers (in the sample), the software simultaneously estimates means and variances of the partworths for (1) the population and (2) each respondent. Each respondent's partworths are "shrunk to the population mean." That is, the reported partworths are a weighted average of the partworths that would best explain that respondent's choices and the partworths that best explains the populations' choices. HB is "Bayesian" because HB uses the data to "update" estimates of the partworths according to Bayes Theorem. (You learned Bayes Theorem in DMD.) HB assumes that the means and variances of each respondent's partworths are "sampled" from the "hyperdistribution," that is, the probability distribution that describes how respondent's partworths vary over the population of consumers. For each "sampled" mean and variance for a respondent, the software "samples" partworths for each respondent. The output of HB estimation is more than a point estimate for each partworth. Rather it is a probability distribution for each and every partworth. When used correctly, predictions are based on these probability distributions rather than the single best partworth estimates for each respondent. While all of this may sound a bit complicated, be assured that today's software takes these distributions into account automatically.

While the automated software frees you from the details of estimation, it does not free you from a need to understand the output. Although HB provides "best" estimates for each respondent, those estimates have very high variance and should be used only with great caution.

On the other hand, the distribution of partworths over the population of consumers is estimated with great precision and can be used to evaluate marketing strategies, new product designs or prices. Managerially, this means that it is reasonable to interpret average partworths by segment and it is reasonable to use the predictive software, but it is not reasonable to assume that each and every respondent's choices can be predicted with high accuracy.

The partworths that you use in the dormitory design exercise were estimated using state-of-the-art HB methods. You can use the Online Simulator (as used in the dormitory design exercise) to display average partworths and average partworths for each segment of the population.

Empirical Bayes (used in software available for your action-learning project). Empirical Bayes (EB) is also a Bayesian method, but it uses a machine-learning-like calculation to "shrink" respondent-level estimates based on population estimates. In theory, the amount of shrinkage should be based on "cross validation." Because cross-validation is computationally intensive, and because Discover seeks to provide quick estimates of partworths, the software for your action-learning project uses a level of shrinkage that works well across many applications. This level of shrinkage is more than adequate for any of your projects.

EB begins by estimating an "aggregate logit model" using traditional methods. By "aggregate," we mean that everyone in the sample has the same partworths. Using the CBC logit method described earlier in this note, EB estimates the market shares of each profile in each choice set. EB then modifies the input data for each respondent as shown in Table 4.[11]

Suppose there are three profiles in the choice question and the respondent chooses Profile A. By definition, for that respondent, the respondent's choice was 100% for Profile A and 0% for Profiles B and C. Suppose now that 42% of the respondents in the sample chose Profile A, 38% Profile B, and 20% Profile C. EB changes the respondent's data to be proportional to (a) the observation for that respondent plus (b) 25% of the population average (third data column of Table 4). EB then normalizes everything to 100% (last data column of Table 4).[12] These augmented data are used in a maximum-likelihood logit analysis to provide respondent-level partworths.[13] Unfortunately, EB does not provide a good indication of the variance of the partworths for each respondent, so you should be careful to avoid analyzing any segment of re-

spondents that contains a relatively few respondents.

Table 4. Empirical Bayes Illustration

	Respondent's choice	Population Averages	Augmented Respondent's Choice	Normalized to 100%
Profile A	100%	42%	100 + (0.25)(42) = 110.5	88.4%
Profile B	0%	38%	0 + (0.25)(38) = 9.5	7.6%
Profile C	0%	20%	0 + 0.25(20) = 5.0	4.0%
			Sum = 125.0	Sum = 100.0%

Appendix 2
References to Learn More about Conjoint Analysis

Books on Conjoint Analysis

Orme, Bryan (2005),*Getting Started with Conjoint Analysis: Strategies for Product Design and Pricing Research*, Research Publishers, LLC. https://www.sawtoothsoftware.com/products/pricing-ordering/81-products/conjoint-analysis-software/954-getting-started-with-conjoint-analysis

Rao, Vithala (2014), *Applied Conjoint Analysis*, Springer. https://www.amazon.com/Applied-Conjoint-Analysis-Vithala-Hardcover/dp/B011W99WYM

Technical Papers from Sawtooth Software (providers of Discover, technical papers are free to download)[14]

Discover-CBC: How and Why It Differs from Lighthouse Studio's CBC Software (2017) https://www.sawtoothsoftware.com/support/technical-papers/169-support/technical-papers/cbc-related-papers/1268-saas-delivered-cbc-for-the-classroom-how-and-why-it-differs-from-ssi-web-s-cbc-software

CBC/HB Technical Paper (2009) https://www.sawtoothsoftware.com/support/technical-papers/hierarchical-bayes-estimation/cbc-hb-technical-paper-2009

Other papers: https://www.sawtoothsoftware.com/support/technical-papers#general-conjoint-analysis.

[1] Statistically, the regression does quite well. The R^2 is 0.99 and all coefficients are highly significant as indicated by their high t-statistics.
[2] For example, Toubia, Olivier, John R. Hauser and Rosanna Garcia (2007), "Probabilistic Polyhedral Methods for Adaptive Choice-Based Conjoint Analysis: Theory and Application," *Marketing Science*, 26, 5, (September-October), 596-610.
[3] Respondents were told that selected respondents would get a case of wine for free (plus change from its stated price). The researchers would choose which case of wine to award based on the respondent's answers. This is known as incentive alignment and covered later in this note.
[4] In real applications, the 48 constraints imposed by the respondent's answers are soft constraints. The estimation procedure recognizes that the respondent might make errors in answering the questions. Often the constraints on the relative size of the partworths, say the partworth of $35 ≥ the partworth of $40, are hard constraints. They are imposed directly in the estimation.
[5] When the estimation procedure "borrows" information from population averages, the effective number of partworths is "estimated" from the data. For five binary attributes, the effective number of partworths would be somewhere between 300 *x* 5 and 1 *x* 5. Technically, the respondent-level partworths are assumed to represented by samples from a "hyperdistribution." If the hyperdistribution collapses so that everyone has the same partworths, then there are 5 degrees of freedom. If the hyperdistribution is very diffuse, then it is as if everyone had different partworth—there would be 300 respondents times 5 degrees of freedom. The effective degrees of freedom is an advanced topic in Bayesian statistics. The degrees of freedcom can be estimated by the tightness of the hyperdistribution. This topic is beyond the scope of this note.
[6] Ding, Min, John Hauser, Songting Dong, Daria Dzyabura, Zhilin Yang, Chenting Su, and Steven Gaskin (2011), "Unstructured Direct Elicitation of Decision Rules," *Journal of Marketing Research*, 48, (February), 116-127.
[7] The odds of picking both envelopes correctly are one in 190. As luck would have it, the first envelope picked by the lottery winner said "automobile." The second did not, so the lottery winner received the consolation prize of $200.
[8] An extreme value distribution describes the distribution of a maximum, which makes sense if the consumer is maximizing various unobserved effects.
[9] The equation is

$$Prob\{choose\ profile\ j\} = \frac{e^{\gamma * utility\ of\ profile\ j}}{\sum_{k=1}^{J} e^{\gamma * utility\ of\ profile\ k}}$$

[10] The parameter, γ, that is used in the equation is known as the "scale factor." Higher γ's mean that the model more accurately represents consumer choices.) Technically, γ is not "identified," it depends on how we scale the partworths. One common method to scale the partworths is to set the partworth of price so that 1 unit of price gives 1 util. Another common method scales the partworths so that the importances add to 100, where the importance of a attribute is the maximum partworth of a attribute minus the minimum partworth of a attribute.
[11] This table is adapted from Discover-CBC: How and Why It Differs from Lighthouse Studio's CBC Software, Sawtooth Software 2017, Appendix A.
[12] The 25% weight is baked into Discover. For professional studies it is best set by "cross validation."
[13] For technically-oriented readers, we replace the 0's and 1's in the likelihood function with fractions such as 0.884, 0.076, and 0.040.
[14] If you are curious about my papers on conjoint analysis, see web.mit.edu/hauser/www. Conjoint analysis is an active research topic. See journals such as *Marketing Science*, the *Journal of Marketing Research*, the *International Journal of Research on Marketing*, and the proceedings of the Sawtooth Software Conferences. (The latter proceedings are available on the Sawtooth Software website.