Women's demand for barrier methods for HIV prevention in South Africa:

Analysis of a discrete choice experiment using the random parameters logit estimator

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Aims: To estimate women's relative preferences and willingness-to-pay (WTP) for HIV prevention products and their characteristics and understand the variation of preferences among different women/market segments.

Data: A discrete choice experiment was conducted among 1017 women in three township communities in Johannesburg, South Africa. Women were presented with choices between different barrier products (microbicides, diaphragm, female condom) and 'what I did last time I had sex' (either: use 'a male condom' or 'no protection'). Characteristics of products included different HIV-prevention efficacies (35% - 95%), pregnancy-prevention efficacies, ability to use in secret or not, and a range of prices.

Methods: The data were analysed with three alternative econometric models: multinomial logit, nested logit, and random parameters logit (RPL). We estimated women's relative preferences for products and their characteristics, and their variation by socio-demographic characteristics. Model results are compared.

Results: The models all generate the same relative ordering of preferences. The RPL model shows significant heterogeneity in tastes between women, some of which can be attributed to socio-demographic characteristics. Results allow for identification of market segments. Microbicides were the most and female condoms the least preferred product. HIV-prevention efficacy was the most important attribute in women's choice. Interpretation of results from the RPL allowing for inter-attribute error-term correlations and simulation of individual WTPs is currently underway.

Conclusions: The variation in women's preferences for products and their attributes suggests that market segmentation of women's barrier methods for HIV prevention will facilitate wider-spread use. The RPL models identify characteristics of such segments and their WTP values for targeting.

1 Introduction

As the HIV epidemic continues to ravage much of sub-Saharan Africa, new infections among women have now surpassed those among men in developing countries []. Young women (age 15-24) are disproportionately affected with prevalence rates three times higher than that of men of the same age[1]. Male and female condoms are known to be effective in reducing sexual transmission of HIV and some sexually transmitted infections (STIs) when used correctly in every sex-act. However, this is very difficult to achieve in most relationships[2-5]. For women, male and female condoms can be difficult to access, in general, and especially difficult to negotiate within steady partnerships[6,7], within which a substantial portion of women are now becoming infected[8]. There is a need for methods that women can initiate and use more discretely[9-12].

Clinical trials are currently underway to test the STI- and HIV-prevention efficacy of microbicides, a new class of products for HIV prevention. At the start of the project a trial was ongoing to test the efficacy of the diaphragm in preventing HIV. This did not show an effect but was part of the study and will thus be included in the analysis [13-15]. Vaginal microbicides, although at the efficacy trial stage, look promising in their ability to decrease the vaginal transmission of HIV and possibly some or all of the other STIs. Ideally microbicides would be available in contraceptive or non-contraceptive formulations[16-18].

In order for these new woman-initiated methods[1] to be most effective, it is critical to facilitate women's access to all barrier methods for HIV-prevention, and once effective new methods are found, it is crucial to ensure access to and use of them as quickly and widely as possible. In this paper, we focus on analysing a discrete choice experiment (DCE) around women's preferences for product attributes of new barrier methods (boxes 1 and 2 in figure 1)[2]. This will help understand/predict uptake of barrier methods by new users and substitution between barrier methods by existing barrier method users. This is part of a larger (PhD) study which explores the determinants of women's demand for new and existing barrier methods for HIV prevention at the user, technology and distribution strategy levels to inform introduction and distribution strategies for new barrier methods in South Africa, and draw broader lessons for lower resource settings (figure 1).

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[1] Throughout this paper we use methods and technologies interchangeably. Method is the standard terminology, but technology portrays the fact that the use of products are being referred to and not HIV risk reduction in terms of methods of behaviour change such as abstinence or partner reduction.

[2] Existing barrier methods to be considered are the male condom and female condom. New methods to be considered are the diaphragm, and microbicides. At the start of this project a trial was also underway to assess the effect of diaphragms in their ability to prevent HIV transmission; this trial showed no impact on HIV incidence [ ]. However, it was part of the discrete choice experiment and will be included in the analysis.

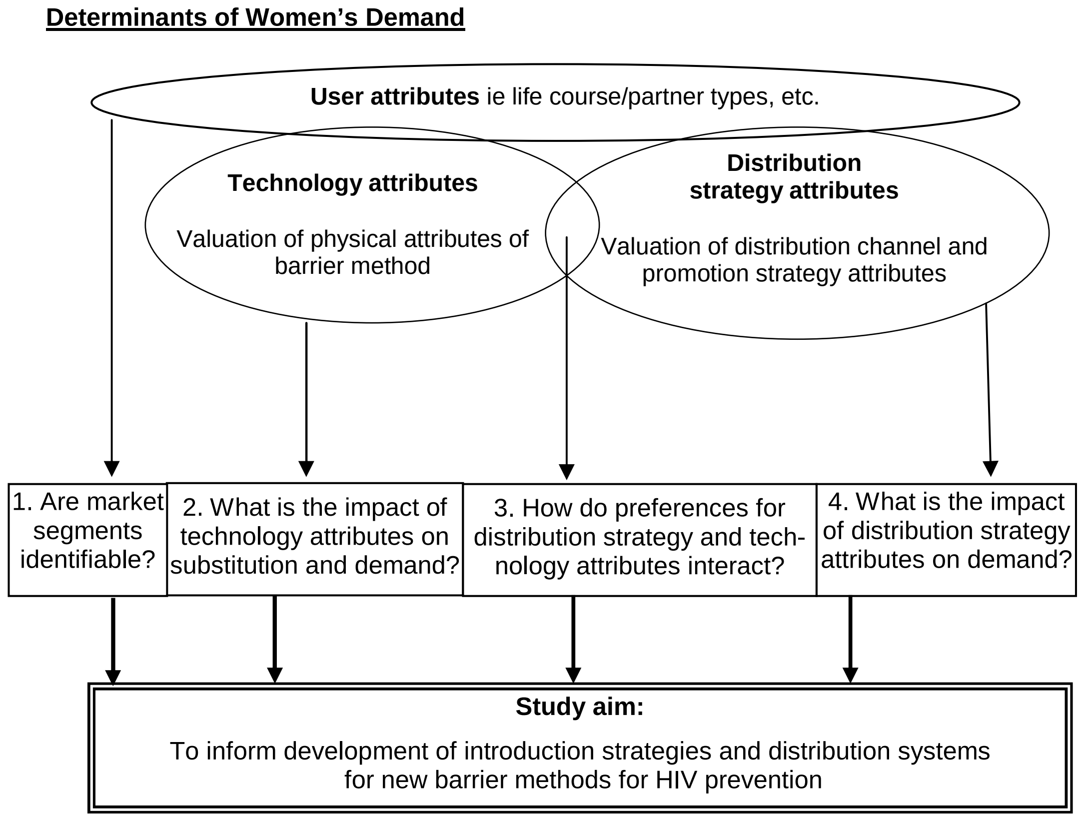

Figure 1 Overview of study

In this paper, first the survey and the specific discrete choice experiment will be described. Section 3 provides the methods, starting with a review of the theory of discrete choice experiments and discrete choice modelling and an overview of the estimation plan. The results are presented in section 4. We end with next steps in bullet points.

2 Methods

To address the question of determinants of women's demand for new barrier methods, we aim to gain insights into women's preferences for these products and their attributes. The most common methods used to obtain values for hypothetical goods are contingent valuation where people are directly asked about their willingness to pay (WTP) and conjoint analysis, where values are obtain indirectly from the choices people make in a choice experiment. There are a number of different question formats, one of which is discrete choice experiments (DCE). DCE are consistent with economic theory and provide values that can be interpreted as marginal or total values. We have chosen to apply a DCE as it provides insights into the trade-offs that women make within the different attributes of the products and obtain values for these different attributes. In this section we provide a brief introduction to DCEs, followed by a discussion of the survey and the specific DCE applied. 2.4 discussed the three discrete choice models that will be applied and we finish by a discussing the specific estimation approach.

2.1 Overview of discrete choice experiment

DCE allows people to choose between alternatives (here A or B) and in some experiment the status quo (here C). Each scenario represents different levels of a number of product/service attributes. Including price as one of the attributes enables estimation of the respondent's willingness to pay (WTP) for specific attributes. The aim of DCE is to estimate the probability of an individual choosing to consume a specific service or set of attributes, x, given their observable individual characteristics (socio-economic status (SES)), s, and the choice alternatives (choice set) available to them, A, of which x is one of the alternatives: $P(x \mid s, A) \quad \forall x \in A$. The advantage of DCE is that respondents are faced with trade-offs between product attribute levels, more closely representing the choices made in everyday life, and are thus more realistic[20]. DCE has its theoretical roots in Random Utility Theory[21] and Lancaster's Theory of Demand[22]. This method allows us to estimate the marginal rate of substitution between barrier methods.

2.2 The survey

A household survey of 1017 adult (18-45 years old) sexually active women was undertaken in three township communities in Johannesburg, South Africa to capture women's views on new barrier methods for HIV prevention that are specifically being developed to make it easier for women to protect themselves. The three communities were chosen to reflect variations in socio-economic status (SES). Within the communities, a representative random sample of women was selected.

The questionnaire was developed based on extensive qualitative research and captured information on demographics, reproductive health histories, directly elicited preferences, and a DCE.

2.3 The experiment

Two discrete choice experiments were undertaken. One on the topic of physical product attributes (the topic of this paper) and one on distribution strategy attributes. The attributes and levels included were chosen after a series of focus group discussions, in-depth interviews, a group attribute prioritisation questionnaire and a pilot. There were a total of 120 physical attribute choice sets and 60 distribution attribute choice sets, totalling 180 choice sets. These choice sets were generated in SPSS to obtain an orthogonal design. There was a generic questionnaire, which was administered with the assistance of a flipchart. There were 20 flipchart versions, each containing a fraction of the design. Each respondent answered 10 discrete choice questions, of which 9 part of the discrete choice experiment, and 1 testing for either: response bias, dominance, or stability, or a hold-out question to test predictive validity.

The DCE section included a warm-up question to help the respondent understand the concept of DCE questions and trade-offs between the attribute levels. To improve realism, no infeasible alternatives were included in the choice sets. Throughout the questionnaire images were used to clarify concepts, and information was given on the products. A male condom, female condom, a diaphragm, and a microbicide applicator filled with lubricant were provided for respondents to inspect as they wish, and ask questions.

In the physical attributes DCE, women had 3 options, 2 barrier methods and attributes and 'Neither, I would do what I did last time I had sex'. This type of experiments generates unconditional demands. That is, it generates the number of women who would not use either of the new methods and the shares of those who would use a new barrier method and in which proportions. The 'Neither' option card had 2 sides, each representing the attribute levels of either having used a condom or having not used a condom, depending what they had previously responded to that question; so 'male condom' goes with 95% protection against HIV and Pregnancy, cannot be used in secret and is available for free. The 'no condom' side contained the attribute levels: 0% protection against HIV, 0% protection against pregnancy, could be used in secret and is free (Table 1 and Figure 2).

2.4 Discrete choice models-

Traditionally, discrete choice experiments have been analysed using the multinomial logit (MNL) model. This model is fairly simple to estimate and interpret and has been mostly widely applied. However, its validity is based on the relatively restrictive assumption of independence of irrelevant attributes (IIA). A relaxing of the assumption of IIA was introduced with the Nested Logit model (NL). The random parameters logit model is the most recent model that allows for preference heterogeneity, i.e. different people can value different attributes differently. A number of other econometric models have also been applied but are not as useful in this application and will not be discussed. We start out with a discussion of estimation using the MNL, and its basic outputs, then will proceed to discuss the less restrictive NL and RPL models.

2.4.1 The multinomial logit (MNL) model

An individual *q*'s utility can be thought of as made up of a systematic component *V* and a random component ε: $\mathrm{U}_{\mathrm{iq}} = \mathrm{V}_{\mathrm{iq}} + \varepsilon_{\mathrm{iq}}$. To obtain an estimatable model of choice behaviour, two assumptions need to be made to remove the unobservable error term in utility function U_{iq}. The first is that there must be some probability that each of the alternatives in the choice set is chosen, given the individuals *s* and the available alternative set *A*, and the second is irrelevance of independent alternatives (IIA) set effect. This means that choices are not affected by the other alternatives presented, the choice between the car and the bus should not depend on the availability of the train, if it does, IIA is violated. The implication of this is that the random terms in the utility function must be independent between alternatives and have identical distributions. When these assumptions hold the following can be estimated using the multinomial logit model (MNL):

$P_i = \dfrac{1}{\sum_{j=1}^{j} \exp-(V_i - V_j)}$ where P_i is the probability of choosing the *i*th alternative, and

$$V_{jq} = \sum_{k=1}^{k} \beta_{jk} X_{jkq}$$

where *X* are the attributes as perceived by individual *q*, and *j* is the alternative with *k* attributes. This model, estimated by the maximum likelihood estimator, can then provide estimates of the utility parameters, *ßs*, for the choice alternatives *j* using the equation above.

To estimate the utility V_{jq} of an alternative j to individual q with specific attributes and levels X, the *ßs* of those attributes can be added as in the equation above. The output will also provide a t-ratio for each utility parameter, when significant this can be interpreted to influence an individual's choice, that is the attribute is important to the decision maker. Goodness of fit for such models is evaluating using the likelihood-ratio index (or the ρ^2 statistic) and an analysis of how well the model predict the actual choices made. Although violations of the IIA assumption is often violated, in the aggregate the model appears quite robust and is the most commonly applied model in marketing.

When adding interaction terms, as we will be doing with socio-demographic characteristics, significance levels for variables included in any of the interactions must be calculated and do not come directly in the model output:

> "the analyst who employs a multiplicative interaction model is typically interested in the marginal effect of X on Y. In the case of Eq. (1), this is $\delta Y/\delta X$ = ß1 + $ß_3 Z$. As a result, the analyst really wants to know the standard error of this quantity and not the standard error of b0, b1, b2, or b3. The standard error ($\sigma^2_{\delta Y/\delta X}$) of interest is:
>
> Y = ß0 + ß1X + ß2Z + ß3XZ *Eq.(1)*
> $\delta Y/\delta X$ = ß1 + $ß_3 Z$
> $\sigma^2_{\delta Y/\delta X} = \sqrt{(var(\hat{ß}1) + Z^2 var(\hat{ß}3) + 2Z cov(\hat{ß}1\hat{ß}3))}$
>
> If the covariance term is negative, as is often the case, then it is entirely possible for $ß_1 + ß_3$Z to be significant for substantively relevant values of Z even if all of the model parameters are insignificant.7" (Brambor, Clark and Golder (Political Analysis (2006) 14:63–82)).

It is because of the latter that we need to be slightly cautious in directly interpreting the significance of the model parameters for the interaction terms.

2.4.2 Nested Logit

The MNL model as shown above is fine when all the choices are close substitutes, including the no purchase option (Ryan, 2003). However when this does not hold, the IIA assumption must be relaxed. When the choice to purchase depends on the expected utility of the other choices, decisions are better represented by a two-stage or hierarchical process. The NL model is quite popular as it relaxes the IIA assumption while maintaining ease of computation. It depicts choices in hierarchical levels with partitioned choice sets. Within the partitions (branches), IIA must hold, but not between the branches, which is where this model relaxes the IIA assumption. The final tree structure is found through trial and error in the search for the lowest log-likelihood at convergence. Elasticity formulae then need to take into account the correlation between alternatives in the same partition. Estimation of models with 2 to 4 levels is done simultaneously.

2.4.3 Random Parameters Logit

Heterogeneity between respondents needs to be taken into account, because multiple observations are obtained from individuals. This is commonly accounted for using the RPL model, a more generalised form of the MNL model. The RPL model relaxes the IIA assumption and can account for multiple observations from respondents, (Johnson 2000;

Revelt 1998) but it cannot incorporate nested decision making processes. The RPL model accounts for both heterogeneity across respondents' observations and in tastes. The model produces a range of coefficient values (preference/tastes variations, ie WTP values) in the population using a distribution and standard deviation. Coefficients distributions are pre-specified by the analyst and can be normal, log-normal, triangular, or uniform. Estimation is achieved by simulation. Outputs predict market shares through calibration. However the calculation of WTP is more intricate since now we are dividing not 2 coefficients, as in the RPL and NL models, but 2 distributions around the coefficients to obtain a WTP value with a distribution. An extension of this RPL model adds correlations in individuals' preferences across attributes. So, if people who have high values for the female condom are also those people who value pregnancy prevention the highest, their preferences are correlated. This correlation is very interesting from a marketing perspective because it guides the development of product categories that could appeal to different market segments.

A problem with the RPL model with correlations is that it is still new there are few applications to follow. The econometric package LIMDEP 8.0/NLOGIT 3.0 was used to estimate the models, following the steps laid out in 'Applied Choice Analysis' 2005 by Hensher, Rose and Greene. Though this book is quite prescriptive, some of the areas that are lacking in detailed guidelines are around specification of the simulation and acceptable outcomes.

We have used Halton draws rather than random draws because it is a more efficient simulation technique makes the model run more efficiently and allows convergence to occur with fewer model iterations [Bhat in HRG2005]. The other advantage is that you get the same estimate with each model run; with random draws the output will change each time, making it very hard to compare different model specification. Generally models with more iterations specified are less likely to achieve convergence in more complex models, including RPL models with correlations. Henscher, Rose, and Greene, 2005 (HRG) suggest 25 Halton draws is sufficient (p615), though 100 is good.

2.4.4 IIA testing

The LIMDEP programme includes a command to test for violations of the IIA assumption, developed by Hausman and McFadden (1984). This should generally be conducted prior to moving on to more advanced models such as nested logit and RPL. However, it involves removing one alternative from the choice set and testing if the choice probabilities remain constant. There are two problems with conducting this test. 1. It assumes a labelled experiment; where removing an alternative means removing something meaningful, e.g. removing bus, from the transport modes car, bus, train. In this case, where the experiments are generic, it does not have any behavioural meaning. We will rather assume IIA is violated, and proceed to the more advance estimation models after exploring the MNL estimator. Then test within the advance models if they are necessary, ie if the nested logit, needs multiple branches (significance levels of inclusive values), and if the RPL actually has random parameters (significance levels of the standard deviations of the random parameters).

2.5 Estimation Approach

The output of the discrete choice models are relative utilities. The simplest form of the models incorporates only product attributes in the utility function. We then proceed to estimate models which consider the effect of socio-demographic characteristics (SDC) on preferences. We start by exploring the MNL, progress to NL, then RPL, then RPL with correlations.

Table 1 Overview of models to be estimated

	Product attributes only (Simple)	Product attributes and SDCs
MNL	Table 4 - 1	Table 5 - 5
NL	Table 4 - 2	Table 5 - 6
RPL	Table 4 - 3a 3b	Table 6
RPL with correlations		Table 7

For generic experiments, adding SDC will quickly expand the number of variables needed to estimate and thus the degrees of freedom. This is because each SDC included means adding a cross product of the SDC with all the attribute variables to obtain an estimate of how the SDC changes women's' preferences for a specific attribute. The variables selected to represent women's' socio-economic status and their self-determinism are by: the women's' employment status (emp), whether they live with their sexual partner (q49), or their use of condoms during the last sex act (q104)). LIMDEP 8.0/NLOGIT 3.0 is used for estimation.

3 Results

When directly asked about there preferred products (figure 2), 49% said microbicides would meet their needs best, 29% said the diaphragm. A much smaller group expressed that the female condom (13%) or the male condom (9%) suited their needs best.

Which of these products do you think would suit your reproductive health needs best. Please think about which of these products you would be most likely to use regularly.

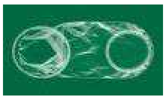 Female condom	 Microbicide	 Diaphragm	 Male condom
13%	49%	29%	9%

Figure 2 Directly elicited preferences

Table 3 shows that 44% of responses to the choice sets of women who were able to use condoms would be not to switch, while only 17% of responses of women who did not use a male condom would be to do the same. This is an encouraging result for policy makers who are concerned for substitution from the condom to newer, likely less effective, products.

Table 2 Difference in response frequencies for women who did and did not use a male condom in their last sex act.

	Switch (A or B)	No Switch (C)	Total
Women who did not use a condom in their last sex act	3466 83%	727 17%	4193
Women who did not use a condom in their last sex act	1073 56%	835 44%	1908

3.1 Multinomial logit

Table 4 shows the simple MNL model results, where no interactions for socio-demographic characteristics are incorporated. Microbicide has the highest utility and female condom the lowest. Most important (with largest coefficient) appears to be the level of efficacy in preventing HIV infection. These results are consistent with a priori expectations and Table 3, where microbicides appear most popular, followed by the diaphragm. There appears to also be high utilities related to not switching (2.97) especially for women who used a condom in their last sex act (3.66). The highest utility obtainable from switching would be to a microbicide that is usable in secret with 95% efficacy in preventing pregnancy and 95% efficacy in preventing HIV provided for free (relative utility 4.61). The least attractive feasible alternative would be a diaphragm, which cannot be used in secret, has 75% efficacy in preventing pregnancy and 35% efficacy against HIV and is sold at R20 (relative utility -1.40). WTP is estimated as ($-\beta_{attribute}/\ \beta_{price}$). WTP for the most preferred product with utility of 4.61 would then be: (-4.61/-0.12) R6.48.

Table 5 shows the MNL model with interactions for socio-demographic characteristics. This shows only the valuation of the HIV attribute of new products to be significantly affected by women’s characteristics. Women who used a male condom in their last sex act and cohabitating women valued the level of HIV protection from new products less.

Note: In this version of the paper it has not been possible to make the full calculations for the standard error of the multiplicative terms, so we must rely on the direct parameter standard errors to obtain an initial sense of the importance of the different variables.

Table 3 Physical no interactions MNL, NL, RPL 10 draws, RPL maximum draws (19),

	MNL			**Nested**			**RPL**	10 draws		**RPL**	19 draws
	1			2				3a		3b	
	Coeff.	Std. Err.	P-value	Coeff.	Std. Err.	P-value	Coeff.	Std. Err.	P-value	Coeff.	P-value
Diaphragm (DG2)	-0.04	0.03	0.235	-0.027	0.04	0.496	-0.028	0.05	0.539	-0.027	0.634
Microbicide(MD2)	0.28	0.03	***0.000***	0.322	0.04	***0.000***	0.343	0.05	***0.000***	0.382	***0.000***
Usable in secret (SEC)	0.04	0.03	0.115	0.048	0.03	0.130	0.065	0.03	***0.057***	0.087	***0.027***
Efficacy in preventing pregnancy (PRG)	1.17	0.08	***0.000***	1.360	0.10	***0.000***	1.498	0.11	***0.000***	1.675	***0.000***
Efficacy in preventing HIV (HIV)	3.39	0.11	***0.000***	4.295	0.15	***0.000***	4.370	0.23	***0.000***	4.800	***0.000***
Price (PRC)	-0.12	0.02	***0.000***	-0.165	0.02	***0.000***	-0.179	0.03	***0.000***	-0.197	***0.000***
No Switch-no condom	2.97	0.12	***0.000***	0.643	0.21	***0.002***	2.944	0.19	***0.000***	3.341	***0.000***
No Switch-condom dummy	0.69	0.03	***0.000***	0.660	0.03	***0.000***	1.237	0.09	***0.000***	1.376	***0.000***
Inclusive Values											
SWITCH				0.330	0.05	***0.000***					
NOSWITCH				1.000	-	***0.000***					
Standard deviations											
UsBDG2							0.733	0.40	***0.070***	0.793	0.219
UsBMD2							0.641	0.30	***0.032***	1.057	***0.002***
UsBSECR							0.054	0.29	0.853	0.410	0.272
NsBPRG							0.062	0.21	0.770	1.815	***0.000***
NsBHIV							3.861	0.38	***0.000***	3.690	***0.000***
NsBPRC							0.085	0.07	0.188	0.028	0.792
NsC							0.118	0.11	0.290	0.543	***0.022***
Female Condom	-0.242					-0.296			-0.315		-0.355

3.2 Nested logit

Many studies with an opt-out option, as we have here, use nested logit estimation. This allows for violations of the IIA assumption between branches, but not within branches. The question posed in the DCE was:

“Here are the products and this is what they do: Would you have used either of these products in your last sex act or would you have still done the same as you did the last time you had sex?”

This implies a 2-stage decision process. There is no reason to expect any difference in the variance of the error structure between A and B because they are exactly the same being a generic alternatives, but we might expect to find a difference between the variance of the error term of the No-Switch and Switch branches. We estimate a 2-level NL model (figure 3).

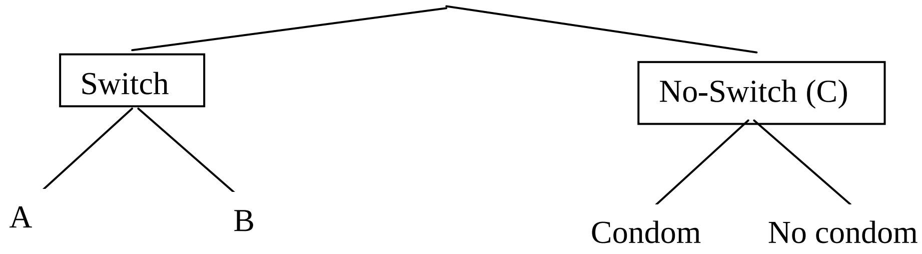

Figure 3 NL tree structure

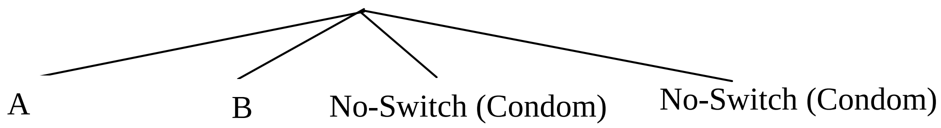

Figure 4 MNL tree structure

Both the simple model (Table 4) and the model with SDC interactions (Table 5) show fairly similar results to the MNL model. The order of preferences are maintained and the diaphragm and secrecy are both not significantly different from 0. The major difference is in the coefficient for No-Switch. In MNL this is 2.97 and in NL it is 0.643.

We test if the variance of the error terms of the no-switch option is different those in the Switch branch. Inclusive values (IV) are generated which are sometimes called dissimilarity parameters. In estimation, one inclusive value is normalised to 1, then the inclusive values of the remaining parameters must be significantly different from one for the nesting to be valid (the Wald test). That then means that the distribution of the error terms are significantly different from those of the normalised branch. Here the IV of ‘No-switch’ is set to 1. If IV for ‘Switch’ is significantly different from 1, the branch is valid and the error structure of A and B are different from C.

We find that the parameters for SWITCH are significantly different from 1. This means that the two levels are valid. If the IV was not significantly different from 1, the model would have collapsed into a single level (equivalent to the MNL model (figure 4)).

Table 4 Physical with interactions MNL-and Nested logit

	MNL 5			**NESTED** 6		
	Coeff.	Std.Err.	P-value	Coeff.	Std.Err.	P-value
Diaphragm (DG2)	0.01	0.04	0.774	0.065	0.05	0.178
Microbicide(MD2)	0.26	0.04	***0.000***	0.292	0.05	***0.000***
Usable in secret (SEC)	0.04	0.03	0.203	0.043	0.04	0.274
Efficacy in preventing pregnancy (PRG)	1.21	0.10	***0.000***	1.444	0.12	***0.000***
Efficacy in preventing HIV (HIV)	3.30	0.13	***0.000***	4.429	0.19	***0.000***
Price (PRC)	-0.11	0.02	***0.000***	-0.163	0.02	***0.000***
No Switch (C)	2.93	0.13	***0.000***	0.601	0.21	***0.005***
$B_{used\ condom}$ (104E)*DG2	0.07	0.05	0.109	0.146	0.06	***0.013***
$B_{cohabitating}$ (49E)*DG2	-0.01	0.04	0.788	-0.024	0.05	0.647
$B_{employed}$ (EMP)*DG2	-0.02	0.04	0.622	0.031	0.05	0.529
B104E*MD2	-0.01	0.04	0.709	-0.015	0.05	0.758
B49E*MD2	0.03	0.04	0.372	0.040	0.04	0.346
BEMP*MD2	-0.01	0.03	0.706	-0.040	0.04	0.331
B104E*SEC	-0.03	0.03	0.376	-0.031	0.04	0.442
B49E*SEC	-0.03	0.03	0.258	-0.052	0.03	0.135
BEMP*SEC	0.01	0.03	0.677	-0.001	0.03	0.984
B104E*PRG	0.04	0.10	0.699	0.055	0.12	0.658
B49E*PRG	-0.05	0.09	0.600	-0.111	0.11	0.301
BEMP*PRG	0.01	0.09	0.941	0.107	0.11	0.310
B104E*HIV	-0.23	0.13	***0.085***	0.086	0.18	0.640
B49E*HIV	-0.21	0.12	***0.091***	-0.376	0.16	***0.018***
BEMP*HIV	-0.06	0.12	0.640	-0.027	0.15	0.858
B104E*PRC	0.00	0.00	0.155	0.001	0.00	0.782
B49E*PRC	0.00	0.00	0.912	0.001	0.00	0.450
BEMP*PRC	0.00	0.00	0.120	0.001	0.00	0.386
C*104E	0.60	0.13	***0.000***	0.712	0.07	***0.000***
C*49E	-0.13	0.12	0.290	-0.067	0.06	0.268
C*EMP	-0.07	0.12	0.532	-0.040	0.06	0.486
SWITCH				0.315	0.04	***0.000***
NOSWITCH				1.000	-	***0.000***
Female condom	- 0.270			- 0.357		

3.3 Random Parameters Logit

Table 4 presents the RPL model with 10 (regression 3a) draws and with the maximum number of draws that achieves convergence (19) (regression 3b). Preference heterogeneity is represented by the standard deviations. Most of the coefficients are larger in magnitude than those produce by the MNL and NL models, especially the no-switch for women who were using a condom is about double the coefficients estimated by MNL and NL. Again, the coefficient for diaphragm is not significantly different from 0, but the coefficient for secrecy does now become significant, increasingly so with more draws. Consistent heterogeneity in preferences is found for microbicides and HIV efficacy. In the model with more draws the standard deviation around diaphragm looses significance (*we would expect this to be true, since what does a standard deviation around an insignificant variable mean*) , and ‘No Switch’ becomes significant.

Question box 1

- Is there a number of iterations below which a model is considered unstable?

There seems to be as much difference in the estimated parameters when moving from few to many iterations with the same estimator as between the estimators, so this can get quite messy. By changing the order of variables in the command syntax, different numbers of iterations can be achieved, generating different results. This can be a never ending process.

- When you compare the different model results (MNL, NL, RPL), how do you know what you are comparing is due to the choice of estimator or specification and not coincidence because of the maximum number of iterations achievable.

To identify some of the sources of heterogeneity we add SDC to the regression (Table 6). Again many of the same messages appear: the coefficient for diaphragm is not significantly different from 0, and Secrecy only becomes significant at higher number of draws. The model estimates from models using more draws also appear to increase the magnitude of many of the coefficients. Women who used a condom had lower preferences for HIV efficacy than women who had not used a condom; women who were living with their partners also had lower preferences for HIV efficacy than those who did not live with their partners. The significantly higher price parameter for employed women is significant in the model with 10 draws but unexpectedly disappears in both other runs.

Far more variation in preferences is detected when the model is run with more draws, while 2 parameters have significant standard deviations in the 8 draws, only 1 is *not* significant in the run with 23 draws. Impact of the products and their attributes on utilities depend on the SDCs. For example, in the model with 23 draws the coefficient for price =βprice+βbpri:q10*condom used+βbpri:q49*cohabitating+βbpri:emp*employed. Note the dummy variables are effects coded so they take on the values of 1 and -1 and not 1 and 0 as in dummy coding. For a women who used a condom in her last sex act, did not live with her partner and was employed this would then be: -0.257+0.020*1+0.010*-1+0.061*1= -0.186. For a woman who did not use a condom, lives with her partner and is unemployed it is -0.328. As mention around equation 1 (page 7), the significance level for price then needs to be calculated incorporating the variances and covariances of the interaction terms. However in this case there is then also a standard deviation around them, making these calculations even more challenging. HRG (2006) only mention the complications of estimating WTP values with random parameters. Normally, WTP values are calculated as follows: -βattribute/βprice. Now, there is a distribution around these which then can generate a standard deviation around the WTP values. In future research we will estimate the standard deviation of the parameters based only on their estimated parameters, ignoring their random characteristics.

Table 5 RPL with interactions 10 draws, RPL with maximum draws with manually generated interactions (8 draws), and with LIMDEP generated interactions (23 draws)

	10 draws LIMDEP generated interactions			**8 draws** manually generated interactions (as done in MNL and NL)			**23 draws** LIMDEP generated interactions		
	Coeff.	Std.Err.	P-value	Coeff.	Std.Err.	P-value	Coeff.	Std.Err.	P-value
Diaphragm (DG2)	0.086	0.056	0.121	0.008	0.044	0.863	0.107	0.08	0.207
Microbicide(MD2)	0.309	0.054	***0.000***	0.287	0.042	***0.000***	0.419	0.08	***0.000***
Usable in secret (SEC)	0.060	0.042	0.151	0.055	0.033	***0.098***	0.104	0.06	***0.077***
Efficacy in preventing pregnancy (PRG)	1.636	0.133	***0.000***	1.292	0.114	***0.000***	2.073	0.19	***0.000***
Efficacy in preventing HIV (HIV)	4.126	0.225	***0.000***	3.723	0.182	***0.000***	5.939	0.50	***0.000***
Price (PRC)	-0.163	0.033	***0.000***	-0.127	0.023	***0.000***	-0.257	0.05	***0.000***
No Switch (C)	2.613	0.211	***0.000***	3.091	0.164	***0.000***	2.583	0.30	***0.000***
$B_{used\ condom}$ (Q10)*DG2	0.199	0.056	***0.000***	0.096	0.052	***0.067***	0.274	0.08	***0.001***
$B_{cohabitating}$ (Q49)*DG2	0.009	0.048	0.852	-0.007	0.048	0.880	0.025	0.07	0.730
$B_{employed}$ (EMP)*DG2	0.049	0.047	0.291	-0.026	0.046	0.573	0.088	0.07	0.211
BMD2:Q10	-0.028	0.053	0.602	-0.017	0.044	0.693	-0.040	0.07	0.591
BMD2:Q49	0.035	0.046	0.447	0.034	0.040	0.403	0.032	0.07	0.621
BMD2:EMP	-0.069	0.045	0.122	-0.010	0.039	0.799	-0.097	0.06	0.134
BSEC:Q10	-0.044	0.042	0.297	-0.030	0.034	0.374	-0.053	0.06	0.364
BSEC:Q49	-0.047	0.037	0.207	-0.043	0.031	0.169	-0.041	0.05	0.411
BSEC:EMP	0.004	0.036	0.911	0.010	0.030	0.749	-0.002	0.05	0.960
BPRG:Q10	0.059	0.128	0.644	-0.076	0.119	0.523	0.003	0.16	0.984
BPRG:Q49	-0.089	0.114	0.438	-0.063	0.102	0.540	-0.118	0.14	0.412
BPRG:EMP	0.086	0.114	0.451	0.004	0.099	0.967	0.160	0.14	0.269
BHIV:Q10	-0.955	0.225	***0.000***	-0.194	0.152	0.200	-1.909	0.39	***0.000***
BHIV:Q49	-0.384	0.178	***0.031***	-0.242	0.136	***0.075***	-0.709	0.28	***0.011***
BHIV:EMP	-0.019	0.176	0.913	-0.031	0.132	0.817	0.086	0.27	0.749
BPRI:Q10	0.021	0.033	0.513	0.002	0.002	0.267	0.020	0.05	0.670
BPRI:Q49	0.007	0.028	0.794	0.000	0.002	0.955	0.010	0.04	0.809
BPRI:EMP	0.047	0.027	***0.075***	0.002	0.001	0.114	0.061	0.04	0.114
C :Q10	0.905	0.183	***0.000***	0.680	0.152	***0.000***	1.446	0.28	***0.000***
C :Q49	-0.223	0.162	0.168	-0.159	0.137	0.244	-0.354	0.23	0.121
C :EMP	-0.023	0.163	0.888	-0.065	0.133	0.623	0.033	0.23	0.886
Parameter standard deviations									
UsBDG2	0.635	0.333	***0.057***	0.494	0.335	0.140	1.893	0.39	***0.000***
UsBMD2	0.783	0.221	***0.000***	0.304	0.243	0.210	1.431	0.30	***0.000***
UsBSECR	0.013	0.245	0.959	0.056	0.172	0.745	0.196	0.35	0.569
NsBPRG	0.083	0.161	0.608	1.456	0.257	***0.000***	0.866	0.29	***0.003***
NsBHIV	4.644	0.409	***0.000***	0.626	0.283	***0.027***	8.719	0.97	***0.000***
NsBPRICE	0.075	0.054	0.163	0.028	0.043	0.508	0.414	0.10	***0.000***
NsC	0.081	0.106	0.448	0.011	0.080	0.888	2.479	0.43	***0.000***
FC	-0.395			-0.295			-0.525		

Note: the prefix on the parameter standard deviations signify the specified distribution. U: specified as a uniform distribution; N specified as a normal distribution. Other options are Triangular, and lognormal.

Utility estimates using the RPL model with correlations show how preferences for different attributes move together (are correlated). This then takes into account the panel nature of the data set with multiple observations from each person. Table 8 shows the RPL model with interactions and correlations. Interestingly, a reordering of the random parameters in the syntax allowed the number of draws to increase from 20 to 39. This is caused by changing of the order in which matrices are multiplied, resulting again in different outcomes and different number of obtainable draws. Many of the same results hold: Preferences for diaphragm and secrecy are not significantly different from 0, although this may change when the full standard errors are calculated. Women who used a male condom in their last sexact, relative to those who had not use any protection, had significantly:

- higher preferences for the diaphragm;
- lower preferences for being able to use a product in secret that those who did not (though the diaphragm parameter was insignificant);
- lower preferences for pregnancy prevention efficacy
- lower preferences for HIV prevention efficacy;
- Higher WTP;
- And higher value on not switching.

Employed women, relative to those not employed, placed lesser value on microbicides and have higher WTP values. Women who used a condom, relative to those who did not use a condom in their last sex act, had higher valuation for not switching, for the diaphragm, lower values for secrecy and HIV, and higher WTP values. Living with a partner did not appear to significantly affect the way women valued the products or their attributes.

Many of the products and attributes still have significant variances, indicating heterogeneity of preferences for those products/attributes. Price and microbicides no longer have significant variance, suggesting they do not need to be specified as random; the variation in preferences has now been explained.

The co-variance matrix shows how preferences were correlated between the different products and their attributes. That is, women who had high values for one, also had high values for the other, or visa versa for negative correlations. Positive correlations were found between preferences for: microbicides and the diaphragm, the diaphragm and HIV efficacy, HIV efficacy and pregnancy efficacy, WTP and microbicides, no-switch and pregnancy efficacy, and no-switch and WTP.

Negative correlations were found between: the diaphragm and pregnancy efficacy, microbicides and HIV efficacy, price and pregnancy efficacy, no-switch and secrecy.

By far the strongest correlation was between HIV and pregnancy efficacy. This suggests that a product would be far more desirable if it had high efficacy against not only HIV but also pregnancy.

Table 6 Physical RPL with correlations: 2 orderings of random parameters

Reordered random variables in syntax: preg, hiv, dg2, md2, secr, price, C(Neither)

max runs: 39

	Coeff.	**Std.Err.**	**P-value**
BDG2	0.137	0.177	0.438
BMD2	1.112	0.18	***0.000***
BSECR	-0.010	0.11	0.933
PRG	4.800	0.50	***0.000***
BHIV	13.510	1.20	***0.000***
BPRICE	-0.549	0.10	***0.000***
C	9.457	0.94	***0.000***
BDG2:Q10	0.555	0.16	***0.000***
BDG2:Q49	0.036	0.13	0.774
BDG2:EMP	0.103	0.12	0.393
BMD2:Q10	0.073	0.14	0.613
BMD2:Q49	0.188	0.12	0.122
BMD2:EMP	-0.273	0.12	***0.020***
BSEC:Q10	-0.231	0.11	***0.041***
BSEC:Q49	-0.158	0.10	0.108
BSEC:EMP	0.070	0.10	0.463
PRG:Q10	-0.953	0.33	***0.003***
PRG:Q49	-0.317	0.28	0.251
PRG:EMP	0.202	0.28	0.472
BHIV:Q10	-3.089	0.60	***0.000***
BHIV:Q49	-0.730	0.47	0.124
BHIV:EMP	-0.138	0.45	0.760
BPRI:Q10	0.147	0.09	***0.098***
BPRI:Q49	0.026	0.07	0.716
BPRI:EMP	0.125	0.07	***0.072***
C:Q10	1.177	0.60	***0.050***
C:Q49	-0.250	0.43	0.563
C:EMP	-0.247	0.42	0.558

Parameter variances (Cholesky matrix)			
UsBDG2	3.145	0.72	***0.000***
UsBMD2	0.044	0.59	0.940
UsBSECR	2.875	0.46	***0.000***
NsPRG	5.653	0.68	***0.000***
NsBHIV	4.295	1.24	***0.001***
NsBPRICE	0.163	0.21	0.437
NsC	1.310	0.45	***0.003***
Parameter co-variances (correlations)			
BMD2:BDG	3.627	0.61	***0.000***
BSEC:BDG	0.255	0.48	0.594
BSEC:BMD	-0.027	0.55	0.962
BDG2:PRG	-0.581	0.29	***0.046***
BMD2:PRG	-0.200	0.30	0.498
BSEC:PRG	0.117	0.20	0.556
BDG2:BHI	1.449	0.44	***0.001***
BMD2:BHI	-1.829	0.39	***0.000***
BSEC:BHI	-0.214	0.29	0.458
BHIV:PRG	15.752	1.47	***0.000***
BPRI:BDG	0.263	0.35	0.457
BPRI:BMD	1.140	0.39	***0.003***
BPRI:BSE	0.275	0.36	0.439
BPRI:PRG	-0.461	0.15	***0.002***
BPRI:BHI	-0.088	0.23	0.703
C:BDG	0.677	0.97	0.484
C:BMD	0.968	0.98	0.325
C:BSE	-2.348	0.87	***0.007***
C:PRG	7.985	1.02	***0.000***
C:BHI	-1.113	0.98	0.257
C:BPR	3.611	0.68	***0.000***
Female condom	-1.249		

4 Next steps:

- Calculation and comparison of utility values generated with the different models
- Estimate and compare WTP for MNL, NL and RPL
- What do we know about market shares and market segmentation? The interactions suggest indeed that certain market segments may be identified, though not as straight forwards as by the characteristics that were chosen. The main grouping heterogeneity explained by the selected SDCs was between women who had used and had not used a male condom. Though it was expected that cohabitating women would be quite different in their preferences for products, this is not coming out strongly. It was expected that especially women who were living with their partners would find secrecy more important, as these are the women who often find it most difficult to introduce condoms into their relationships. However the sign of 'BSEC:Q49' is negative, though not significant at conventional p-values, rather than the expected positives sign. .