Introduction to Discrete Choice Modelling and MECS

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Contents

1 Introduction

Researching the transition from business as usual biomass cooking to modern energy cooking services in the MECS programme requires innovation and design of technology to facilitate that transition. To date very few consumers in DFID priority countries have adopted modern energy cooking services, and so it is not always easy to determine what parameters, designs, products, services are key to enabling the transition. Designers are faced with a range of decisions they need to make when designing technology or thinking about consumer value propositions and it is important that consumer opinions inform such decisions.

There are a number of approaches to design and product development. In order to help inform thinking within MECS, we propose a particular survey methodology that has worked well for Gamos. The survey technique is based on a discrete choice modelling approach as a means of exploring consumer preferences relating to cooking devices. Discrete choice modelling reports for six countries (Ghana, Kenya, Myanmar, Tanzania, Uganda, and Zambia) are already available on the MECS website. This working paper lays out the reasoning behind using Discrete Choice Modelling.

Inclusive innovation has been gaining momentum as a concept since the mid-2000s. It refers to the idea that products, services or organisational arrangements can be introduced into new contexts in ways that reduce poverty through one or more of the following: (i) meeting the needs of the poorest in society; (ii) engaging the poor in business or (iii) actively reducing societal problems e.g. climate change. Three types of inclusive innovation have been predominately discussed in the literature: (i) grassroots innovation; (iii) base of the pyramid innovation and; (iii) below the radar innovation. These types of inclusive innovation are deemed to create benefits for individuals, communities and/ or countries in terms of money, time and opportunities. There is however, recognition that innovative activity is hampered in its level of inclusivity by a range of technological and social factors. These have traditionally been examined from the supply side. However, recent work in the renewables field highlighted that a series of complex demand side contextual factors cannot be ignored. Specifically, it highlights the importance to end users of a technology's usability, its ability to fit with various environmental factors and prevailing habits in a household or community. Discrete choice modelling survey has been developed as a means of exploring demand side factors.

The reports to date contain only a brief introduction to the methodology, so the purpose of this document is to give a more detailed understanding of the methodology, its strengths and weaknesses, and to present an overview of the findings. This document is also intended to stimulate debate within the MECS team around the kinds of information and market characteristics that remain unknown, and which could be addressed using discrete choice surveys in the future.

2 What is Discrete Choice Modelling?

Choice modelling creates a mathematical model that aims to represent people's decision making processes. Based on a number of input parameters, the model tries to predict how a population would make choices between different options. The approach belongs to a family of modelling techniques developed in the field of marketing and econometrics that attempt to assign some kind of value to non-market resources.

There are several names used for different survey based techniques in this field so it may be worth giving an overview of some of these. **Contingent valuation** (often referred to as '**Stated preference**') was initially developed as means of attributing some kind of financial value to resources that cannot be bought and sold, yet have some kind of value. For example, contingent valuation provided a means of quantifying the loss of environmental amenity resulting from the Exxon Valdez oil disaster and was used to assess financial damages awarded[1]. This uses questions of the form "how much compensation would you demand for the destruction of X area?". However, results can often be skewed because of protest responses for example, and respondents need not take account of affordability or other constraints on values. One problem with stated preference is that when asked a relatively direct question, people are able to think through what they want to say and change it according to who they are speaking to. If a well-suited lawyer is asking the question, the response is likely to be different to the answer given to a community activist that is well known to them.

Economists concerned with understanding consumer behaviour and consumer demand in particular developed theories based on the concept of utility i.e. consumers make rational choices that maximise utility. However, they came to realise that purchasing decisions are often actually based on additional factors, most of which are unobservable (e.g. budget constraints, branding, store experience). **Revealed preference** theory provided a means of understanding consumer preferences for bundles of attributes. A key feature is that it based on an analysis of actual purchasing behaviour. Clearly this has limited value when researching potential markets for products that do not yet exist, so consumers have no relevant purchasing history. This also led them on to conduct willingness to pay experiments which, in the context of an evaluation, can be quite informative.

However, Choice modelling, also referred to as conjoint analysis[2], can be designed as revealed preference studies, based on previous purchasing choices, but it can also be designed as an experiment to explore selections between hypothetical choices (confusingly referred to as stated preference choice modelling). It is this application that makes it useful for exploring a market for a future product, particularly when it is difficult for a consumer to state what they would like about a product if they do not yet have exposure to the product.

It is often referred to as discrete choice modelling because participants are asked to make discrete choices between two (or more) options. By combining factors into two 'discrete' choices, and getting comparison between multiple pairs of choices, it is possible to gain valuable insights into individual factors. This is in contrast to stated preference because the thought process each respondent is going through in order to make what is effectively a complex choice between options in front of them is hidden and ultimately only revealed when the analysis is undertaken. In short – it is very difficult for respondents to 'game' the system based on their beliefs about what the person asking the question might want or be able to provide. It is a survey-based statistical technique used in market research that helps determine how people value different attributes (feature, function, benefits) that make up an individual product or service[3].

The methodology has become popular in the fields of marketing and transport studies, and more recently in health economics. In the energy sector it has been used to consider consumer preferences with regards types of heating system, appliance efficiency levels, and fuel efficiency level of vehicles.

3 Objectives of DCE in MECS

When thinking of the design of a modern energy cooking service, a range of decisions and compromises need to be made based on consumer preferences. But which are the right design decisions? The MECS programme took a number of design decision points and used discrete choice experiments as a means of understanding consumer preferences regarding various aspects of the design and functionality of modern energy cooking services. In the experiments run to date, the aspects explored were based on the design decisions made by

[1] https://en.wikipedia.org/wiki/Contingent_valuation

[2] The term discrete choice experiment tends to be used in most places, although in America the techniques are referred to as choice based conjoint analysis.

[3] https://en.wikipedia.org/wiki/Conjoint_analysis

Gamos in designing the first eCook protype. Of course, the methodology can be applied to explore an alternative range of design aspects.

Gamos wanted to gain an understanding of a large number of design aspects, too many to include in a single choice model, so they were divided into three design domains:

- Cooking processes – cooking capability (boiling, frying), speed (power), use of lid, number of hobs
- Stove – capacity (number of people), smoke emissions, portability and looks
- Additional functionality – lights, mobile phone charging, TV, financing options, ability to clean.

The survey has also been used to gather valuable data on cooking practices (e.g. the mix of fuels used and the timing of meals), and the quality of electricity supplies. Data on expenditure on cooking fuels is especially useful as this represents disposable income that can be substituted by modern energy cooking services.

4 Design of the DCE Survey

As stated, discrete choice experiments enable understanding of user priorities pertaining to selected products and with which the consumer need not be so familiar. It focuses on the parameters of design involved and asks respondents to make choices between two discrete options (hypothetical technical solutions, or products) with different design parameters. Essentially it asks “Would you like product A with these types of characteristics or would you like product B which has a different set of characteristics?”.

Choice models are set up using choice cards, based on the key parameters identified, each of which has a limited number of ‘levels’. In MECS surveys, each design domain was assigned between 4 parameters, each parameter having between 2 and 4 levels (see Table 1). Each design domain also included a cost parameter (not represented in the table), which was considered to be a continuous variable. This enables willingness to pay figures to be calculated for different features of a cooking device.

Table 1 Parameters and levels

Parameter	No. levels	Level 1	Level 2	Level 3	Level 4
Cooking processes					
Type of cooking	2	Boil only	Boil & fry		
Power (speed of cooking)	3	slow	normal	Fast	
Use of lid	3	No lid	Pot with lid	Sealed pot	
Number of hobs	3	Single hob	2 hobs	4 hobs	
Stove					
Capacity (people)	3	Cooks for 4 people	Cooks for 6 people	Cooks for 8 people	
Capacity (devices)	3	always need to use with another stove	sometimes need to use with another stove	you can do all your cooking on it	
smoke emissions	3	No smoke	gives same smoke as charcoal fire	gives same smoke as wood fire	
Portability	2	cannot be moved (too heavy)	can be carried in/out of the house		
looks	2	Looks plain	Looks good		
Functionality					
Devices	4	2 hobs	2 hobs + 3 LED lights	2 hobs + charge mobile phone	2 hobs + television
Availability	2	only works on sunny days	works on sunny and rainy days		
Financing	3	pay each month (utility)	lease over 6 years	lease over 3 years	
Cleaning	2	awkward to clean	Easy to clean		

The number of combinations, n, is:

$$n = l_1 \, x \, l_2 \, x \, l_3 \, _{x.....}$$

Where:

l_i = number of levels in the i^{th} parameter.

So there are 54 possible combinations of design parameters for the Cooking processes experiment. 54 choices would be too much for the respondent so fractional orthogonal design[4] is used to reduce the number of choices to 16 choice cards per technology (Mangham, Hanson, & McPake, 2009). Orthogonal design ensures that all possible combinations are adequately covered, and that the stats package can unpack the responses down to the values assigned to the individual parameters.

In our case, a simple constant comparator approach was used (De Bekker-Grob et al., 2010), in which one of the 16 choice cards was used as a 'reference'[5], and the 15 resulting pairs presented respondents with a choice between this comparator and each of the other choice cards. The respondent must choose one of the two cards presented; an example is presented in Figure 1.

The literature suggests that respondents get fatigued when presented with too many choices, and a review suggested studies rarely used more than 16 choices (De Bekker-Grob, Ryan, & Gerard, 2012). Given that we ideally wanted commentary on three sets of 16 cards (48), rather than present all 16, it is possible to have two

[4] Using SPSS software.
[5] The constant comparator choice card was selected on the basis that the mix of levels represented a mid-level of attractiveness, so one would expect the number of times the comparator was chosen and reject to be roughly balanced.

sets of respondents answering half the questions each, and then analyse as a whole. Therefore, for each design domain the choice cards were split in two sets (with 7 & 8 pairs in each), included in a Questionnaire A and Questionnaire B. We then hypothesised that, moving on to another design domain within the same questionnaire, the respondent would be prepared to answer another two sets of 7 or 8 pairs (22 to 23 choices in total, spread out over the questionnaire).

14	Choice A	Choice B
Cost per month	1600 KSH/month	800 KSH/month
Cooking Functions	Can boil and fry	Can only boil
Cooking speed	Slow	Slow
Flavour	No smokey flavour	Smokey flavour
Type of pot	Pot with lid	Sealed pot (cannot stir)
Number of hobs	2 hobs	1 hob

Figure 1 Example of choice card

Descriptor data was also gathered from respondents, such as age, gender, level of education and so on. Two composite descriptor variables have been calculated representing characteristics of households that might be expected to influence attitudes towards, and eventual adoption of, modern energy cooking devices. A poverty index has been calculated from five variables including the level of education of the respondent and the quality of the dwelling. A technological aptitude index has been calculated from variables representing personal use of media, phones and the internet services. Preferences have then been disaggregated by descriptors and indices to highlight particular aspects that may be more important to specific customer segments.

According to Rose (2009) "an archetypal SC experiment might require choice data be collected on 200 respondents, each of whom are observed to make eight choices, thus producing a total of 1600 choice observations". However, the survey design includes other questions that can be used to disaggregate the data. Splitting the sample between, say, male and female means that the sample size must increase again. If we believed 200 was sufficient for insight into the attributes, then 300 is needed if data is to be disaggregated. (Orme 2010[i])

To a large extent, sample size is determined by budgetary constraints, although there is a minimum sample size below which results are likely to be meaningless. The WHO guidelines suggest the sample size must be more than 30, and a review of exercises suggests that standard error reduces only marginally for sample sizes over 300.

One of the leading experts in choice modelling states:- "For robust quantitative research where one does not intend to compare subgroups, I would recommend at least 300 respondents**. For investigational work and developing hypotheses about a market, between thirty and sixty respondents may do**." Orme (2010) (authors' emphasis). This calls into question what the survey is intended to achieve. The proposal describes a market research survey to derive insights into market segments, which implies that a high degree of confidence (demanded for robust quantitative research) is not required.

We believe that we want a reasonable confidence, but do not need a sample that yields 99% confidence. Therefore our approach to the sampling has been based on 'what question fatigue do we expect….. what within the budget is feasible….what confidence levels would this give….are these sufficient?"

We think that the sample should ideally be 300, but we can get reasonable market insights with 200 with one degree of disaggregation (assuming a reasonable spread of the disaggregating attribute across the sample). Sample sizes for the DCE surveys conducted to date range from around 200 to 300.

5 Analysis

Data sets derived from choice modelling are quite different to those from other types of surveys. Each choice comprises a pair of choice cards i.e. two records are generated for each of the questions. The data is, therefore, 'expanded' into a matrix of continuous and categorical dummy variables that represent the characteristics of each choice (the level for each parameter), along with a categorical 'choice' variable – the dependent variable indicating whether the respondent chose or rejected the choice card in the pair presented (scored 1 if the option was chosen, and 0 for the rejected option) (World Health Organisation, 2012).

The analysis used binary logistic regression to fit predictive models to the data for each design domain because the dependent variable was a dichotomous categorical variable (representing whether the choice card was chosen or not). All of the parameters were entered into the model, which calculated regression coefficients for each, along with p values indicating whether the parameter was significant in the model. The modelling was done using SPSS. The two main figures to look for in output tables are the beta coefficients (B), which reflect the strength of preference for each attribute, and whether each coefficient is significant in the model (Sig). If a variable is significant (Sig<0.05), then the larger the B value (positive or negative), the more important it is in the making a choice. Other statistics presented include the standard error (S.E.), which is a measure of how precise the beta value is likely to be – a large standard error means that that the actual beta value may lie within a wider range. The odds ratio (Exp(B)) is the change in odds resulting from a unit change in the predictor variable, and is another measure of the influence the variable has on people's choice, as is the Wald statistic. As all variables have been separated out into dichotomous dummy variables, the degrees of freedom (df) for all variables is 1.

Where the cost variable is significant in a model, a measure of willingness to pay (also known as implicit price) can be derived for each attribute from the ratio of the coefficients (Hanley, Mourato, & Wright, 2001):

$$WTP = \frac{-\beta_x}{\beta_c}$$

where:

$\beta x =$ coefficient of any parameter
$\beta c =$ coefficient of cost parameter

For model convergence, the data should have little or no collinearity. The reasons for this have more to do with information theory than anything else. To understand why this is, take the following example[6]:

If a car dealership sells both luxury cars and used low-end vehicles, the decision to buy a car from this dealership is the sum of the individual contribution of each of the following to the total utility.

- Price

[6] From Wikipedia.

- Marque (BMW, Chrysler, Mitsubishi)
- Origin (German, American)
- Performance

Using multinomial regression on the sales data however will not tell us what we want to know. The reason is that much of the data is collinear since cars at this dealership are either:

- high performance, expensive German cars
- low performance, cheap American cars

There is not enough information, nor will there ever be enough, to tell us whether people are buying cars because they are European, because they are a BMW or because they are high performance. The reason is that these three attributes always co-occur and in this case are perfectly correlated, i.e. all BMW's are made in Germany and are of high performance. These three attributes: origin, marque and performance are said to be collinear or non-orthogonal. When exploring models, data should be checked for collinearity.

6 Findings so far

6.1 Design preferences

A summary of the choice preferences across all six countries for all three design domains is presented in Table 4 to Table 6. One striking feature is the high degree of consistency across countries.

For example, relating to cooking processes:

- there is a universal preference for a device that can both boil and fry. This is consistent with the finding that large numbers of people (roughly one third) cook on only a single device (see Table 3).
- In most countries people had a preference for a lid (rather than an open pot), but not for a sealed pot. This highlights a potential challenge if designing a sealed vessel such as a rice cooker of pressure cooker.
- It was interesting to find that in most countries, choices revealed a clear preference for a device that did **not** impart a smoky flavour to the food. This is in contrast to stated preferences evident from lengthy and animated discussions that we have experienced in focus groups.

Table 2 Fuel stacking

Country	Proportion of respondents fuel stacking (2 or more cooking fuels) (%)
GH	71%
KE	62.9
TZ	58.2
ZM	47.4
MM	46.2
UG	25.3

Relating to stove design:

- There is universal preference for a high capacity device that can cook for larger numbers of people.

- Only in Myanmar was there an apparent preference for a device that could cook all of the foods prepared. This does not appear to be a design requirement because people are accustomed to cooking with multiple devices (see Table 3), with the notable exception of Uganda. Indeed in Ghana there was even a preference for a device that would always need to be used in conjunction with another device.
- There was almost universal preference for a portable device, which is consistent with the finding that a substantial proportion of respondents cooked both indoors and outdoors (except Myanmar, see Figure 2).

Table 3 Cooking devices

Country	Proportion of samples with single cooking device (%)
MM	38
TZ	35
ZM	43
GH	22
KE	42
UG	72

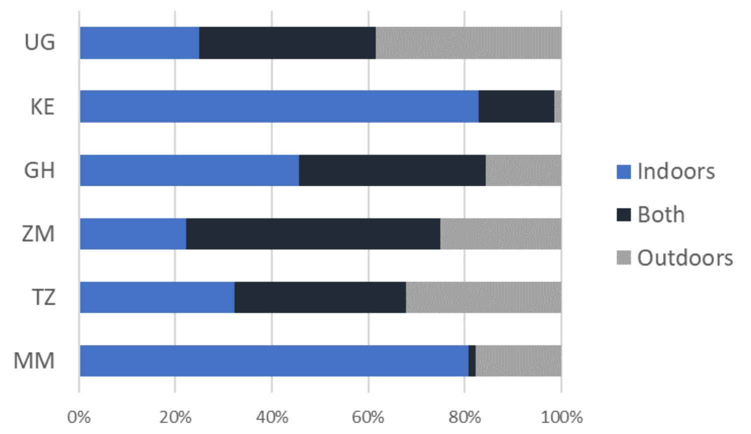

Figure 2 Location for cooking

Relating to functionality options:

- A preference for a device that can cook all days (regardless of weather) was evident across all countries except Uganda (which may reflect a poverty status issue).
- In all countries except Tanzania, people preferred a lease financing arrangement to a utility style rental model where they would pay a monthly fee forever.
- In all countries except Tanzania, having a device that is easy to clean appears to be important.

Although not included in this paper, further analysis was conducted to explore differences in preferences between different groups of respondents. The effects of five demographic variables plus two constructed, composite variables were investigated:

- Gender
- Settlement (rural/urban)
- Choice of main cooking fuel
- Size of household
- Age of respondent
- Technical proficiency
- Poverty status

Table 4 Comparison of design preferences across countries - Cooking processes

Cooking processes

	MM		TZ		ZM		GH		KE		UG	
	• Cooking – prefer to be able to both boi • Cost. • Hobs – people prefer double hobs, but • Lid – people have a strong preference f • Taste – there was a clear preference fo		• Cooking – prefer to be able to bo • Cost – preference for low cost de • Power – people preferred a devi • Taste – there was a clear prefere		• Cooking – prefer to be able to bo • Cost. • Hobs – people prefer multiple h • Lid – people have a strong prefe		• Cooking – prefer to be able to bo • Cost – preference for low cost de • Hobs – people prefer double hol • Lid – people have a strong prefe • Taste – there was a clear prefere		• Cooking – prefer to be able to bo • Cost. • Hobs – people would like multip • Lid – people have a strong prefe • Speed – would like a stove that c • Taste – there was a clear prefere		• Cooking – prefer to be able • Cost. • Hobs – people have a stron • Speed – it appears that peo • Taste – there was no prefer	
	beta	sig	beta	sig	beta	sig	beta	sig	beta	sig	beta	sig
Cooking(1)	2.255	**0**	0.275	**0.019**	1.138	**0**	1.268	**0**	0.721	**0**	0.275	**0.002**
SpeedMed(1)	0.246	0.232	0.218	0.135	0.224	0.11	0.525	**0**	0.417	**0.001**	-0.41	**0**
SpeedFast(1)	0.442	**0.042**	1.101	**0**	0.155	0.306	0.238	0.127	0.646	**0**	-0.334	**0.003**
Flavour(1)	-0.996	**0**	-1.42	**0**	-0.201	0.14	-0.807	**0**	-0.495	**0**	-0.181	0.076
PotLid(1)	1.521	**0**	0.277	0.136	1.409	**0**	1.362	**0**	0.357	**0.006**	0.257	0.077
PotSealed(1)	-0.159	0.45	0.076	0.599	0.143	0.366	-0.203	0.216	-0.041	0.741	-0.02	0.858
@2hob(1)	1.013	**0**	-0.038	0.776	0.558	**0**	1.12	**0**	0.413	**0**	0.85	**0**
@4hob(1)	-0.065	0.792	0.203	0.202	0.502	**0.002**	0.34	0.052	0.354	**0.006**	0.591	**0**
CPCOSTC	-0.531	**0**	-0.416	**0**	-0.413	**0**	-0.937	**0**	-0.552	**0**	-0.392	**0**

Table 5 Comparison of design preferences across countries - Stove design

Stove													
MM			TZ			ZM		GH		KE		UG	
• Capacity – they want to be able to cook			• Capacity – people want to be abl			• Capacity – people want to be abl		• Capacity – people want to be abl		• Capacity – people want to be abl		• Capacity – people want to b	
• Capacity – people want to be able to dc								• Capacity – people would prefer t					
• Cost.			• Cost – preference for low cost de			• Cost.		• Cost.		• Cost.		• Cost.	
• Portable – people would like a device t						• Portable – people would like a d		• Portable – people would like a d		• Portable – people would like a d		• Portable – people would lik	
• Smoke – people would prefer a device			• Smoke – people would prefer a			• Smoke – people strongest prefe		• Smoke – people would prefer a		• Smoke – people would prefer a		• Smoke – people would pre	
	beta	sig		beta	sig	beta	sig	beta	sig	beta	sig	beta	sig
People6(1)	-0.136	0.419	STPeople(	0.079	0.588	0.468	0.001	0.62	0	0.409	0.001	-0.241	0.024
People8(1)	0.437	0.001	STPeople8	0.464	0	0.93	0	0.981	0	0.724	0	0.442	0
SupplementSom	-0.289	0.186				-0.378	0.011	-0.389	0.004	-0.15	0.209	0.063	0.534
SupplementAll(1	0.848	0	STSuppler	-0.03	0.838	-0.033	0.814	-0.067	0.655	-0.051	0.669	0.122	0.235
WoodSmoke(1)	-0.534	0	STWoodSı	-1.865	0	-1.303	0	-1.742	0	-0.552	0	-0.371	0
CharcoalSmoke(	-0.562	0.001	STCharcoa	-0.964	0	-0.21	0.125	-0.407	0.002	-0.209	0.098	-0.242	0.027
Portable(1)	0.986	0	STPortabl(	0.219	0.062	0.417	0	1.381	0	0.374	0	0.508	0
Looks(1)	-0.008	0.94	STLooks(1	-0.064	0.587	0.178	0.1	0.212	0.038	-0.057	0.548	0.049	0.557
STCOSTC	-0.786	0	STCOSTC	-0.463	0	-0.454	0	-1.083	0	-0.522	0	-0.253	0

Table 6 Comparison of design preferences across countries - Functionality

Functionality

	MM		TZ		ZM		GH		KE		UG	
	• Availability – people had a strong prefe • Finance – people have a strong preference for leasing models over simply n • Cleaning – preference of a device that was easy to clean.		• Availability – people had a stron • Cost		• Accessories – TV, then mobile pl • Availability – people had a stron • Finance – people have a strong p • Cleaning – preference of a devic • Cost		• Accessories – TV, then mobile pl • Availability – people had a stron • Finance – people have a strong p • Cleaning – preference of a devic • Cost		• Accessories – TV • Availability – people want a stov • Finance – The ability to lease mc • Cleaning – having a device that v • Cost		• Accessories – TV and chargi • Availability – people appea • Finance – people have a str • Cleaning – preference of a • Cost	
	beta	sig	beta	sig	beta	sig	beta	sig	beta	sig	beta	sig
LED(1)	-1.623	**0**	-0.151	0.372	0.345	**0.036**	0.791	**0**	0.691	**0**	0.218	0.055
Mob(1)	-0.103	0.582	0.133	0.487	0.523	**0.002**	1.118	**0**	0.646	**0**	0.679	**0**
TV(1)	0.396	0.073	0.239	0.196	0.716	**0**	1.289	**0**	0.736	**0**	0.708	**0**
Availabe(1)	1.489	**0**	1.804	**0**	1.111	**0**	0.983	**0**	0.977	**0**	-0.161	**0.046**
@6yr(1)	0.894	**0**	0.026	0.875	1.152	**0**	1.031	**0**	0.349	**0.006**	0.619	**0**
@3yr(1)	0.503	**0**	-0.058	0.707	1.282	**0**	0.322	**0.004**	0.525	**0**	0.568	**0**
Cleaning(1)	0.91	**0**	-0.207	0.101	0.257	**0.027**	0.499	**0**	0.375	**0**	0.324	**0**
FUCOSTC	-0.011	0.9	-0.506	**0**	-0.509	**0**	-2.058	**0**	-0.365	**0**	-0.235	**0**

6.2 Energy and cost data

Obviously national data collection from DHS and MTF surveys have more representative sample, however, as an insight into energy and costs data, the choice modelling respondents were asked what fuels they used for cooking, and for each of these they were then asked questions on consumption and costs. This data has been used to estimate the consumption of energy for each fuel. The complexion of cooking fuel choices in each country is presented in Figure 3.

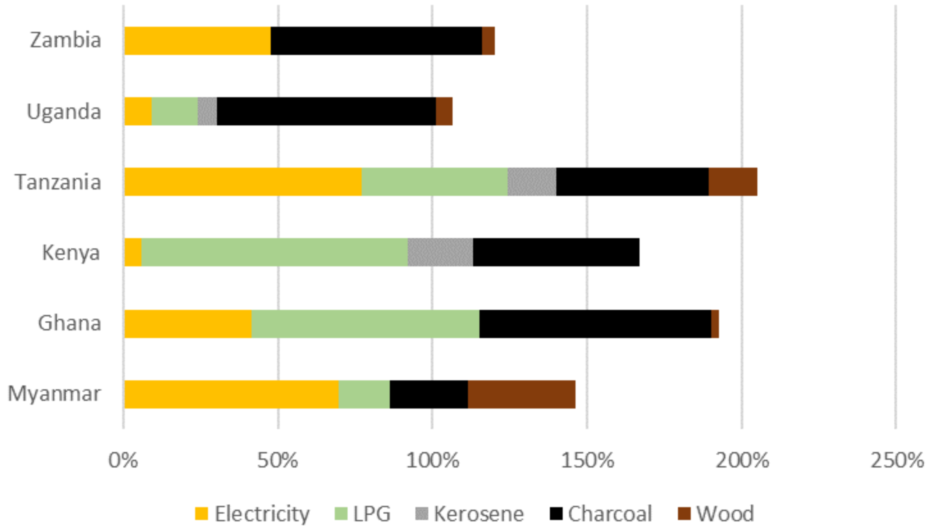

Figure 3 Proportion of households using fuels for cooking

Monthly household expenditure on cooking fuels has been estimated and is presented as cumulative distribution curves in Figure 4. This monthly expenditure represents disposable income that can be substituted for repayments on a modern energy cooking device. In practice, it is likely that households would be prepared to pay a premium for a device that offers an improved experience over biomass stoves. Median values range from 9 USD/month in Myanmar to 19 USD/month in Zambia (Table 7), meaning that half of the samples pay more than these amounts.

Table 7 Median monthly expenditure on cooking energy

	MM	TZ	ZM	GH	KE	UG
Median (local currency)	13000	40000	190	70	1100	40000
conversion	1500	2200	10	5.57	104	3700
USD/month	8.67	18.18	19.00	12.57	10.58	10.81

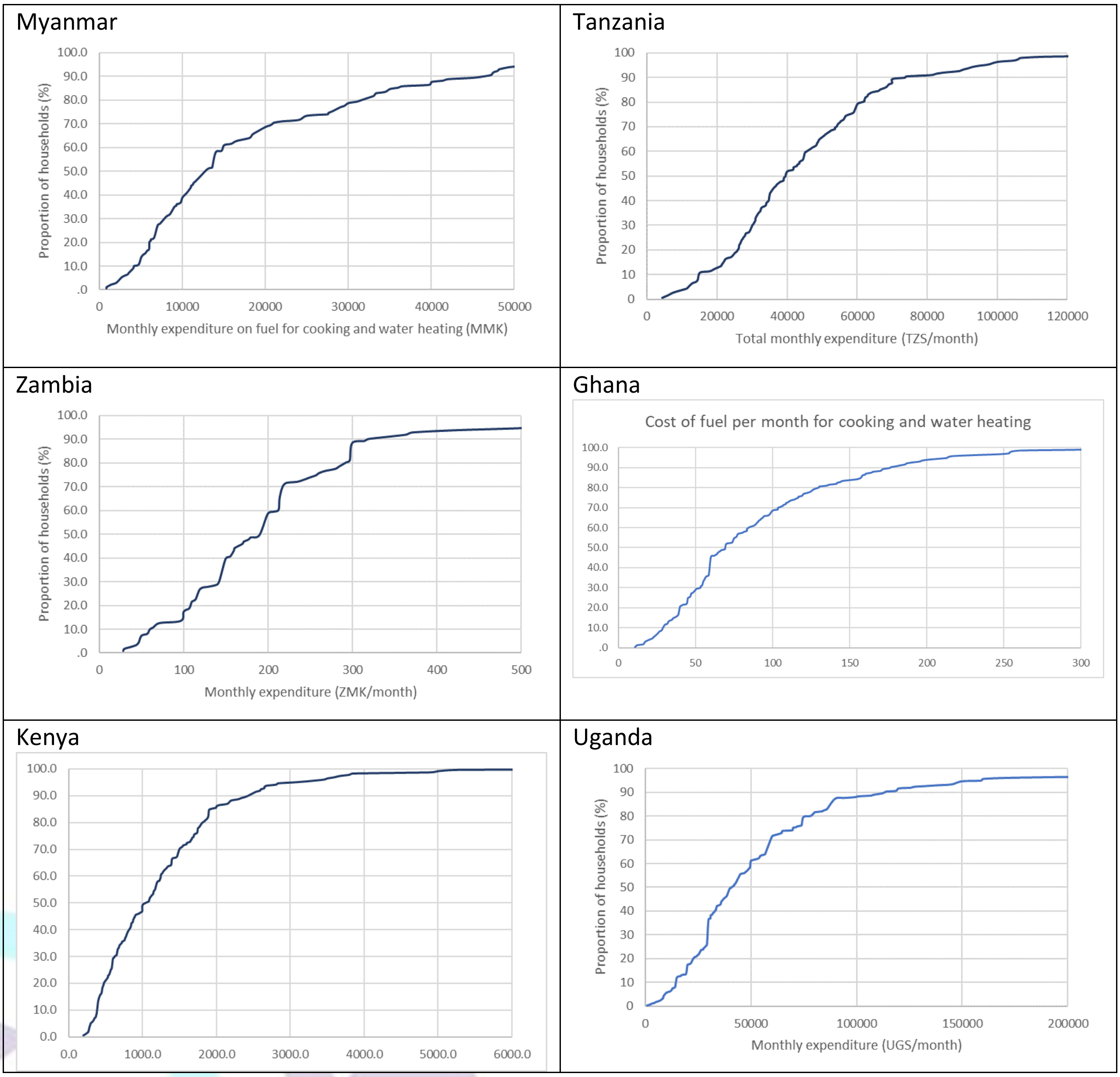

Figure 4   Monthly household expenditure on cooking fuels

Figure 5 indicates that resistance to changing cooking fuels is strongest in Uganda, and lowest in Myanmar and Tanzania.

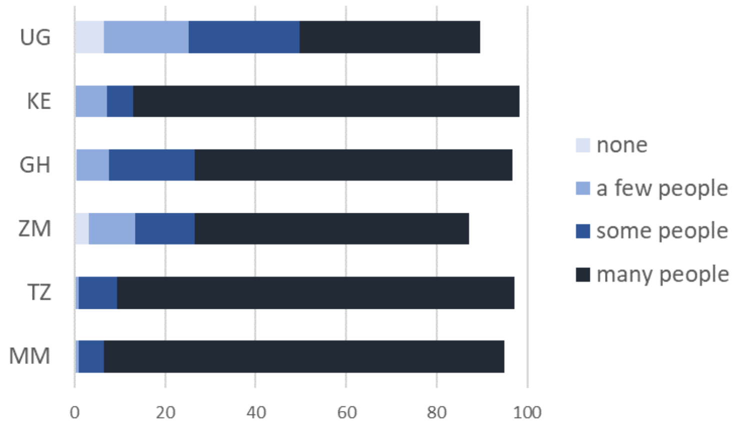

Figure 5 How many people would switch to modern energy (gas/electric) if fuels cost were the same

[i] Orme, B. (2010) Getting Started with Conjoint Analysis: Strategies for Product Design and Pricing Research. Second Edition, Madison, Wis.: Research Publishers LLC. http://www.sawtoothsoftware.com/download/techpap/samplesz.pdf