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Analyzing Partially Confounded Factorial Conjoint Choice Experiments Using SAS/IML®

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ABSTRACT

Completely Confounded Factorial Conjoint Choice Experiment (CCFCCE) design allows estimation of main effects and interaction effects. Since some of the effects will be confounded with the blocks in completely confounded factorial design, the conjoint choice design was extended to use of partially confounded factorial design, which is call Partially Confounded Factorial Conjoint Choice Experiment(PCFCCE). A 2^8 partially confounded factorial design with two replicate was applied to CCE in this study. In this study, all the responses were assume to be independent and hence the multinomial logit model follows. The log likelihood is nonlinear and hence the newton-raphson method is needed to estimate the parameters. PROC IML was used to generated the Newton-Raphson procedures. The result showed that all main effects and some of the first-order interaction effects were significant.

INTRODUCTION

Conjoint analysis is an efficient, cost-effective, and most widely used quantitative method in marketing research to understand consumer preferences and value trade-off[2]. Value can be interpreted by consumer as the received of multiple benefits from a price that is paid. In reality, a consumer wants the most preferable attributes or features at the lowest possible price while an organization wants maximize profits by minimizing cost of providing those features and to ahead of its competitors. Conjoint analysis involves more complex survey design and analysis, and more effort by respondents since they are forced to make difficult trade-offs. By this, company, organization or researchers can access what consumers truly value in reality or their willingness to trade off one attribute for another by using mathematical and statistical technique, rather than asking respondents to state the importance of each attribute. In conjoint choice experiments, respondents choose from a set of product alternatives in choice set. A base alternative which is normally a “none” option is added to the set of product alternatives to make the choice more realistic[1].

In a CCE, products are defined in terms of attributes (or factors) that play an important role in determining consumer’s purchasing decisions. For example, in a tablet computer preference study, the relevant attributes of tablet computer may be 3G, warrantee, memory, flexibility, battery, camera, ram and price, where all the attributes have two levels. Full profiles are product descriptions that specify a level for each attribute and a choice set is a set consisting of two or more full profiles. A choice set for the tablet computer is show in Table 1. The choice set has three alternatives two profiles and a neither. Depending on the experimental design, a choice set can have any number of alternatives. Given a number of choice sets, the respondents task is to choose the most preferred alternative from each choice set. The data generated provide important information about the utility of each level of each attribute which are then analyzed to determine the importance of the attributes on consumer preferences.

Completely Confounded Factorial Conjoint Choice Experiments (CCFCCE), that had been constructed by [5]. These designs allow estimation of main effects and interaction effects. Since some of the effects will be confounded with the blocks in complete confounded factorial design, thus, the conjoint choice designs were extended to the use of partially confounded factorial design, which are called Partially Confounded Factorial Conjoint Choice Experiment(PCFCCE) designs. In this method, each replicate does not share the same confounded effects. Therefore, all the effects can be estimated.

The use of PCFCCE is consistent with random utility theory. For each choice set a consumer must choose between two products each with a different set of product attributes or neither. In this study, all the responses were assume to be independent and hence the multinomial logit model follows. The log likelihood is nonlinear and hence the newton-raphson method is needed to estimate the parameters. PROC IML was used to generated the Newton-Raphson procedures.

Table 1: Choice Set

Survey form			
4	Option A	Option B	Option C
Price	RM 2250	RM 1750	
3G	No	Yes	Neither
Warranty	1 year	2 year	Option A
Memory	32GB	64GB	or
Flexibility	Yes	No	Option B
Battery	8 hours	10 hours	
Camera	3-Megapixel	5-Megapixel	
Ram	512MB	1GB	

2. PARTIALLY CONFOUNDED FACTORIAL DESIGN IN CONJOINT CHOICE EXPERIMENT

The technique of confounded factorials is based on confounding certain effects, usually higher-order interactions, to be confounded with blocks, thus making it impossible to separate confounded effects from block effects[4]. A treatment Combination or profile is a particular combination of the levels for each of the factors, where two or more treatment combinations are arranged in a choice set, where each combination is one of the alternative (or option). When designing conjoint choice experiment as confounded factorials, it is necessary to

1. determine how to assign treatment combination to blocks to assure main effects and lower order interactions are not confounded with block and,
2. to determine how to identify choice sets.

Since two treatment combinations are included in a choice set, no information on a factor will be obtained if a choice set contains alternatives with the same level of an attribute. Thus, for each choice set we should choose the treatment combinations so that no two alternatives have the same level of any factor. Again, since some of the effects will be confounded with the blocks in confounded factorial design, the conjoint choice designs were extended to the use of partially confounded factorial designs, which are called as Partially Confounded Factorial Conjoint Choice Experiment (PCFCCE) designs. In this method, there will be at least two replicates and each replicate does not share the same confounded effects. This approach allows some information on the confounded effects to be obtained partial information from other replicates except the replicates where consist of the blocks they are confounded with. Therefore, all the effects can be estimated.

In this study, 2^n partial confounded factorial designs for CCE will be developed to

1. avoid confounding main effects and lower order interactions with blocks if possible
2. to identify choice sets for which no two alternatives in a choice set have the same levels of a factor.

2.1 IDENTIFYING BLOCKS

To develop $2^{\boldsymbol{n}}$ designs, we first arrange the treatment combinations into the required block size in a confounded factorial. Suppose we are interested in constructing $2^{\boldsymbol{n}}$ factorial designs confounded in $2^{\boldsymbol{p}}$ blocks ($\boldsymbol{p} < \boldsymbol{n}$), where each block contains exactly $2^{\boldsymbol{n-p}}$ treatment combinations. We select p independent defining effects (or contrasts) to be confounded, where by "independent" we mean that no effect chosen is the generalized interaction of the others. The blocks may be generated by the use of the p defining contrasts and the modular equations $\mathbf{L_1}$, $\mathbf{L_2}$, ..., $\mathbf{L_p}$(mod 2) associated with these effects. By doing this, $2^{\boldsymbol{p}} - \boldsymbol{p} - 1$ other effects will be confounded with blocks. These effects are generalized interaction of those p independent effects initially chosen. One must ensure that the $[\boldsymbol{p} + (2^{\boldsymbol{p}} - \boldsymbol{p} - 1)]$ effects to be confounded with blocks are not effects that might be non-negligible. Failing to do this will cause the main and lower order interaction effects to be biased.

2.2 IDENTIFYING CHOICE SETS

The second aspect of design construction involves selecting choice sets so that the criterion of all alternatives representing different factor levels, discussed above, is met. For this condition to hold, both alternatives in a choice set must be complements of each other. For example 001010 and 110101 are complements. To ensure each treatment combination has its complement in the same block, it is necessary for the word length of all defining contrasts to be even, where word length is the number of letters (the name of the factors denoted by 1,2, ...k or A, B, ...) in the defining contrast.

Let consider an example of single replicate 2^5 design (32 treatment combinations)with five factors (A, B, C, D, E, F) confounded in 2^2 = 4 blocks of 2^{5-2} = 8 treatment combinations. The defining contrasts are ABCD and BCDE. A represent factor 1, B represent factor 2, C represent factor 3, D represent factor 4 and E represent factor 5. There is $2^2 - 2 - 1 = 1$ generalized interaction, giving by ABCD $*$ BCDE = $AB^2C^2D^2E$ = AE. The linear combinations corresponding to both defining contrasts are:

$$L_1 = x_1 + x_2 + x_3 + x_4 \quad \text{and} \quad L_2 = x_2 + x_3 + x_4 + x_5 \tag{1}$$

where xi is the level(0 or 1) for the ith factor. Each of the 32 treatment combinations will yield a particular pair of values of $r_1 = L_1 (\text{mod } 2)$ and $r_2 = L_2 (\text{mod } 2)$, that is (r_1, r_2) = (0,0),(0,1),(1,0) or (1,1). The design is Treatment combinations with same (r_1, r_2) are assigned to the same block as shown in Table 2 below. Notice that the word length formed by the 2 defining contrasts is even and when all word lengths of the defining contrasts are even, treatment combinations and their respective complement are in a same block. In this example, the treatment combination (00000) and its complement (11111) are both in block 1. To apply the design in Figure 2.1 to CCE, a separate questionnaire is developed for each block. Each questionnaire contains 4 choice sets where a treatment combination is paired with its complement to form a choice set. If needed, respondents may be grouped to form blocks. For example a questionnaire for a block could be assigned to panel or some other blocking criteria. However, if blocking is not feasible, respondents can be randomly assigned to questionnaires.

Table 2: Blocks Design

(r_1, r_2)	(0,0) Block 1	(0,1) Block 2	(1,0) Block 3	(1,1) Block 4
	00000 11111	11000 00111	10000 01111	01000 10111
	01100 10011	10100 01011	11100 00011	00100 11011
	01010 10101	10010 01101	11010 00101	00010 11101
	00110 11001	11110 00001	10110 01001	01110 10001

2.3 QUESTIONNAIRE DESIGN

Application of using 2^n partial confounded factorial design used in the conjoint choice experiment was constructed to study consumer's preferences about Tablet for University Students.

A tablet is great multipurpose equipment for college and university students. The tablet is conveniently to carry, it is a tool that combine a notebook and smart phone, it is also useful in word-processing, Internet surfing, entertainment, digital books, SMS, etc.

In this study, eight attributes of tablet with two level each were used to evaluate consumer's purchasing decisions toward tablet by using PCFCCE. The associated attributes were price (factor A), 3G (factor B), warranty (factor C), internal memory (factor D), flexibility (factor E), life of battery (factor F), quality of camera (factor G) and Ram (factor H) as shown in Table 3.

Three defining contrast were used to construct eight blocks of size 32 for each replicate. The defining contrasts were: ABCDEF, DEFG and CDEH for replicate I, and ABCD, ABEF and ABCDEFGH for replicate II. For each replicate there were 8 fractions and each fraction contained 16 choice sets. An extra choice set was used to check if the respondents answered the questions sincerely or not but was not used in the analysis. Each choice set consisted of three options, two tablet descriptions and a neither.

The word lengths of all defining contrasts are even, then each treatment combination has its complement in the same block. All the treatment combinations were arranged in such a way that each pair of compliment combinations was assigned to the same choice set. This is ensure that no overlap of levels will occur in each choice set. The differences between attribute levels are informative. The tables in Appendix 1 showed the 2^8 design of replicate I followed by replicate II.

Table 3: Attributes of the Tablet

	Attributes	Low level	High level
1	Price	RM 2250	RM 1750
2	3G	No	Yes
3	Warranty	1 year	2 year
4	Memory	32GB	64GB
5	Flexibility	No	Yes
6	Battery	8 hours	10 hours
7	Camera	3-Megapixel	5-Megapixel
8	Ram	512MB	1GB

3. ANALYSIS FOR PARTIALLY CONFOUNDED FACTORIAL CONJOINT CHOICE EXPERIMENTS

The use of partially confounded factorial CCE (PCFCCE) is consistent with random utility theory. For each choice set a consumer must choose between two products each with a different set of product attribute attributes or neither. Probably, the consumer chooses the alternative with the largest utility. A random utility function, $\boldsymbol{U}_{\text{iskj}}$ may be expressed by:

$$U_{iscj} = V_{iscj} + \epsilon_{iscj} \qquad (i = 1, ...16;\ s = 1, ..., S;\ c = 1, ..., 16;\ j = 1, ...3,) \tag{2}$$

where $\boldsymbol{U}_{\text{iscj}}$ is the $\boldsymbol{s}^{\text{th}}$ consumer's utility of choosing alternative $\boldsymbol{j}$ from the $\boldsymbol{c}^{\text{ th}}$ choice set of the $\boldsymbol{i}^{\text{ th}}$ block, $\boldsymbol{V}_{\text{iscj}}$ is the systematic portion of the utility function, and ϙijcj is the random component. The probability that a consumer will choose alternative *j* for a particular choice set is given by:

$$\text{Prob}\{j \text{ is chosen}\} = \text{prob}\{V_{iscj} + \epsilon_{iscj} \geq V_{iscl} + \epsilon_{iscl}, \text{ for all } l \in C_{isc}\}, \tag{3}$$

where $\boldsymbol{C}_{\text{isc}}$ is the relevant choice set.

The random component are assumed to be independent with a Gumbel distribution, the multinomial logit model follows[3]:

$$\text{Prob}\{j \text{ is chosen}\} = \frac{e^{v_{iscj}}}{\sum_{j \in C_{isk}} e^{v_{iscl}}} \tag{4}$$

if $\boldsymbol{V}_{\text{iksj}}$ is assumed to be linear in the parameters, it may be decomposed into additive parts so that the utility of an alternative may be represented as a linear function of its own attributes. The model equation for the systematic component of the utility, $\boldsymbol{V}_{\text{iscj}}$, may be expressed as

$$V_{iscj} = \mathbf{x}'_{iscj}\beta \tag{5}$$

where $\boldsymbol{x}_{\text{iscj}}$ is the vector of attribute levels, and $\boldsymbol{\beta}$ is a vector of parameter coefficients to be estimated.

This additive decomposition allows estimation of interaction term if the design permits.

The form of the models is:

$$\begin{aligned} y_{iscj} &\sim \text{indep. multinomial } (\pi_1,\ \pi_2,\ \pi_3) \\ f_{y_{iscj}}(y_{iscj}) &= \textstyle\prod_{i=1}^{16} \prod_{s=1}^{S} \prod_{c=1}^{16} \prod_{j=1}^{3} \pi_{iscj}^{y_{iscj}}. \end{aligned} \tag{6}$$

The density function can be modified

$$\begin{aligned} f_{y_{iscj}}(y_{iscj}) &= \textstyle\prod_{i=1}^{16} \prod_{s=1}^{S} \prod_{c=1}^{16} \prod_{j=1}^{3} \pi_{iscj}^{y_{iscj}} \\ &= \textstyle\prod_{i=1}^{16} \prod_{s=1}^{S} \prod_{c=1}^{16} \{\exp\left[\sum_{j=1}^{2} y_{iscj} \log\left(\frac{\pi_{iscj}}{\pi_{isc3}}\right) + \log(\pi_{isc3})\right]\}. \end{aligned} \tag{7}$$

where $\theta_{iscj} = \log\left(\frac{\pi_{iscj}}{\pi_{isc3}}\right)$, $b(\theta_{iscj}) = \log(1 + \sum_{j=1}^{2} \exp(\theta))$, $a(\phi) = 1$.Let $\pi_{iscj} = E[Y_{iscj}]$, then $g(\pi_{iscj}) = \log\left(\frac{\pi_{iscj}}{\pi_{isc3}}\right) = \mathbf{x_{iscj}}'\beta$.

$$\begin{aligned} f_{y_{iscj}}(y_{iscj}) &= \textstyle\prod_{i=1}^{16} \prod_{s=1}^{S} \prod_{c=1}^{16} \\ &\quad \exp\left[\sum_{j=1}^{2} (y_{iscj}\mathbf{x_{iscj}}'\beta) - \log(1 + \sum_{j=1}^{2} \exp(\mathbf{x_{iscj}}'\beta))\right] \end{aligned} \tag{8}$$

This model belongs to the class of generalized linear models (GLMs).

To illustrate the iterative procedure of Newton-Raphson as it applies to the multinomial logistic regression model, we need an expression for the first and second derivative of $\boldsymbol{\beta}$(Eq.6). The first derivative of $\boldsymbol{\beta}$ in multinomial has the form.

$$l'(\beta) = \frac{\partial L(\beta)}{\partial \beta} = \sum_{j=1}^{2}(y_j x_j - x_j \mu_j) = \begin{pmatrix} x_1 & x_2 \end{pmatrix} \begin{pmatrix} y_1 - \mu_1 \\ y_2 - \mu_2 \end{pmatrix} = x^T(y-\mu) \tag{9}$$

In PCFCCE, ($\boldsymbol{y}$1, $\boldsymbol{y}$2) will have 3 form, (1,0), (0,1) and (0,0) which are the responder choose one of the option: option A, option B or option C. The second derivative of $\boldsymbol{\beta}$ can be obtained from the estimate asymptotic covariance of $\boldsymbol{\beta}$.

$$\begin{array}{lrcl} & [-l''(\beta)]^{-1} & = & \widehat{cov}(\hat{\boldsymbol{\beta}}) \\ & \widehat{cov}(\hat{\boldsymbol{\beta}}) & = & (X^T \hat{W} X)^{-1} \\ \text{where} & W & = & \text{blockdiag}(w_i) \\ \text{and} & w_i & = & \begin{pmatrix} \mu_1(1-\mu_1) & -\mu_1\mu_2 \\ -\mu_1\mu_2 & \mu_2(1-\mu_2) \end{pmatrix} \end{array} \tag{10}$$

Together with the first and second derivative of **L**($\boldsymbol{\beta}$). The Newton-Raphson procedures can be applied as follows.

$$\begin{aligned} \beta^{(1)} &= \beta^{(0)} + [-l''(\beta^{(0)})]^{-1} * l'(\beta^{(0)}) \\ &= \beta^{(0)} + (X^T W X)^{-1} * X^T(Y-\mu) \end{aligned} \tag{11}$$

The new value of $\boldsymbol{\beta}^{(1)}$is the next approximation for the root. We let $\boldsymbol{\beta}^{(0)} = \boldsymbol{\beta}^{(1)}$ and continue in the same manner to generate $\boldsymbol{\beta}^{(1)}$, $\boldsymbol{\beta}^{(2)}$, ..., until successive approximations converge.

The PCFCCE Newton-Raphson was developed by PROC IML. The estimates of the elements of β, t-ratio and p-value can obtain in PCFCCE Newton-Raphson. The SAS code for the PROC IML is provided as the following.

```
/* Input data
data_x as design matrix for all the Option B
data_y as number of respondes follow by option A, option B and option C
       follow by the choice set.
number_of_responde_in_each_block as number of responder in each block
r as number of replicate (partially confounded factorial)
p as number of confounded factorial*/
==================================================================================
proc iml;

data_x={
         1 1 1 1 -1 -1 1 -1,
         1 1 1 1 1 1 1 1,
         .....
         1 -1 -1 1 1 1 -1 1};
data_y={
         1 25 0 10 14 2 7 16 3 13 11 2 9 16 1 11 11 4 17 8 1 20 4 2
         10 9 7 5 19 2 8 15 3 5 17 4 10 13 3 12 12 2 3 22 1 13 9 4
         .....
         22 2 3 9 8 10 6 7 14 2 18 7 26 1 0 8 8 11 10 11 6 7 17 3};
number_of_responde_in_each_block=
       {26 27 24 25 25 22 25 26 26 27 27 21 28 25 25 27};
r=2;
p=3;
number_of_fix_effects=ncol(data_x);
number_of_choice_set=2**(ncol(data_x)-p-1);
number_of_option=ncol(data_y)/nrow(data_x);
```

```
/* Design X matrix: Given all the Option B design matrix
associated with the main effects and first order interaction effects*/
data_x=data_x@{-1, 1};

/* In clude first order Interaction effects (x12,x13,...x18,..x21..x78)*/
do i=1 to number_of_fix_effects;
    do j=i+1 to number_of_fix_effects;
        i_x=data_x[,i]#data_x[,j];
        if j=2 then
            IX=i_x;
        else
            IX=IX||i_x;
    end;
end;
data_x=j(nrow(data_x),1,1)||data_x||IX;

/* Follow the "number_of_responde_in_each_block" design the X matrix*/
do i=0 to number_of_choice_set-1;
    do j=0 to number_of_choice_set-1;
        xi=j(number_of_responde_in_each_block[i+1],1,1)@
        data_x[(number_of_choice_set)*(number_of_option-1)*i+
        (number_of_option-1)*j+1:(number_of_choice_set)*
        (number_of_option-1)*i+(number_of_option-1)*j+2,];
        if i=0 && j=0 then
            X=xi;
        else
            X=t(t(X)||t(xi));
    end;
end;

/* Assume Beta = 0*/
beta=j(ncol(data_x),1,0);
wc=0||number_of_responde_in_each_block;

/* Design Y matrix, responded in multinomial ((1,0), (0,1) or (0,0))*/
do i=0 to nrow(data_x)/(number_of_option-1)-1;
    do j=0 to number_of_option-2;
        if data_y[number_of_option*i+j+1]^=0 then
            do;
                a=j(number_of_option-1,1,0);
                a[j+1]=1;
                yi=j(data_y[number_of_option*i+j+1],1,1)@a;
                if i=0 & j=0 then
                    Y=yi;
                else
                    Y=t(t(Y)||t(yi));
            end;
    end;
    if data_y[number_of_option*i+3]^=0 then
        do;
            a=j(number_of_option-1,1,0);
            yi=j(data_y[number_of_option*i+3],1,1)@a;
            Y=t(t(Y)||t(yi));
        end;
end;
```

```
/* Use Newton-Raphson to estimate the fixed effect coefficients*/
do con =1 to 5; * when test < 10E-8 then converged;

/* Compute mean of the multinomial (mu) by using logit link*/
eta=exp(X*beta);
mu1mu2=shape(eta,nrow(eta)/(number_of_option-1),number_of_option-1);
pi3=1+mu1mu2[,1]+mu1mu2[,2];
pi1=mu1mu2[,1]/pi3;
pi2=mu1mu2[,2]/pi3;
mu=pi1@{1,0}+pi2@{0,1};

/* Compute and design block diagonal matrix for information matrix*/
do i=1 to ncol(number_of_responde_in_each_block);
    wa=mu[(sum(wc[1:i])*(number_of_option-1)*number_of_choice_set+1):
    (sum(wc[1:i+1])*(number_of_option-1)*number_of_choice_set)];
    wb=shape(wa,nrow(wa)/(number_of_option-1),number_of_option-1);
    ww=sparse(diag(wa#(1-wa))-diag(wb[,1]#wb[,2])@{0 1,1 0});
    if i=1 then
        W=ww;
    else
        do;
            ww[,2]=ww[,2]+(sum(wc[1:i])*(number_of_option-1)*number_of_choice_set);
            ww[,3]=ww[,3]+(sum(wc[1:i])*(number_of_option-1)*number_of_choice_set);
            W=W//ww;
        end;
end;
n_beta=beta+(inv(t(X)*full(W)*X)*t(X)*(Y-mu));
test=t(n_beta-beta)*(n_beta-beta);
if test<0.0000001 then
    do;
        con=7;
        beta=n_beta;
        COV=sparse(diag(inv(t(X)*full(W)*X)));
        COV=COV[,1];
        T_value=abs(beta/sqrt(COV));
        p_value=(1-probt(T_value,sum(data_y)-ncol(X)-1))*2;
        print "done estimation";
        print beta T_value P_value;
    end;
else
    do;
        con=1;
        beta=n_beta;
    end;
end;
run;
```

4. RESULTS

A survey in the form of partially confounded CCE was conducted to collect the data of respondent's preferences on eight attributes of tablet. There are 28(256) descriptions(treatment combinations) of the product and it is impossible for a respondent to answer all the descriptions. With the use of CCE, information on attributes associated with respondents preference or choice can be obtained without asking each respondent more than a moderate number of choice sets. PCFCCE divided the descriptions within each replicate into eight fractions of each with 16 choice sets. Two replicates were used and the partial information of effects that are confounded with blocks in a replicate can be obtained from another replicate.

Students from Faculty of Engineering and Science(FES) and Faculty of Creative Industry(FCI) of University Tunku Abdul Rahman were chosen randomly as the respondents for this survey. There were 406 students from the two faculties with each responded only once the survey. In average each fraction was responded by nearly 25 students. Each student was responded to 17 choice sets with 3 alternatives each but only 16 choice sets were used in the data analysis. Hence, there are 19488 responses in total with each block of students responded to 48(16 choice sets x 3 alternatives) responses. Therefore, there are 48 observed proportions for each block or fraction and a total 768 observed proportions.

From the result obtained, all main effects and some of the first-order effects are statistically significant (**p-value** < 0.05). The estimates of the elements of $\boldsymbol{\beta}$, the standard errors of the estimates and the p-value were provided in Appendix 2.The significant first-order interaction effects were price and warranty, price and flexibility, price and battery, 3G and flexibility, warranty and memory, warranty and flexibility, memory and ram, flexibility and battery and flexibility and camera. All the effects can be estimated by using the estimated coefficient values generated by **PROC IML**. These coefficients are estimated based sum to zero restriction. Thus, the other coefficients not shown in the table can be obtained using this restriction. For instance, the coefficient for lower price of tablet is 0.11400. Since there were only two level for the price of tablet, the higher price of tablet is -0.11400. Similarly, the coefficients for other effects were obtained in the same manner.

The main effects of the attributes may be interpreted using the estimated coefficients. For example, the effect of flexibility is 0.849(0.927-0.078) and the odds of choosing it is 2.336($\boldsymbol{e}^{0.849}$), while the effects of not flexibility was 1.005(0.927+0.078) which translated into an odds of 2.733($\boldsymbol{e}^{0.1.005}$). Thus the odds ratio for a consumer choosing the tablet when the tablet is flexible versus not flexible is 0.855(2.336/2.733). This also means the odds of a respondent choosing a flexible tablet is 0.855 times the odds of a respondent choosing the not flexible tablet. Similarly, the odds of choosing a tablet with 3G is 1.191 times of the odds of choosing a tablet without 3G. The odds of choosing a tablet with longer duration warranty is 1.279 times of the odds of choosing a tablet with shorth duration warranty. A summary table of the least square means, the odds and the odds ratios is attached in Appendix 3.

The significant interaction effects indicated that including interactions in the model was important. The significant effects between price and warranty showed that the odd ratios for a respondent choosing a 2years warranty versus 1year warranty was 1.525 when the tablet with lower price. Where choosing a higher price tablet, the respondent choosing a 2years warranty versus 1year warranty was 1.072 as shown in table below. This means that. This means that respondents will pay more attention to warranty, when the tablet price was low.

CONCLUSION

In CCE, interactions among attributes were common. In this study, the conjoint choice designs were extended to the use of partially confounded factorial design, which were called Partially Confounded Factorial Conjoint Choice Experiment (PCFCCE) designs. In a partially confounded factorial design, effects that were confounded with blocks in different replicate can be estimated partial information from other replicates. In this method, each replicate did not share the same confounded effects. Therefore, the lost of information of significant effects can be avoided using PCFCCE. Although all the effect can be estimated, only main effects and first-order interaction effects were concerned. Main effects estimates were unbiased with the presence of first-order interactions. Higher order of interaction was normally assumed to be negligible.

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APPENDIX

Appendix 1: Block Design

1	2	3	4	5	6	7	8
11111111	11111001	11111101	11111011	11111110	11111000	11111100	11111010
0	110	10	100	1	111	11	101
11110010	11110100	11110000	11110110	11110011	11110101	11110001	11110111
1101	1011	1111	1001	1100	1010	1110	1000
11101010	11101100	11101000	11101110	11101011	11101101	11101001	11101111
10101	10011	10111	10001	10100	10010	10110	10000
11100111	11100001	11100101	11100011	11100110	11100000	11100100	11100010
11000	11110	11010	11100	11001	11111	11011	11101
11011000	11011110	11011010	11011100	11011001	11011111	11011011	11011101
100111	100001	100101	100011	100110	100000	100100	100010
11010101	11010011	11010111	11010001	11010100	11010010	11010110	11010000
101010	101100	101000	101110	101011	101101	101001	101111
11001101	11001011	11001111	11001001	11001100	11001010	11001110	11001000
110010	110100	110000	110110	110011	110101	110001	110111
11000000	11000110	11000010	11000100	11000001	11000111	11000011	11000101
111111	111001	111101	111011	111110	111000	111100	111010
10111001	10111111	10111011	10111101	10111000	10111110	10111010	10111100
1000110	1000000	1000100	1000010	1000111	1000001	1000101	1000011
10110100	10110010	10110110	10110000	10110101	10110011	10110111	10110001
1001011	1001101	1001001	1001111	1001010	1001100	1001000	1001110
10101100	10101010	10101110	10101000	10101101	10101011	10101111	10101001
1010011	1010101	1010001	1010111	1010010	1010100	1010000	1010110
10100001	10100111	10100011	10100101	10100000	10100110	10100010	10100100
1011110	1011000	1011100	1011010	1011111	1011001	1011101	1011011
10011110	10011000	10011100	10011010	10011111	10011001	10011101	10011011
1100001	1100111	1100011	1100101	1100000	1100110	1100010	1100100
10010011	10010101	10010001	10010111	10010010	10010100	10010000	10010110
1101100	1101010	1101110	1101000	1101101	1101011	1101111	1101001
10001011	10001101	10001001	10001111	10001010	10001100	10001000	10001110
1110100	1110010	1110110	1110000	1110101	1110011	1110111	1110001
10000110	10000000	10000100	10000010	10000111	10000001	10000101	10000011
1111001	1111111	1111011	1111101	1111000	1111110	1111010	1111100

1	2	3	4	5	6	7	8
11111111	11101110	11111010	11101011	11111110	11101111	11111011	11101010
0	10001	101	10100	1	10000	100	10101
11111100	11101101	11111001	11101000	11111101	11101100	11111000	11101001
11	10010	110	10111	10	10011	111	10110
11110011	11100010	11110110	11100111	11110010	11100011	11110111	11100110
1100	11101	1001	11000	1101	11100	1000	11001
11110000	11100001	11110101	11100100	11110001	11100000	11110100	11100101
1111	11110	1010	11011	1110	11111	1011	11010
11001111	11011110	11001010	11011011	11001110	11011111	11001011	11011010
110000	100001	110101	100100	110001	100000	110100	100101
11001100	11011101	11001001	11011000	11001101	11011100	11001000	11011001
110011	100010	110110	100111	110010	100011	110111	100110
11000011	11010010	11000110	11010111	11000010	11010011	11000111	11010110
111100	101101	111001	101000	111101	101100	111000	101001
11000000	11010001	11000101	11010100	11000001	11010000	11000100	11010101
111111	101110	111010	101011	111110	101111	111011	101010
10101010	10111011	10101111	10111110	10101011	10111010	10101110	10111111
1010101	1000100	1010000	1000001	1010100	1000101	1010001	1000000
10101001	10111000	10101100	10111101	10101000	10111001	10101101	10111100
1010110	1000111	1010011	1000010	1010111	1000110	1010010	1000011
10100110	10110111	10100011	10110010	10100111	10110110	10100010	10110011
1011001	1001000	1011100	1001101	1011000	1001001	1011101	1001100
10100101	10110100	10100000	10110001	10100100	10110101	10100001	10110000
1011010	1001011	1011111	1001110	1011011	1001010	1011110	1001111
10011010	10001011	10011111	10001110	10011011	10001010	10011110	10001111
1100101	1110100	1100000	1110001	1100100	1110101	1100001	1110000
10011001	10001000	10011100	10001101	10011000	10001001	10011101	10001100
1100110	1110111	1100011	1110010	1100111	1110110	1100010	1110011
10010110	10000111	10010011	10000010	10010111	10000110	10010010	10000011
1101001	1111000	1101100	1111101	1101000	1111001	1101101	1111100
10010101	10000100	10010000	10000001	10010100	10000101	10010001	10000000
1101010	1111011	1101111	1111110	1101011	1111010	1101110	1111111

Appendix 2: Coefficient Estimates

effect	betahat	secovbhat	t.ratio	p.value
Intercept	0.92689	0.03507	26.42762	0.00000
Price	0.11397	0.01416	8.05111	0.00000
3G	0.08731	0.01415	6.17202	0.00000
Warranty	0.12285	0.01415	8.68283	0.00000
Memory	0.12059	0.01416	8.51771	0.00000
Flexibility	-0.07838	0.01415	-5.53956	0.00000
Battery	0.08832	0.01416	6.23712	0.00000
Camera	0.09579	0.01415	6.76905	0.00000
Ram	0.11192	0.01416	7.90232	0.00000
Price 3G	0.19353	0.03441	5.62402	0.00000
Price Warranty	0.08812	0.03443	2.55915	0.01052
Price Memory	0.01583	0.03437	0.46072	0.64502
Price Flexibility	-0.07190	0.03460	-2.07821	0.03773
Price Battery	-0.08420	0.03434	-2.45186	0.01424
Price Camera	0.05000	0.03435	1.45529	0.14564
Price Ram	-0.02352	0.03426	-0.68668	0.49231
3G Warranty	0.06080	0.03440	1.76720	0.07724
3G Memory	0.02052	0.03430	0.59815	0.54976
3G Flexibility	-0.10804	0.03446	-3.13516	0.00173
3G Battery	0.01658	0.03429	0.48360	0.62869
3G Camera	-0.00136	0.03430	-0.03954	0.96847
3G Ram	-0.02493	0.03419	-0.72908	0.46598
Warranty Memory	0.09663	0.03404	2.83833	0.00455
Warranty Flexibility	-0.07001	0.03432	-2.04022	0.04137
Warranty Battery	0.00540	0.03413	0.15816	0.87433
Warranty Camera	0.01055	0.03411	0.30939	0.75704
Warranty Ram	-0.01479	0.03400	-0.43485	0.66368
Memory Flexibility	0.01308	0.03424	0.38208	0.70242
Memory Battery	0.00248	0.03403	0.07288	0.94190
Memory Camera	0.04090	0.03399	1.20329	0.22891
Memory Ram	-0.08077	0.03387	-2.38458	0.01713
Flexibility Battery	0.13209	0.03416	3.86670	0.00011
Flexibility Camera	-0.10305	0.03417	-3.01543	0.00258
Flexibility Ram	-0.02435	0.03412	-0.71363	0.47548
Battery Camera	-0.06257	0.03403	-1.83881	0.06599
Battery Ram	0.00895	0.03393	0.26383	0.79192
Camera Ram	-0.02396	0.03392	-0.70637	0.47998

Appendix 3: Estimates, Least Square Mean, Odds and Odds Ratio

Effects		Estimates	Least Square Mean	Odds	Odds Ratio
Intercept		0.926886679			
Price	High level	0.113965147	1.040851826	2.831628042	1.255997772
	Low level	-0.113965147	0.812921532	2.254484924	
3G	High level	0.087314743	1.014201422	2.75716071	1.190804925
	Low level	-0.087314743	0.839571936	2.315375636	
Warranty	High level	0.122854432	1.049741111	2.856911399	1.278527294
	Low level	-0.122854432	0.804032247	2.234532976	
Memory	High level	0.120592269	1.047478948	2.850455905	1.272755885
	Low level	-0.120592269	0.80629441	2.239593576	
Flexibility	High level	-0.078379526	0.848507153	2.336156723	0.854910023
	Low level	0.078379526	1.005266205	2.732634617	
Battery	High level	0.088317365	1.015204044	2.759926486	1.193195175
	Low level	-0.088317365	0.838569314	2.313055352	
Camera	High level	0.095793106	1.022679785	2.780636296	1.211169246
	Low level	-0.095793106	0.831093573	2.295828024	
Ram	High level	0.111922628	1.038809307	2.82585029	1.250877439
	Low level	-0.111922628	0.814964051	2.259094459	

Interaction effects				Estimates	Least Square Mean	Odds	Odds Ratio
Price	1	Warranty	1	0.088121849	1.251828107	3.496729514	1.524936183
Price	1	Warranty	0	-0.088121849	0.829875545	2.293033343	
Price	0	Warranty	1	-0.088121849	0.847654115	2.334164742	1.071934721
Price	0	Warranty	0	0.088121849	0.778188949	2.177525083	
Price	1	Flexibility	1	-0.07189843	0.89057387	2.4365275	0.740406505
Price	1	Flexibility	0	0.07189843	1.191129782	3.290796991	
Price	0	Flexibility	1	0.07189843	0.806440436	2.239920639	0.987121455
Price	0	Flexibility	0	-0.07189843	0.819402628	2.26914391	
Price	1	Battery	1	-0.084195327	1.044973864	2.84332421	1.008278152
Price	1	Battery	0	0.084195327	1.036729788	2.819979987	
Price	0	Battery	1	0.084195327	0.985434224	2.678974907	1.412025762
Price	0	Battery	0	-0.084195327	0.64040884	1.897256395	
3G	1	Flexibility	1	-0.108037335	0.827784561	2.288243656	0.688779752
3G	1	Flexibility	0	0.108037335	1.200618283	3.322170329	
3G	0	Flexibility	1	0.108037335	0.869229745	2.385073031	1.061110093
3G	0	Flexibility	0	-0.108037335	0.809914127	2.24771496	
Warranty	1	Memory	1	0.096626246	1.266959626	3.55004268	1.544093536
Warranty	1	Memory	0	-0.096626246	0.832522596	2.29911116	
Warranty	0	Memory	1	-0.096626246	0.82799827	2.288732727	1.049099362
Warranty	0	Memory	0	0.096626246	0.780066224	2.181616736	
Warranty	1	Flexibility	1	-0.070013099	0.901348486	2.462922089	0.743203598
Warranty	1	Flexibility	0	0.070013099	1.198133736	3.313926486	
Warranty	0	Flexibility	1	0.070013099	0.79566582	2.215915907	0.983406363
Warranty	0	Flexibility	0	-0.070013099	0.812398674	2.253306457	
Memory	1	Ram	1	-0.08077351	1.078628066	2.940642415	1.064279704
Memory	1	Ram	0	0.08077351	1.01632983	2.763035323	
Memory	0	Ram	1	0.08077351	0.998990548	2.715539238	1.470190929
Memory	0	Ram	0	-0.08077351	0.613598272	1.8470657	
Flexibility	1	Battery	1	0.132093508	1.068918026	2.912226841	1.553983674
Flexibility	1	Battery	0	-0.132093508	0.62809628	1.874039535	
Flexibility	0	Battery	1	-0.132093508	0.961490062	2.615590964	0.916170967
Flexibility	0	Battery	0	0.132093508	1.049042348	2.854915793	
Flexibility	1	Camera	1	-0.103048133	0.841252126	2.319269177	0.98559471
Flexibility	1	Camera	0	0.103048133	0.85576218	2.353167234	
Flexibility	0	Camera	1	0.103048133	1.204107444	3.333782162	1.488371364
Flexibility	0	Camera	0	-0.103048133	0.806424966	2.239885987	