2013-05: Stated Choice design comparison in a developing country: Attribute Nonattendance and choice task dominance (Working paper)

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Published

2013

ISSN 1837-7750

Griffith Business School

Discussion Papers Economics

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No. 2013-05

Series Editor: A/Prof. Fabrizio Carmignani and A/Prof. John Forster

Stated Choice design comparison in a developing country

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Abstract

Comparison of experimental Stated Choice (SC) designs is important in appropriately using different designs for any given context. The importance of using appropriate experimental designs is due to the impact that experimental designs have in accurately estimating model parameters, standard errors and derived measures, such as Willingness-To-Pay and Welfare. Despite the existence and use of a variety of SC designs, the health economic literature reports the use of predominantly fractional factorial orthogonal designs. This study extends existing design literature by using varying literacy levels as proxies for respondents' cognitive ability to investigate the 'robustness' of fractional factorial orthogonal and efficient designs to choice task simplification. Comparing the robustness of designs helps to further explain why designs provide differing standard error parameter estimates.

Key words: Stated Choice, experimental design, choice task simplification, cognitive burden, Indian primary health care, Attribute nonattendance

JEL Codes: I1, I11, C93

1. Introduction

Experimental designs constitute a vital component of all Stated Choice (SC) studies. The choice of design gives the researcher flexibility in answering a given set of research questions. This flexibility may assist in over-coming survey limitations due to financial constraints, help control for behavioural choice factors and may increase model accuracy.

Comparison of designs is important in appropriately selecting designs for any given context. The importance of using appropriate experimental designs is due to the impact that experimental designs have in accurately estimating model parameters and derived measures, such as Willingness-To-Pay and Welfare (Hess et al. 2008). As

such, this paper seeks to empirically compare two contrasting and widely used fractional factorial designs (efficient and orthogonal) among samples of illiterate, literate and highly literate respondents.

There exists several broad categories of designs that emphases different modelling and behavioural aspects. In the SC literature, designs that restrict the matrix of choice tasks to an orthogonal array are foundational. However, designs that relax the orthogonality constraint and allow for non-zero prior parameter estimates are increasingly common.

Reviews of SC studies in transport and environmental economics reveals that there is an increasing diversity of designs used in SC studies (Bliemer et al., 2011, Ferrini et al., 2007). In contrast, the health economic literature is firmly centred on applying orthogonal designs. The diversity of different designs used in health economics has shrunk during the period 2001-2008, compared to the period 1990-2000 (de Bekker-Grob et al., 2010).

While this diversity of experimental design usage in health economics is not problematic per se, it does suggest that applied researchers are not benefiting from the variety of designs that may aid their research.

Given the importance of experimental designs to SC estimates it is surprising that more evaluations of designs are not present. In the health economic literature evaluation of designs is restricted to a handful of studies (Carlsson et al., 2003, Viney et al., 2005). These studies do not empirically compare across experimental designs that possess differing assumed foundations.

The work of Louviere and others (Louviere et al., 2009, Louviere et al., 2011) identify the importance of designs, but acknowledge the limited existing empirical work necessary to draw conclusions.

This study evaluates the performance of two designs for patient's choice of health care provider in rural north India. In so doing, it is the first known non-simulated evaluation of efficient and orthogonal designs in the health economics literature. This study also contributes to the wider body of SC empirical design work. The evaluation of the respective designs is based on: 1) standard errors of the parameter estimates, 2) dominant alternatives and 3) data set specific statistical significant parameters. The

study is also the first, known, to empirically evaluate designs among illiterate and literate respondents.

The paper is structured with a Literature review in part 2. The review outlines a typology of experimental designs and the importance of designs to SC estimates. Part 3 defines the data, the location of sample districts, designs used and the process of selecting attributes. The empirical results are presented in part 4. These include: full trade-off and stated Attribute Nonattendance (ANA) coded multinomial logit (MNL) models, design comparisons and dominant alternative measures with high-predicted probabilities, by literacy and design. A discussion and concluding remarks are made in part 5.

2. Literature Review

Stated Choice experimental design typology draws on terminology that is indigenous to the SC literature and also comes from the statistical experimental design literature. The use of design typology appears confusing as terms such as ‘efficiency’ is used in differing ways to define designs. This section aims to elucidate the relationship between different experimental design categories and their likely effect on parameter estimates. A clearer understanding of differences between designs typologies assist in explaining why many standard design comparison measures are not appropriate when empirically comparing designs based on different assumptions.

2.1 Design Typology

At the broadest level experimental designs are categorised according to a design’s orthogonality. Designs that have uncorrelated design attribute levels are referred to as orthogonal. This property of orthogonality presents a welcome feature that parameters are estimated independently of one another. As a result, the covariance matrix is also diagonal, with off-diagonals equal to zero indicating no cross variances.

A secondary means of categorising the different designs is done by focusing on the parameter priors used. A broad grouping of efficient designs is made according to their use of non-zero priors in running designs. This use of non-zero priors is in contrast to stating no priors, or implicitly using zeros for all priors.

For the purposes of this research the terms *orthogonal* and *efficient* are used to referrer to fractional factorial orthogonal and efficient designs. Efficient designs use non-zero priors and allow for some correlation across levels. The term '*efficient*' follows use of the same by Scarpa et al. (2008) and Bliemer et al. (2011). An alternate group of designs make no assumptions about priors and may be termed *'orthogonal'* following the use of the same by Bliemer et al. (2011).

2.1.1. Efficiency

Efficient designs use non-zero priors as a foundation on which to maximise the determinant of the Fisher Information matrix. The Fisher Information matrix, which is equal to the negative of the expected value of the Hessian[1] of the log likelihood, is the expected value of the observed information. Equation (1) shows the equality between the Fisher Information matrix and the expected value of the Hessian. Here θ is a vector of true parameters and $\tilde{\theta}$ the corresponding statistics.

$$I(\theta) = -E\left(\frac{\partial^2 log\, L(\theta)}{\partial\tilde{\theta}\ \partial\tilde{\theta}'}\right) \qquad (1)$$

Scarpa et al. (2008) outlines in detail the statistical foundation of efficient designs. The authors identify that the asymptotic variance-covariance (AVC) matrix, which is the inverse to the information matrix, is a function of the utility of coefficients θ and the matrix of choice attributes **x**. Therefore, the structure of information matrix in equation (1) can be expanded to better reflect the experimental nature of SC methods. Incorporating the design matrix **x**, along with the information matrix $\boldsymbol{\theta}$ is defined as

$$I(\theta,\ \mathbf{x}) \qquad (2)$$

By maintaining the Information matrix equality to the negative of the expected value of the Hessian matrix, any given $I(\theta,\ \mathbf{x})$ provides for the local maximum of θ for the log likelihood function. Constructing experimental designs with the assistance of

[1] A negative Hessian that is a definite symmetric matrix then θ (vector of parameters) is a strict local maximum of the log likelihood function (Simon et al. 1994)

knowledge of parameters prior to the survey increases the information. Efficient designs, for any given sample size, are expected to inform parameter estimates with lower standard errors (Bliemer et al., 2009).

While methods differ on how to estimate non-zero priors (Kanninen, 2002, Huber et al., 1996) and how to use them (Ferrini et al., 2007, Rose et al., 2009, Sándor et al., 2001, 2005) they all make use of the assumption that the true parameters will be non-zero. The condition of orthogonality is not necessarily maintained in efficient designs.

The literature evaluating the efficiency of design is limited to comparisons of either orthogonal or efficient designs. Viney et al. (2005) conducted an empirical study comparing orthogonal designs. Scarpa et al. (2008) in their comparison clearly differentiate between orthogonal and efficient designs and state that efficiency comparison across the two groups, based on standard measures (D-, A-errors and D-efficiency)[2] is not meaningful. This is due to differing assumptions. The study by Bliemer et al. (2011) is the only known one to empirically compare orthogonal and efficient designs.

An important feature of experimental designs that effect the amount of information a design captures relates to the existence of dominant alternatives. Dominant alternatives, in the strict sense, occur when "all attributes of the first alternative are preferred to all the attributes of the second" (Viney et al., 2005). Strict dominance of an alternative causes the probability of the alternative to tend towards 1 and so little or no trade-off information is gathered. Weaker dominance produces the same information problem to varying degrees.

2.2 Designs and Estimates

Of ultimate importance and interest to this study is the effect of experimental designs on parameter estimates. Behavioural aspects of SC methods impose an intermediary effect on parameter estimates. This section outlines the limited literature on how experimental designs affect parameter estimates. It goes on to frame how cognitive

[2] D-error = $\det(\Omega(\beta, x_{nsj}))^{1/k}$; A-error = $\text{trace}(\Omega(\beta, x_{nsj}))$; D-efficiency = $100/[S|(X'X)^{-1}|^{1/k}]$ where S is the number of observations, k the number of attributes and X the design matrix.

burden in answering SC tasks elicits choice task simplification heuristics by respondents.

Experimental design assumptions are likely to directly affect a given model's estimated parameters. Several studies identify influential design features affecting parameter estimates. The recent study of Bliemer et al. (2011) provides a good overview of these potential designs effects. The authors indicate that the following effects are likely:

1) Efficient designs may provide higher t-values (Toner et al., 1999a, Toner et al., 1999b)
2) The level of statistical efficiency of a design is positively correlated to greater error variance (Louviere et al., 2008); and

Method of dividing choice task (i.e. blocking) from the full set of available choice tasks may be more important than design in effecting model estimates (Hess et al., 2008).

The work of Louviere et al. (2008) and Hess et al. (2008) provide two distinct possible explanations for how experimental designs affect parameter estimates. The study by Louviere et al. argues that as cognitive burden of a choice task increases so too does the level of choice inconsistency. In turn, this consistency induces higher error variance in modelling.

Findings from Bliemer et al. (2011) provide empirical evidence supporting the earlier work of Toner and others (1999a,b) that efficient designs provide lower standard errors compared to fractional factorial orthogonal designs.

This present study draws on the work of both Louviere et al. (2008) and Bliemer et al. (2011) by using literacy levels as a proxy for respondents' cognitive ability to investigate the 'robustness' of an orthogonal and efficient design to choice task simplification.

2.2.1. Cognitive Burden

The cognitive burden, as argued by Louviere et al. (2008), in SC surveys is an important consideration in designing experiments. This is likely to be particularly so

in many developing country contexts where population are more likely to have lower aggregate levels of education.

The combined hypothetical nature and the expectation that respondents trade-off all attributes and their levels, in any given choice, task makes SC methods potentially cognitively demanding. The experimental nature of SC methods provides several mechanisms through which cognitive demand on respondents may be affected. A few likely factors include: the size of the experimental design (Louviere et al., 2008); information format of survey (Hoehn et al., 2010), incorporation of 'cheap-talk' text during survey to help respondents' consider making choices that reflect their current preferences and resources (Özdemir et al., 2009, Meenakshi et al., 2012)**,** the use of visual aides to complement text (Arentze et al., 2003).

Hensher (2006) confirms the positive correlation between a design's cognitive load and respondents employing simplifying strategies to make the task of trading-off attributes less demanding. Collins (2012) identifies 11 simplifying or choice heuristic strategies. These strategies include: lexicographic choice, regret minimisation, referencing and prospect theory, and majority of confirming dimensions heuristics.

Modelling SC data assuming that all attributes are traded-off against one another, when respondents have not done so is another possible avenue contributing to biased parameter and WTP estimates. Collins (2012) identifies three possible reasons for survey respondents to resort to Attribute Nonattendance (ANA), these are: 1) disinterest in attribute; 2) context dependent factors (i.e. fatigue); and 3) strategic behaviour. In many cases the most likely explanation for ANA is disinterest in a given attribute, giving rise to preference heterogeneity.

Accounting for ANA by respondents is possible through stated and inferred methods. Stated methods invite respondents to indicate directing whether they ignored attributes and if so nominate which attributes. Inferred methods utilise modelling techniques to identify ANA within sub-groups of respondents. This study implemented a stated ANA method.

The relationship between ignoring attributes and information collected by designs is of particular interest in low education context, such as rural north India. As such, in comparing the error variance of contrasting experimental designs, this study assesses

the ‘robustness’ of orthogonal and efficient designs to respondents ignoring attributes. In this study, ‘robustness’ of designs is measured by the proportion of dominant alternatives remaining in a choice task after accounting for ignored attributes.

3. Empirical study: data

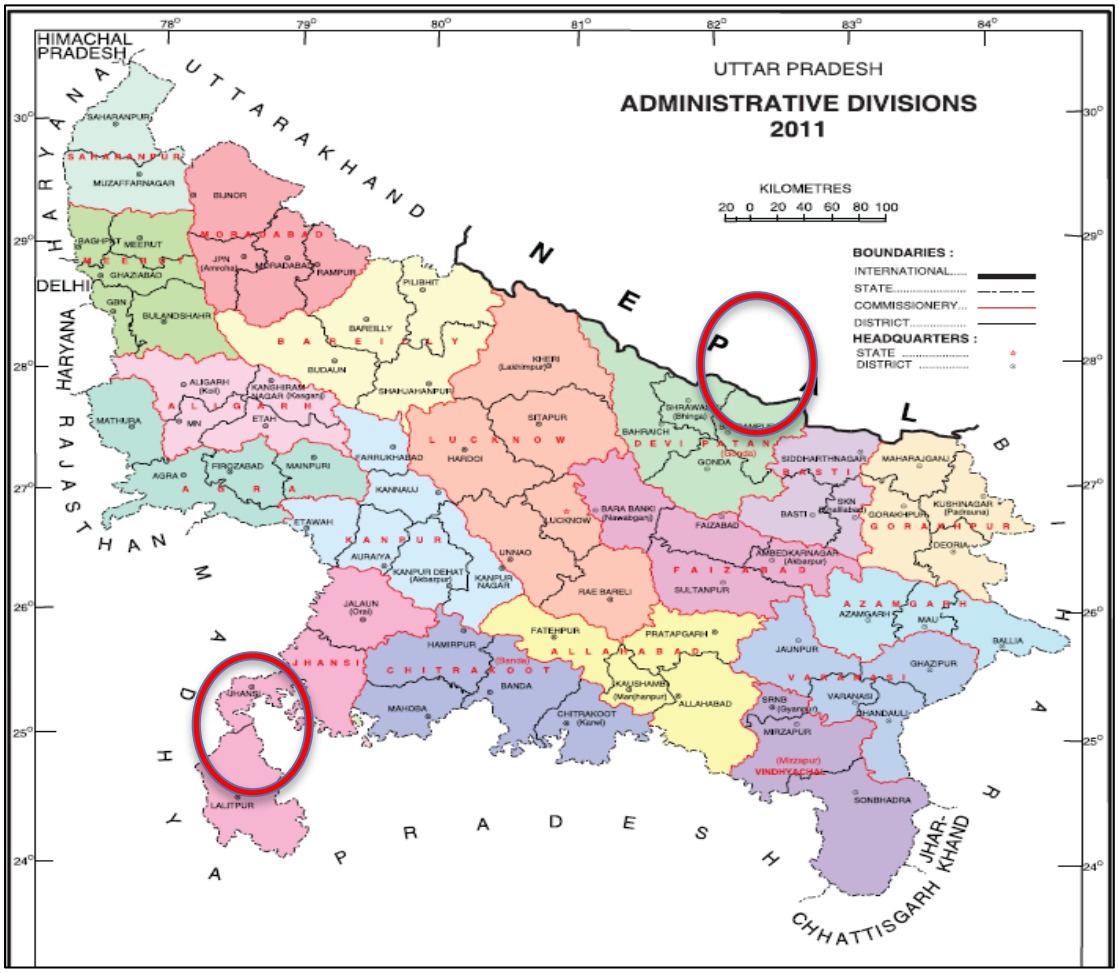
The north Indian context of this study provides a rich opportunity to evaluate SC designs using survey respondents who have diverse levels of literacy. This section outlines the samples used, the details of the choice tasks and how they were formed.

3.1 Sample

Uttar Pradesh (UP) is India’s most populous state, one of India's poorest and has relatively high levels of illiteracy. UP has a population of approximately 195 million and per capita GDP income (PPP) of US$1,586. It’s size and per capita income is comparable with the national figures of Brazil (size) and Kenya (income) (The Economist, 2011). Approximately, 49 percent of the population aged 18 year and above are illiterate in UP (Government of India, 2001).

The state may be divided into four economic and administrative regions. Those districts in the west, closest to Delhi, have higher incomes than those in the east. The central region, districts surrounding the capital (Lucknow) have relatively moderate-income levels. The forth region, is referred to as the Bundelkhand and encompasses the seven southern most districts surrounded by Madhya Pradesh. Figure 2 shows the sampled districts in the eastern and Bundelkhand regions of UP.

Figure 1: Map of Uttar Pradesh



Source: (Government of India, 2011)

Survey respondents came from two districts in UP. The districts of Lalitpur (bottom left of Figure 2) and Balrampur (middle right of Figure 2) are from the Bundelkhand and eastern regions. These districts approximately represent the interquartile range of mean per capita income across UP. Based on state wise aggregate data of UP's 70 districts in 2003, Lalitpur[3] is ranked 25th and Balrampur – 56th (Government of Uttar Pradesh, 2006).

A total of 622 respondents were sampled across four villages in September 2012. Rural blocks and their corresponding villages were selected in a stratified quasi-random sampling frame. District administrative blocks were randomly selected and from selected blocks, gram panchayats (local level of administration with elected

[3] Aggregate income figures for the Bundelkhand are moderate, but urban incomes are thought to mask particularly low rural incomes. Official data supporting this hypothesis are not available.

council governing a collection of 4-7 villages) were then randomly selected. A total of 5598 choice tasks were completed. The Lalitpur sample 366 respondents who answered a total of 1647 choice tasks from each design and in Balrampur a sample of 256 respondents answered 1152 choice tasks for each design. Each respondent answered choice tasks from only one design.

A select set of demographic characteristics of the sample answering orthogonal and efficient choice tasks is presented in Table 1. Respondents of each design were statistically similar in respect to their levels of literacy, gender, religious orientation and mean household income. The mean household income of orthogonal respondents is 55836 Indian rupees (INR) and for efficient respondents 56234 INR.

Table 1: Demographic characteristics of sample

	Orthogonal Design (%)			Efficient Design (%)		
Education	Illiterate:	Literate:	Highly Lit.:	Illiterate:	Literate:	Highly Lit.:
	53.7	27.8	18.5	53.2	26.7	20.2
Gender	Male:	Female:		Male:	Female:	
	50.5	49.5		51.8	48.2	
Religion	Hindu:	Muslim:		Hindu:	Muslim:	
	78.9	21.1		81.5	18.5	

3.2 Designs

Orthogonal and efficient designs, each having 4 labelled alternatives and 4 attributes – 2 with 3 levels and 2 with 2 levels, were administered. The dimensions of the experimental designs are parsimonious as possible to avoid unnecessary cognitive burden among respondents. The attributes and the corresponding number of levels selected were price and recommendation (3 levels) and medicine and distance (2 levels). Categorical levels are effects coded.

Designs were generated using 36 choice tasks. These tasks were blocked into 4 groups of 9. The blocking employed by the software Ngene (Choice Metrics, 2012) does not maintain orthogonality within each block. The blocking column is orthogonal to the design. The attributes and associated levels are listed in Table 2. The prices in brackets represent the prices used in the pilot study, with the final prices listed below. Both designs were generated using the Ngene software.

The presentation of each choice task contained several elements to aide respondents in making reliable trade-offs. The design matrix (number of alternatives, attributes and levels) was kept as small as possible to reduce the cognitive burden. Visual aides are used to depict each attribute level. Also, cheap talk text is included at the start of each task. An example of the layout and presentation of choice tasks is provided in Appendix 1.

The alternatives were chosen following a literature review and earlier qualitative phase of research. The most commonly used "doctor" types for treatment of a 3-day-old fever is unqualified doctor, government doctor and private doctor. A 'no choice' alternative is also given.

Attributes were selected following qualitative and quantitative analysis of interviews with health care providers and consumers. A concurrent Mixed Method data collection and analysis was used to inform selection of attributes (Creswell et al., 2011). Qualitative data from 32 structured interviews with doctors (14) and consumers (18) and 15 semi-structured interviews with key informants. Key informants included elected village heads and social workers (Accredited Social Health Activist and Anganwadi workers).

Within the structured interviews respondents were asked to rank the importance of doctor characteristics. The 3 most important doctor characteristics for consumers were price, trust and travel distance. From a list of 4 characteristics describing trust the following 3 were given as equally important: listens, recommendation and qualification – religious beliefs of doctor were universally ranked last.

The second component of the exploratory Mixed Methods process was conducting a pilot SC survey and collecting revealed preference (RP) data from respondents' most recent experience of suffering from a 3 day old fever. Sixteen respondents were surveyed from four selected villages in Fatehpur district in May 2012.

The RP data indicated that the price levels in the SC survey were too low, relative to market conditions.

Table 2: Attribute levels

Doctor Type	Price (INR)	Medicine	Distance	Recommendation

Unqualified	(30, 60, 90) 50, 100, 150	Pill, Pill & Injection	At Home, In village,	Positive, No Recommendation, Negative
Government qualified	(1, 10, 20) 1, 25, 50	Free, Extra Charge	In village, 5-15 kms	Positive, No Recommendation, Negative
Private qualified	(70, 140, 210) 100, 200, 300	**Uncertain Treatment**	In village, 5-15 kms	Positive, No Recommendation, Negative
None of the above	0	0	0	0

Note: Values in brackets pilot study values and those not main study values

The SC pilot design was fractional factorial orthogonal, comprising 36 choice tasks blocked into 4 sets of 9 tasks each. The Multinomial Logit (MNL) model is used to estimate parameters of the pilot and subsequent data. The closed form MNL model is used to keep this study's results consistent with other empirical comparisons. The results of this pilot experiment are provided in Table 3.

Table 3: MNL pilot results

	Coefficient	St. Error	t-ratio	p-value
Unqualified Dr				
Constant	0.950	0.952	1.00	0.318
Price	-0.009	0.008	-1.04	0.296
Medicine (pills & injection)	0.095	0.194	0.49	0.623
Travel (in village)	0.051	0.193	0.27	0.790
Recommend (+ve)	0.539	0.265	2.04	0.042
Recommend (-ve)	0.117	0.273	0.43	0.669
Government Dr				
Constant	0.950	0.908	1.05	0.295
Price	-0.002	0.024	-0.09	0.928
Medicine (extra charge)	-0.538	0.186	-2.89	0.004
Travel (5-15 kms)	-0.564	0.186	-3.03	0.002
Recommend (+ve)	0.277	0.264	1.05	0.294
Recommend (-ve)	-0.231	0.262	-0.88	0.377
Travel x Recom (+ve)	0.120	0.261	0.46	0.647
Travel x Recom (-ve)	-0.276	0.273	-1.01	0.312
Private Dr				
Price	-0.004	0.006	-0.61	0.542
Travel (5-15 kms)	-0.736	0.290	-2.54	0.011
Recommend (+ve)	0.484	0.384	1.26	0.208
Recommend (-ve)	-0.599	0.454	-1.32	0.187
Travel x Recom (+ve)	0.248	0.500	0.50	0.620
Travel x Recom (-ve)	-0.354	0.492	-0.72	0.472

$\rho^2 = 0.119$, LL = -141.

The estimated parameters from the pilot study were used as the priors in designing the efficient design. The same fractional factorial orthogonal design, with amended price levels, is used as the orthogonal design in the main survey. Both designs in the main

study have 36 choice tasks and are blocked into 4 groups of 9 tasks. The blocking process in allocating choice tasks for the four groups was done randomly.

4. Empirical study: results

The sign of parameters of the full trade-off data (Table 4) are in line with expectations. The price and travel variables for the three types of 'doctor' are all negative and strongly significant. The exception is the travel to unqualified doctor within the village (base: at home), which is not significant. These doctors generally operate only within the immediate village context.

The medicine attribute parameter signs for unqualified and government doctors are also a prior expectations. The expectation of receipt of a combined pill and injection (base: pill) from an unqualified doctor is positive and significant in both designs. The expectation of paying extra for medicine (base: free) from government doctors is estimated with a negative, significant parameter in both designs.

The full trade-off MNL model produces surprising parameter estimates for the main-effect and interaction recommendation parameters. These parameters are generally not statistically significant. The fact that local unqualified doctors are well known to villagers reduces the need for consumers to rely on the recommendations of others to assist their choice among these providers. Both designs estimate a negative coefficient for positive recommendations (base: neutral) in each qualified provider type.

The parameter estimates of designs, assuming full attribute trade-offs, are presented in Table 4. Comparing the sign of coefficients from the pilot study (Table 3) with those of the efficient design full trade-off model (Table 4) show that 12 of the 21 variables are the same. Of the 9 unmatched variables 5 are not statistically significant at the 95 per cent level in the efficient design full trade-off model.

Table 4: Full trade-off – MNL model by design type

Attribute	**Orthogonal**					**Efficient**				
	Co-eff	St. Err	t-ratio	Lower (95%)	Upper (95%)	Co-eff	St. Err	t-ratio	Lower (95%)	Upper (95%)
Unqualified Dr										
Constant	0.175	0.265	0.66	-0.344	0.694	-1.765	0.540	-3.27	-2.824	-0.707
Price (INR)	-0.020	0.001	-13.93	-0.023	-0.017	-0.020	0.002	-12.58	-0.023	-0.017
Medicine (pills & inject.)	0.136	0.054	2.51	0.030	0.243	0.162	0.058	2.79	0.048	0.276
Travel (in village)	0.077	0.055	1.41	-0.030	0.184	-0.074	0.057	-1.31	-0.185	0.037
Recommend (+ve)	-0.036	0.074	-0.49	-0.181	0.109	-0.017	0.075	-0.23	-0.164	0.130
Recommend (-ve)	-0.039	0.079	-0.49	-0.193	0.116	-0.143	0.093	-1.55	-0.325	0.038
Government Dr										
Constant	-0.895	0.251	-3.56	-1.387	-0.402	-2.654	0.542	-4.89	-3.717	-1.591
Price (INR)	-0.011	0.003	-3.97	-0.017	-0.006	-0.011	0.004	-2.98	-0.018	-0.004
Medicine (extra INR)	-0.465	0.054	-8.68	-0.570	-0.360	-0.326	0.093	-3.53	-0.508	-0.145
Travel (5-15 kms)	-1.622	0.056	-29.17	-1.731	-1.513	-1.553	0.066	-23.64	-1.682	-1.425
Recommend (+ve)	0.099	0.074	1.35	-0.045	0.244	-0.337	0.096	-3.50	-0.526	-0.149
Recommend (-ve)	-0.109	0.077	-1.41	-0.260	0.043	-0.026	0.090	-0.29	-.202	0.151
Travel x Recom (+ve)	-0.033	0.074	-0.45	-0.177	0.111	0.168	0.082	2.05	0.007	0.328
Travel x Recom (-ve)	0.022	0.081	0.27	-0.137	0.181	-0.129	0.108	-1.19	-0.341	0.083

Private Dr										
Price (INR)	-0.017	0.001	-12.18	-0.019	-0.014	-0.028	0.003	-9.35	-0.034	-0.022
Travel (5-15 kms)	-1.203	0.095	-12.68	-1.388	-1.017	-1.642	0.122	-13.44	-1.882	-1.403
Recommend (+ve)	-0.343	0.124	-2.77	-0.587	-0.100	-0.053	0.155	-0.34	-0.357	0.251
Recommend (-ve)	0.246	0.145	1.70	-0.038	0.530	-0.828	0.175	-4.73	-1.171	-0.485
Travel x Recom (+ve)	-0.110	0.148	-0.75	-0.400	0.179	-0.177	0.184	-0.96	-0.537	0.183
Travel x Recom (-ve)	-0.010	0.171	-0.06	-0.344	0.325	-1.044	0.198	-5.27	-1.433	-0.656
None	-5.677	0.333	-17.06	-6.329	-5.025	-6.919	0.573	-12.08	-8.041	-5.797

Note: INR – Indian rupee

Model fits		
LL (ASC only model)	-2890.191	-2862.065
LL (β)	-1848.916	-1933.290
ρ^2	0.36	0.32
Respondents	311	311
Observations	2799	2799

A comparison of the two designs modeled in Table 4 indicates that the efficient design and sample data produce better model fit compared to the orthogonal design assuming full attribute trade-off. The log-likelihood score for the efficient design is -1933.290 compared to -1848.916. The efficient design estimated 14 statistically significant variables compared to 10 in the orthogonal design. A surprising result of a comparison of the estimated parameters in Table 4 is that the standard errors of the all parameters are lower in the orthogonal design.

The full trade-off data does not account for the ANA recorded from respondents. Table 5 shows that on average between 35-39 per cent of all attributes in choice tasks were ignored by respondents. This proportion is constant across literacy levels. The

data shows no meaningful difference in the proportion of ignored attributes between the two designs.

This data also shows that respondents answering the efficient design survey ignored attributes more evenly across all attributes. The range of ignored attributes for the orthogonal design across each literacy level is above 17.00. In contrast, the efficient design had a lower range across all literacy levels that descend as literacy increases. The range of ignored attributes for efficient designs is 13.77 for illiterate respondents, 11.83 for literate respondents and 6.56 for highly literate respondents.

Table 5: Attribute Non-Attendance (% of observations)

Design Type	Literacy level	Unqual/Gov Dr/ Priv Dr			Unqual/ Gov Dr	Total	Choice Tasks (n)
		Price	Travel	Recom.	Med		
Orth	Ill. Lit	2.35	5.68	19.38	10.86	38.27	1620
	Lit	2.94	6.93	20.42	7.31	37.60	1053
	Hi. Lit	1.59	7.94	19.05	7.14	35.72	126
							2799
Eff	Ill. Lit	3.21	5.80	16.98	10.74	36.73	1620
	Lit	3.36	8.66	15.19	11.82	39.03	981
	Hi. Lit	4.55	9.09	11.11	11.62	36.37	198
							2799

Note: Literacy levels are self-reported.

Using the same data as given in Table 4, but with ANA recoded, the efficient design and sample data again provide a better model fit. The parameter estimates for the ANA data is presented in Table 6. The log-likelihood score is lower for the efficient design at -1954.265 compared to -1795.026. The MNL model estimated 15 statistically significant variables for the efficient design compared to 14 in the orthogonal design. Again, however, the standard errors of the orthogonal design parameter estimates are consistently lower.

Allowing for ANA changes the sign of positive recommendation and travel x recommendation parameters in both designs. In the efficient design the positive recommendation parameters (base: neutral) for all three-doctor types change sign and become positive. This change also occurs in the efficient design's interaction term.

Fewer changes in sign result in the orthogonal design. The positive recommendation for the unqualified doctor does change to become positive.

The effect of ignoring attributes may increase the likelihood that choice tasks contain dominant alternatives. This effect, along with the presence of dominant choices in the original design, contributes to alternatives having a high-predicted probability of being chosen. Table 7 presents the percentage of observations with a predicted probability of at least 80 percent, by design and literacy level, once stated ANA are accounted. The results show that for both designs the percentage of alternatives with high-predicted probabilities falls has literacy rises.

Table 6: Stated Attribute Non-Attendance – MNL model by design type

Attribute	**Orthogonal**					**Efficient**				
	Co-eff	St. Err	t-ratio	Lower (95%)	Upper (95%)	Co-eff	St. Err	t-ratio	Lower (95%)	Upper (95%)
Unqualified Dr										
Constant	0.620	0.197	3.14	0.234	1.006	1.190	0.226	5.26	0.747	1.633
Price (INR)	-0.020	0.001	-14.69	-0.022	-0.017	-0.015	0.001	-11.19	-0.018	-0.012
Medicine (pills & inject.)	0.210	0.056	3.76	0.100	0.319	0.184	0.057	3.24	0.073	0.296
Travel (in village)	0.076	0.056	1.35	-0.034	0.186	-0.023	0.055	-0.43	-0.131	0.085
Recommend (+ve)	0.160	0.081	1.96	0.000	0.319	0.193	0.078	2.47	0.040	0.346
Recommend (-ve)	-0.252	0.090	-2.81	-0.428	-0.076	-0.161	0.094	-1.71	-0.346	0.024
Government Dr										
Constant	-0.397	0.188	-2.11	-0.766	-0.029	0.835	0.223	3.75	0.399	1.271
Price (INR)	-0.014	0.003	-4.90	-0.019	-0.008	-0.019	0.003	-6.26	-0.026	-0.013
Medicine (extra INR)	-0.636	0.058	-11.01	-0.749	-0.523	-0.685	0.074	-9.22	-0.830	-0.539

Travel (5-15 kms)	-1.779	0.060	-29.57	-1.897	-1.661	-1.631	0.063	-26.08	-1.753	-1.508
Recommend (+ve)	0.184	0.082	2.24	0.023	0.346	0.044	0.089	0.5	-0.131	0.219
Recommend (-ve)	-0.238	0.089	-2.68	-0.413	-0.064	-0.384	0.083	-4.61	-0.547	-0.221
Travel x Recom (+ve)	0.000	0.002	0.19	-0.004	0.005	0.060	0.089	0.68	-0.114	0.235
Travel x Recom (-ve)	-0.057	0.081	-0.71	-0.216	0.101	-0.098	0.101	-0.97	-0.296	0.100
Private Dr										
Price (INR)	-0.014	0.001	-14.63	-0.016	-0.013	-0.010	0.001	-8.97	-0.013	-0.008
Travel (5-15 kms)	-1.372	0.104	-13.22	-1.575	-1.168	-1.651	0.130	-12.72	-1.906	-1.397
Recommend (+ve)	-0.076	0.133	-0.57	-0.338	0.185	0.447	0.156	2.86	0.141	0.753
Recommend (-ve)	-0.057	0.181	-0.32	-0.413	0.298	-0.352	0.175	-2.01	-0.695	-0.010
Travel x Recom (+ve)	0.105	0.146	0.72	-0.182	0.392	0.533	0.155	3.44	0.229	0.837
Travel x Recom (-ve)	-0.276	0.194	-1.42	-0.656	0.105	-0.002	0.180	-0.01	-0.355	0.351
None	-5.110	0.287	-17.80	-5.672	-4.547	-3.457	0.270	-12.79	-3.987	-2.927

Note: INR- Indian rupees

Model fits

LL (ASC only model)	-2881.626	-2862.065
LL (β)	-1795.026	-1954.265
ρ^2	0.38	0.32
Respondents	311	311
Observations	2799	2799

Illiterate and literate respondents of orthogonal design surveys had the highest percentage of dominant alternatives. Table 7 presents the average predicted probabilities of each design once stated ANA are recoded, according to literacy levels. These respondents, once stated ANA are considered, faced choice tasks that had on average 47-48 percent of alternatives with predicted probabilities above or equal to 0.8. For the same design, highly literate respondents on average faced 42.86 per cent dominant alternatives in choice tasks.

Given an approximately equal proportion of ANA as in the orthogonal design, the proportion of dominant alternatives given to efficient design respondents is markedly lower. Illiterate and literate respondents of the efficient design faced on average between 31 and 32 per cent dominant alternatives with predicted probabilities above 0.8. The equivalent percent for highly literate respondents was 24.75. The proportion of dominant alternatives in the efficient design is between 16-18 per cent points lower than for the orthogonal design.

Table 7: Predicted probabilities >=0.8

		Unqual	Gov't Dr	Priv. Dr	Total
Orth	Ill. Lit	11.60	34.01	1.98	47.59
	Lit	13.58	33.24	1.61	48.43
	Hi. Lit	9.52	30.95	2.38	42.86
Eff	Ill. Lit	1.42	29.26	-	30.68
	Lit	2.04	29.56	-	31.60
	Hi. Lit	1.01	23.74	-	24.75

Weighting the total predicted probabilities from Table 7 with the proportion of choice tasks answered by each literacy group for each design shows that at the aggregate level the orthogonal design had a statistically greater proportion of dominant choices. This weighting shows that 47.7 per cent of alternatives were dominant for the orthogonal design compared to 30.6 per cent for efficient designs.

The difference across designs in the percentage of alternatives with high-predicted probability of being selected is a likely factor explaining the way orthogonal design, ANA coded parameter estimates consistently had lower standard errors.

5. Discussion and Conclusion

The outcomes of running the MNL models, assuming full trade-off and stated ANA for the two designs, produce parameter estimates with lower standard errors for data generated with the orthogonal design. This finding is contrary to the results of Bliemer et al. (2011). However, this study shows that this surprising result is partially explained by the orthogonal design being less robust to respondents ignoring attributes and thereby inducing greater levels of attribute dominance within choice tasks.

The higher proportion of dominant choice alternatives in the orthogonal design is in contrast to the equal number of ignored attributes across the two designs. Assuming that this equality is a proxy for the cognitive burden of the two designs, the higher frequency of dominant alternatives among the orthogonal design suggests that the efficient design is more robust in light of respondents' attempts to simplify choice tasks.

To better understanding the relationship between SC cognitive burden and respondents' literacy levels, the differences in the proportion of attributes ignored across the three literacy levels is important. In the context of north India, the difference in educational attainment between the illiterate and those who complete 10 years of schooling, has little bearing on their respective likelihood of simplifying choice tasks. Most clearly, those rated as highly literate (with more than 10 years of schooling/education) recorded lower proportions of ignored attributes.

The difference in the proportion of ignored attributes across literacy levels is in contrast to the findings of Arentze et al. (2003) based on work in South Africa. One possible explanation for the differing conclusions regarding the effect of literacy on perceived task complexity is due to the use of subjective measures of literacy. The effectiveness of a given period of schooling may differ significantly across countries and regions.

Expanding the work of Louviere et al. (2008) this study shows that standard errors are not only related to design complexity, but also design robustness to respondents ignoring attributes. The differences in the proportion of ignored attributes levels across attributes and literacy levels, combined with the higher predicted probabilities suggest that choice task respondents' motivations for simplifying task may differ according to the design. While certainly a positive correlation exists between a design's complexity, the amount of respondents fatigue induced and amount of ANA, the consistent total proportion of ignored attributes for each literacy level indicates that fatigue is not the only reasons for ANA.

The sizeable difference in the number of choice tasks with dominant alternatives between the two designs introduces the possibility that the orthogonal design's weaker robustness to ANA may be strategically exploited more frequently by respondents.

One important limitation of the study is its inability to account for the effects of blocking on choice tasks. While concluding that efficient designs offered much to improve parameter estimation, Hess et al. (2008) also argues that random blocking of choice tasks induces poor design performance.

This empirical study shows that efficient designs perform consistently well in respect to model fit and parameter significance. Even though these measures are dataset specific, the body of evidence is building supporting the wider use of experimental designs using non-zero priors.

The results of this empirical study highlight the importance of SC design robustness to attribute dominance in contributing to lower standard errors. Although these results are inconclusive regarding whether orthogonal or efficient designs produce a better combination of accuracy and statistical significance, they do show that ANA among illiterate, literate and highly literate respondents does affect standard errors more pronouncedly for orthogonal design generated data.

Appendix 1

3.7 Final survey – 22364

कल्पना करें कि आपको 2 दिनों से बहुत तेज़ बुखार है । ऐसी स्थिति में पहले दिन आपने आराम किया और paracetamol लिया, लेकिन इससे आप ठीक नहीं हुय ।

आपने ईलाज का चुनाव करते समय आप इस बात को याद रखें कि आपको दो दोनों से बहुत तेज़ बुखार है और ऊपर दिए गए डॉक्टरों का विवरण भी मौजूद है । इन डॉक्टरों का विवरण आपके गाँव के नजदीकी डॉक्टरों के विवरण से अलग हो सकता कै । अगर आपको यह choice मिलें और आपकी मौजुदा स्थिति जैसे कि पैसा और वक़्त को ध्यान में रखते हुए किसे चुनेंगे ?

	झोला छाप	प्राइवेट MBBS	सरकारी MBBS	कोर्इ अंगेज़ी डॉक्टर नहीं
दाम	 Rs.50	 Rs.100	 Rs.25	
दवा	 गोली + सूई लगाना	इलाज तय नहीं	 एक्सट्रा रूपया Rs.+	
दूरी	 घर में	 5-15 kms	 गाँव में	
राय	 None	 Positive	 Negative	

Dr Choice: _____ _____ _____ _____

जब आपने जवाब चुना तो किन "factors" के अनदेखा किया ? ___ ___ ___

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