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Choice of Rice Production Practices in Ghana: A Comparison of Willingness to Pay and Preference Space Estimates

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Abstract

Rice has been identified as an important food security crop in Ghana. However, there is a production deficit and new technologies to reduce the deficit are not widely adopted. Although poor adoption by farmers' is often linked to constraints such as access to information, farmers' perceptions of the technologies are also important. We apply an advanced discrete choice experiment to evaluate farmers' preferences for rice production practices. Specifically, we generate willingness to pay (WTP) estimates using willingness to pay space (WS) and compare these with values from the indirect or preference space (PS) method. Our modelling also accounts for the effects on WTP estimates of farmers' stated attribute importance (SAI) information. Empirical results from WS and PS models reveal that on average, farmers value higher yields and are negatively affected by higher risk of crop failure and labour requirements. Comparing the performance of the two models, we find the WS model provides a superior fit to our data and reduces the likelihood of producing implausible WTP estimates. Further, SAI inclusion did not produce much variation in our WTP estimates.

Keywords: *Adoption*; *discrete choice experiment*; *preference space*; *stated attribute importance*; *willingness to pay space*.

JEL classifications: *Q12, Q18*.

1. Introduction

In Ghana, rice is an important cash crop that forms an integral part of the Ghanaian diet, and is essential in ensuring food security among rural and urban households. The crop represents 34% of expenditure on cereals, with a per capita demand estimated at 68 kg per year (Ackah and Aryeetey, 2012). Despite the essential role of the

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crop in ensuring food security, its production is bedevilled with challenges such as weed control, water management, unavailability of suitable varieties, adverse soil conditions, poor market systems and insufficient labour (Oteng, 1997). Currently, domestic rice demand exceeds local supply by about 70%.

Over the years, many governments have introduced policies related to specific technologies aimed at addressing some of the challenges in rice production (Ragasa *et al.*, 2013). However, evidence indicates poor adoption levels among farmers (Ibrahim and Florkowski, 2015). Poor adoption of new technologies has been of both policy and research interest since the days of Feder *et al.* (1985), with most studies attributing farmer adoption to socio-economic characteristics and information awareness (Kariyasa and Dewi, 2013). However, Dalton (2004) notes that low adoption is not only driven by socio-economic characteristics but that it is also a function of failure of the technology development process to account for technology characteristics that producers value.

A large body of literature reports on potential technology characteristics that are appealing to farmers. For instance, Keelan *et al.* (2010) documents five key technology characteristics that affect farmers' adoption decisions: relative advantage in terms of benefits; compatibility; complexity; triability; observability. Adesina and Zinnah (1993) show that farmers' perception of technology attributes, such as returns in terms of output, is relevant for their adoption decisions. Other studies, such as De Brauw and Eozenou (2014) and Jaeck and Lifran (2013) note the effect of profitability and risk on low adoption. A major limitation of conventional modelling approaches to the study of farmers' adoption decisions is that they are based on actual choices, which means that one cannot investigate the possible adoption drivers for prospective technologies.

A better understanding of the technology characteristics that farmer's value would be useful in guiding agronomists and policy-makers in the design of and support for new technologies. Discrete choice experiments (DCEs) are an established method for identifying behavioural drivers of choice. In DCEs, respondents are presented with hypothetical scenarios and asked to make choices between them. The application of DCEs in developing countries is growing in empirical applications. Most of the studies (Birol *et al.*, 2006; Ouma *et al.*, 2007) address the issue of unobserved preference heterogeneity using the mixed logit (ML) model.

The ML model is a generalisation of the conditional logit model and is used to account for unobserved preference heterogeneity by assuming random parameters for model coefficients. Through its random parameter specification, the model introduces random preference variations assuming specific distributions over the sampled population. The ML model requires that specific distributions are adopted for the random parameters. Common distributions include the lognormal, which guarantees that the monetary attribute has the correct sign, and the normal that allow for both positive and negative preferences.

In most empirical applications, willingness to pay (WTP) values, which are the marginal rate of substitution between an attribute and a monetary attribute (Birol *et al.*, 2006), are calculated post estimation. Train and Weeks (2005) note the potential challenges associated with calculating WTP distributions within the mixed logit framework. Given that the parameters in the ML model are random parameters, the distribution of the derived WTP estimates is given by a ratio of the assumed distribution of the monetary and non-monetary attributes. For instance, where a coefficient for the monetrary attribute is specified as lognormally distributed and the coefficients for non-monetary attributes are normally distributed, then the distribution of the WTP values becomes a ratio of normal to lognormal, a distribution that, as Scarpa *et al.* (2008) point out, can be counter-intuitive.

The WTP problems associated with the ML model have resulted in an ongoing debate about its suitability in deriving WTP values. While some studies attempt to resolve the problem by adopting measures such as a fixed price coefficient (Revelt and Train, 1998), others apply individual level parameters conditioned with individual choices to generate a distribution of WTP (Greene *et al.*, 2006; Hensher *et al.*, 2006). Train and Weeks (2005) criticise the fixed price coefficient approach and suggest a re-parameterisation of the model such that the parameters are direct WTP estimates instead of marginal utility coefficients. Such an estimation procedure ensures that appropriate distributions are assumed for the WTP values. The direct estimation of WTP is referred to as estimation in willingess to pay space (WS), whereas models leading to the calculation of WTP from estimated marginal utilities (indirect approach) are operating in preference space (PS).

In spite of the potential advantages of the WS approach, there are no empirical applications in the agricultural adoption literature, and only a limited number of applications in other fields of economics. These studies, however, report conflicting findings about the performance of WS and PS models. For example, Train and Weeks (2005) employed classical and hierarchical Bayes models to compare PS and WS models and found that PS models are superior to WS models. This finding was corroborated by Hole and Kolstad's (2012) study on job choices by Tanzanian clinical officers. However, Scarpa *et al.* (2008) and Rose and Masiero (2009) have demonstrated superiority of WS models in their cases.

We apply and compare the WS and the PS models to examine farmers' preferences for production technology characteristics that farmer's value with the primary aim of providing guidelines to policy-makers. An additional feature of our application is to account for the effect of attribute non-attendance (ANA – the situation where respondents in a choice experiment study base their selection on a subset of attributes instead of the full set) on WS and PS estimates. There is increasing evidence in the literature that respondents in DCE applications tend to ignore some attributes when making choices. Failure to account for ANA results in biased WTP estimates (Hess and Hensher, 2013). Accounting for ANA in our application ensures unbiased estimation of the values farmers attach to the technology attributes.

Our empirical data are from a DCE conducted in Ghana, on rice farmers' preferences for rice production practices. Following Balcombe *et al.* (2014), we apply stated attribute importance (SAI) ranking questions at the end of the DCE survey to account for ANA behaviour in the model. Our choice of SAI over the common binary type questions often applied in the DCE literature is based on previous findings that respondents do not necessarily ignore attributes but rather attach low weight to them (Hess and Hensher, 2013).

The remainder of the paper is organised as follows. Section 2 presents the WTP estimation approaches. Section 3 presents a description of the choice experiment procedure. This is followed by empirical results and discussion in section 4. Section 5 concludes the paper with policy and methodological implications.

2. WTP Estimation Techniques

In the DCE literature, the standard approach is to estimate WTP in preference space (PS), where marginal utility coefficients are first estimated, followed by the calculation of WTP. The alternative of estimating in willingness to pay space (WS) addresses the challenges associated with WTP in PS, by reformulating the PS model so that the estimated coefficients directly represent the WTP values for the attributes. In the WS specification WTP values are directly estimated, such that appropriate distributions for the values are assumed from the outset.

In this section, we first specify the PS model. We then derive the WS model and concluded with the specification of the SAI model. The Random Utility Model (RUM) is the econometric basis for DCEs. The main assumption of RUM is that individuals choose the alternative that provides the highest utility among a set of alternatives. Based on RUM, we specify the utility, U_{nit} of individual n for choice i made in choice occasion t as the sum of two components: the systematic component, $V(X_{nit}, \beta_n)$ that is a function of alternative attributes j; and the random component, ε_{nit}, representing unmeasured variation in preferences. That is,

$$U_{nit} = V_{nit}(X_{nit}, \beta_n) + \varepsilon_{nit}. \tag{1}$$

To implement (1), we need to specify a distribution for the error term. Assuming that the error terms are independently and identically drawn from a Gumbel distribution, we have the conditional logit model (CLM). In the context of the CLM, the probability that individual n will choose alternative i among a set of J alternatives is given by McFadden (1974) as:

$$\Pr(i) = \frac{\exp(\beta' x_{nit})}{\sum_{j=1}^{j=J} (\beta' x_{njt})}. \tag{2}$$

To account for preference heterogeneity and address the independence from the irrelevant alternative (IIA) shortcoming of CLM, the ML model is applied. Under the ML model, the coefficient vector β is unobserved for each n and varies with the population density $f(\beta_n|\theta)$, where θ is a vector of parameters of a continuous population distribution. Since the analyst does not observe β_n, the unconditional choice probability is given as an integral over all possible variables of β_n:

$$P_{nit}(\beta_n) = \int \frac{\exp(\beta'_n x_{nit})}{\sum_{j=1}^{j} \exp(\beta'_n x_{njt})} f(\beta_n|\theta) d\beta_n. \tag{3}$$

To derive WTP within the PS model, we draw a distinction between monetary, M_{nkt}, and non-monetary attributes, x_{nkt} in equation (1):

$$U_{nkt} = \beta_{nm} M_{nkt} + \sum_{k=1}^{k} \beta_{nk} x_{nkt} + \varepsilon_{nkt}. \tag{4}$$

Note in this application the coefficient (β_{nm}) is positive in all our specifications because we use a monetary gain variable, such as gross margin instead of cost, where β_{nm} and β_{nk} are parameters for the monetary and non-monetary attributes, respectively. The part-worth or WTP for an attribute k can be written as the ratio of its coefficient to that of the monetary attribute as in equation (5):

$$WTP = \frac{\beta_{nk}}{\beta_{nm}}. \quad (5)$$

At a population level, the distribution of WTP is given by the ratio of the two distributions assumed for the monetary and non-monetary attributes. Despite the challenges this may raise, the model is widely applied. We now turn our attention to the WS model, which is a re-parameterisation of the PS model. We re-formulate (4) such that the coefficients obtained are direct estimates of WTP:

$$U_{nkt} = \beta_{nm}\left[M_{nkt} + \sum_{k=1}^{k} \beta_{nk}^{*} x_{nkt}\right] + \varepsilon_{nkt} \quad (6)$$

where $\beta_{nk}^{*} = \beta_{nk}/\beta_{nm}$ and β_{nm} is a normalising constant.

Thus, the formulation in (6) shows that β_{nk}^{*}, the coefficients derived from the model, are WTP values.

2.1. SAI, a measure of non-compensatory behaviour

The underpinning assumption of the DCE is that individuals make a trade-off between all attributes provided in the experiment. However, research has revealed that people may ignore some attributes in their choice-making process, which is evidence of non-compensatory behaviour. Failure to account for this type of choice behaviour may bias welfare estimates (Kragt, 2013). Empirical studies have often applied ANA procedures to examine non-compensatory behaviour. However, recent evidence shows that respondents do not necessarily ignore attributes, rather they attach less importance to them (Hess and Hensher, 2013). Therefore, measuring ANA by a simple '*Yes*' or '*No*' question of whether one ignored an attribute may be misleading.

In this paper, we follow Balcombe *et al*. (2014) to model SAI information by conditioning it on the utility parameter, which is similar to accounting for a characteristic of an individual in a choice experiment. SAI was measured on a scale of one to R (where R = 7), with one as the highest ranked attribute (most important) and R the lowest ranked (Balcombe *et al*., 2014). The SAI data were then normalised to range from 0 (more importance) to 1 (less importance) using the expression:

$$Z_{nk} = \frac{SAI_{nk} - 1}{R_k - 1} \quad (7)$$

where R_k is the lowest value given to attribute k. Therefore, an attribute ranked as 1 is deemed as ignored in the choice-making process.

From equation (1), the marginal utility, β_{nk} for the kth attribute is:

$$\beta_{nk} = \gamma_k + u_{nk} \quad (8)$$

where γ_k is the mean and u_{nk} is the *i.i.d.* vector with variance covariance matrix. Incorporating Z_{nk} in equation (8) as an explanatory variable to shift the mean, results in:

$$\beta_{nk} = \gamma_{0(k)} + \gamma_{1(k)} Z_{nk} + u_{nk}. \quad (9)$$

As a rule of thumb, if the explanatory variable, Z_{nK} is not significant, then equation (9) reverts to equation (8). That is, $\gamma_{0(k)}$ in equation (9) equals γ_k in equation (8) because $\gamma_{1(k)}$ is zero. However, if Z_{nk} is significant, then γ_k is equivalent to $\gamma_{0(k)}$ + $\gamma_{1(k)} Z_{nk}$.

2.2. Model estimation

The specified PS and WS models were estimated in Stata 13 (StataCorp. 2013) using programmes written by Hole (2007) and Gu *et al.* (2013). The WS model estimation can either be performed within the ML framework to account for only preference heterogeneity or within the generalised multinomial logit (GML) framework to account for both scale and preference heterogeneity. We apply the GML model in this paper to account for both sources of heterogeneity (Fiebig *et al.*, 2010 provide more details on the GML model). In total, five models were estimated: three using the PS approach: (CLM, standard ML, ML with SAI) and two using the WS (standard GML, GML with SAI) and allowing for correlation among random parameters. Apart from the CLM, all models were estimated by simulated maximum likelihood method using 1,000 Halton draws. We assumed a lognormal distribution for the monetary attribute, which is the gross margin, and a normal distribution for the remaining attributes; yield, labour and dummies of cultivar choice (medium and late cultivars), weed control (mechanical and chemical weeding), cropping pattern (rice-fallow and double rice system) and risk attributes.

3. Choice Experiment Description and Data

The data for our analysis were collected through a choice experiment survey conducted in the two most important rice producing regions in Ghana (Figure 1), Northern and Upper East.

The main aim of the survey was to identify farmers' preferences for rice production practices.

3.1. Attributes selection

Based on expert interviews, focus group discussions and relevant attributes established in the literature, we described a rice production technology using seven attributes. Four of these attributes are quantitative (yield, gross margin, labour and risk) while three are qualitative (cultivar choice, weed control technology and cropping pattern).

Yield and gross margin attributes were included to account for the relative advantage of new technologies. Also, as is the practice in the choice experiment literature, the gross margin attribute serves as the monetary attribute. The labour attribute is an essential component of the rice production system, since it is usually scarce during the production season, while labour requirements differ amongst technologies used: varietal choice (maturity period) and agronomic practices (weed control and cropping pattern). Uncertainty of production in developing countries is a major concern to most farmers. Farmers are typically assumed to be risk averse but evidence in the literature shows that this may not always be true (Engle-Warnick *et al.*, 2006). We therefore test the risk behaviour of farmers through the inclusion of the risk attribute. The risk attribute was defined as the probability of crop production failure under the alternative farming systems over a period of 10 years. Table 1 provides a description of the attributes in the study.

3.2. Experimental design

A pilot study conducted in February 2014 was used to generate priors for an efficient design. A total of 36 choice sets were generated using NGENE software

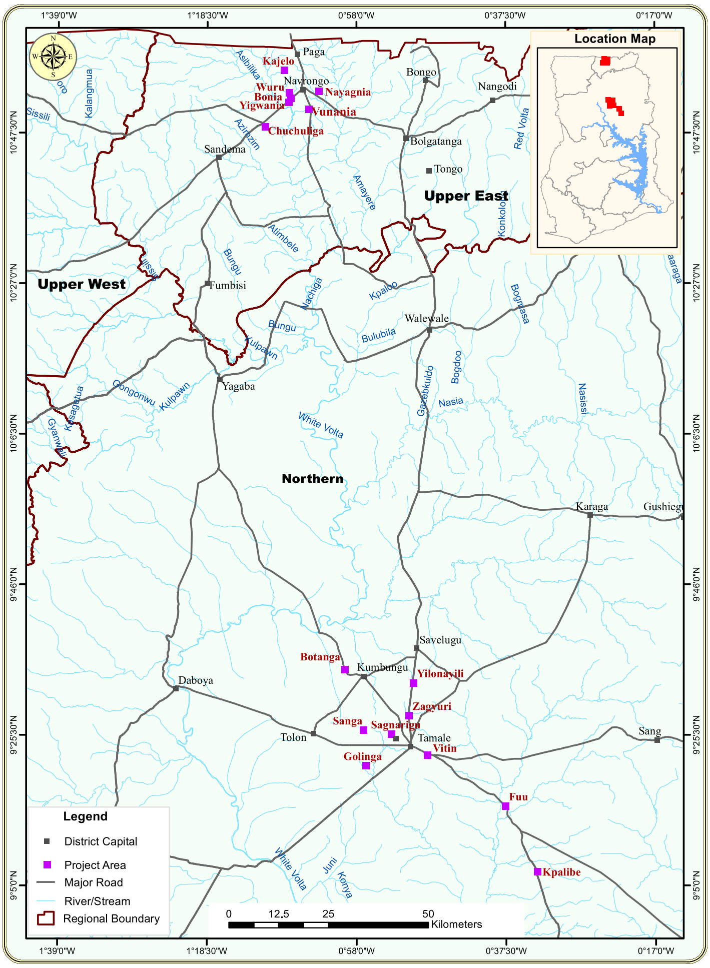

Figure 1. Map of study area indicating survey sites

(ChoiceMetrics, 2012). Using a blocking system, the choice sets were divided into three blocks with each consisting of 12 choice sets, each with two alternatives and the status quo, their current production system.

3.3. Survey administration and data collection

We designed and administered the DCE survey to 306 randomly selected rice farmers via the face-to-face interview technique. Six well-trained research assistants from the Ministry of Food and Agriculture conducted the interviews. Each respondent faced 12 choices, with each set offering three alternative farming systems. The choice experiment was conducted as a part of a larger survey that focused on the productivity and food security of rice producing households in Ghana. The first part of the survey asked questions on respondent's socio-economic characteristics as well as current farming practices. The choice sets followed. Debriefing questions were asked at the end of the survey (see online Appendix S1) to verify consistency in choices made. The

Table 1
CE attributes and levels

Attributes	Descriptions	Levels
Yield	Average rice equivalent yield per acre under alternative technology options for each production season	20 bags, 30 bags, 40 bags
Gross margin	Additional gross margin provided by alternative technology options per season	200 GHS, 400 GHS, 600 GHS
Labour	Additional labour requirement under different technology options per season	6 man-days, 12 man-days, 18 man-days
Cultivar choice	Maturity period of the crop varieties associated with alternative technologies	90 days, 120 days, 150 days
Weed control technology	Method of weed control associated with alternative technologies	Manual, mechanical, chemical
Cropping pattern	Type of crop cultivated in a given year under different technology options	Rice–vegetable system, rice–fallow system, double rice system
Risk	Likelihood of total production failure occurring under alternative technology options	1 in 10, 3 in 10, 5 in 10

data collection process began at the end of the 2013/2014 growing season and lasted for 5 weeks. Figure 2 illustrates a sample choice set.

3.4. *Descriptive statistics of sampled farmers*

A brief description of the sampled farmers in terms of socio-economics and SAI ranking information is provided in Table 2. The mean age is 41 years, suggesting a youthful population. In addition, we note that nearly 80% of the respondents are males because men predominantly cultivate cash crops like rice in Ghana. For the SAI rankings, we find that *yield* is perceived as most important, followed by *gross margin,* and *cropping pattern* is the least important attribute. This finding confirms the assertion by Nweke and Akorhe (1983) that rice farmers have both profit and food security objectives. This information is used in the estimation of PS and WS models to examine their effects on the marginal utilities.

3.5. *Questionnaire coding and processing*

We coded the quantitative attributes (yield, gross margin, labour and risk) using stated attribute levels as presented in the choice set and the categorical variables (cultivar choice, weed control and cropping pattern) were dummy coded. Although effects coding was an option, we preferred the dummy coding approach because it allows for a straightforward interpretation of model coefficients. A base scenario was included in the choice experiment to avoid forced choices, with the attribute levels identified from survey information about the respondent's current farming system.

For the risk attribute, we tested the effect of different specifications using a formulation based on prospect theory. We did this by re-specifying risk into two deviation variables: (i) All stated choice (*SC*) attributes greater than (individual specific) current risk levels were classified as a positive risk deviation (higher risk); (ii) All those less

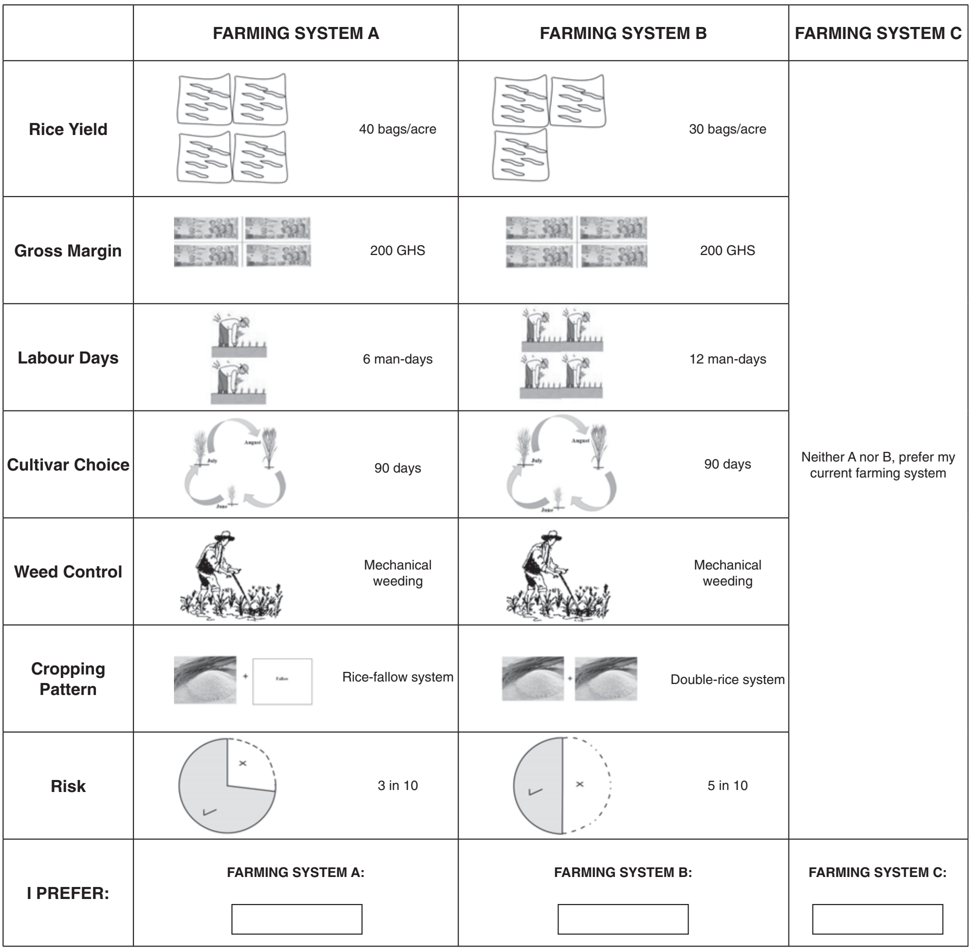

Figure 2. Sample choice set

than (inidividual specific) current risk levels are classified as negative risk deviation (lower risk). An illustration of the risk specification is presented in Table 3, using an example with three choice alternatives where the third one is the status quo choice. Individual 1 (first three rows in Table 3) faces a choice problem where the self-reported probability of crop failure in the status quo choice is 4 out of 10. The risk of crop failure for the technologies offered in alternatives A and B are lower. Therefore, for this individual, alternatives A and B reduce risk and thus have negative risk values of $-3/10$ and $-1/10$, both values that are calculated as changes in risk relative to the status quo.

In the case of individual 2 (where self-reported risk is 2/10), alternative A is less risky relative to the status quo, while alternative B is riskier; and these deviations are captured in the Negative risk and Positive risk variables. In addition to the risk deviation variables, our modelling uses an interaction between the *SC* risk levels and the status quo indicator: zero for new farming systems and one for the status quo

Table 2
Sample descriptive statistics

Variable	Definition	Mean	SD
Age	Age of respondents	41.35	10.96
Farmer organisation	Member of farmer organisation (Yes = 1)	0.54	0.49
Non-farm activity	Alternative livelihood (Yes = 1)	0.56	0.49
Educational status	Years of formal education	1.95	3.87
Gender	Sex of respondent (Female = 1)	0.23	0.42
Stated attribute importance (1 high, 7 low)			
Yield	Average rice yield per acre	1.65	0.97
Gross margin	Additional gross margin under alternative technology	1.91	0.88
Labour	Additional labour requirement under alternative technology	4.68	1.15
Cultivar choice	Maturity period of crop varieties under alternative technologies	3.60	1.05
Weed control	Method of weed control	4.16	1.32
Cropping pattern	Variety of crop cultivated	4.82	1.24
Risks	Probability of crop failure under alternative technologies	5.35	2.02

Notes: Ranking levels: 1 = most important, 2 = very important, 3 = moderately important, 4 = neutral, 5 = less important, 6 = not important, 7 = not important at all.

Table 3
An illustration of how the risk variables were constructed

Individual	Farming system	Risk	Negative risk	Positive risk
1	A	1/10	−3/10	0
	B	3/10	−1/10	0
	SQ	4/10	0	0
2	A	1/10	−1/10	0
	B	3/10	0	1/10
	SQ	2/10	0	0

alternative. This was done to test if respondent sensitivity to risk depended on whether the risk was attached to the current farming system or a new technology.

4. Empirical Results and Discussion

4.1. Standard models

Table 4 presents the estimation results for the basic model, CLM[2] (Model 1), a ML model (Model 2) allowing for preference variation in six attributes, and the GML model (Model 3) that accounts for preference and scale heterogeneity in WS. In the GML case, the number of random parameters reduces from six to five because the

[2]Robustness of the CLM was tested using bootstrap algorithm with 500 replications. The bootstrap CLM yielded similar parameter estimates.

Table 4
CLM, Correlated ML and GML estimates

	Model 1	Model 2		Model 3	
	CLM	ML correlated		GML correlated	
	Mean γ	Mean γ	SD γ	Mean γ	SD γ
Gross margin	2.64***	0.54 [l]***	1.53***	1(fixed)	–
	(0.19)	(0.19)	(0.19)		
Yield	0.04***	0.03***	–	0.01***	–
	(0.01)	(0.01)	–	(0.00)	–
Labour	−0.17***	−0.02***	–	−0.00***	–
	(0.01)	(0.01)	–	(0.00)	–
Early cultivar[b]					
Medium cultivar	−0.13*	−0.17**	–	−0.03**	–
	(0.07)	(0.08)	–	(0.01)	–
Late cultivar	−0.14**	−0.13	–	−0.05**	–
	(0.06)	(0.08)	–	(0.02)	–
Manual weeding[b]					
Mechanical weeding	0.06	−0.19**	–	−0.02	–
	(0.07)	(0.09)	–	(0.01)	–
Chemical weeding	−0.03	0.02	–	0.03**	–
	(0.06)	(0.07)	–	(0.01)	–
Rice–vegetable system[b]					
Rice–fallow system	0.06	0.01[n]	0.44***	0.01[n]	0.05***
	(0.05)	(0.07)	(0.11)	(0.01)	(0.01)
Double rice cropping	0.29***	0.24***	–	0.02	–
	(0.09)	(0.13)	–	(0.02)	–
SQ risk	0.54***	−1.22[n]***	2.00***	0.47[n]	0.72
	(0.04)	(0.48)	(0.36)	(0.58)	(0.46)
Negative risk	−0.55***	−0.69[n]***	0.72***	−0.15[n]***	0.12***
	(0.04)	(0.07)	(0.09)	(0.01)	(0.01)
Positive risk	−0.33***	−0.31[n]***	0.42***	−0.17[n]***	0.15***
	(0.04)	(0.06)	(0.05)	(0.01)	(0.01)
SQ	−1.87***	−4.01[n]***	3.71***	−10.80[n]***	5.76***
	(0.21)	(0.82)	(1.08)	(2.17)	(1.34)
Scale parameter (tau)				2.97***	
				(0.31)	
Log likelihood	−2,989.50	−2,491.85		−2,465.45	
P > chi	0.00	0.00		0.00	
N	11,016	11,016		11,016	
NP	13	34		30	

Notes: b = base for dummy coding, l = lognormally distributed, n = normally distributed, *N* = number of observations, NP = number of parameters, standard errors in parentheses and ***, **, * represents significant at 1%, 5% and 10%, respectively. Covariance matrix in online Appendix S2.

monetary attribute was normalised to one based on the formulation in (6), but the scale parameter is freely estimated.

Model 1 estimates show significance in most attributes and expected signs on coefficients. The positive sign on *yield* and *gross margin* suggests higher utility associated with higher levels of these attributes. Labour has a negative sign, which signifies that farmers are less attracted to labour-intensive technologies. *Early crop cultivars* are also more preferred to *medium* or *late cultivars* as revealed in the negative and significant coefficients of *medium* and *late cultivars*. Weed control technology, on the other hand, is not significant. The *double cropping* attribute is significant, implying that in the presence of adequate water, farmers would prefer to cultivate rice all year round. In terms of risk, farmers have a negative preference for higher risk as shown by the parameters of the *risk* attributes in the model.

In Model 2, all attributes are significant except *late cultivar*, *chemical weeding* and *rice–fallow system*. The derived standard deviations of the parameters of most random coefficients are significant, indicating parameters are heterogeneous. The absolute value of *negative risk* is higher than *positive risk*, suggesting that sampled farmers do not exhibit loss aversion under this model. This may result from the risky nature of the production system.

Model 3 results indicate that farmers place a positive value on *yield* and *chemical weeding* and negative values on *labour*, *cultivar choice* and *risk*. Moreover, most of the estimates of the standard deviation of the distribution of the random parameters are significant, an indication of heterogeneity in WTP. Also, generally, the standard deviations for Model 3 are lower than Model 2. The scale parameter, tau, is also significant at the 1% level, indicating that scale heterogeneity is important. The covariance matrix of Models 2 and 3 results (see Tables S1 and S2 in online Appendix S2) reveal most of the values are significant, suggesting inter-dependence among the random taste parameters. Using information criteria, Model 3 which accounts for both preference and scale heterogeneity is the preferred model (see discussion under section 4.4).

4.2. SAI within preference and willingness to pay space

We accounted for SAI using a covariate approach. Therefore, interaction terms represent change in marginal utility as the SAI variable moves from highest importance to lowest: the marginal utility held by those with the lowest level of stated importance is given by the sum of the base parameter and the interaction effect. Consequently, if heterogeneous preference exists between respondents who attach high importance to the attributes, herein referred to as 'high rankers-HR' and those who attach less importance (low rankers-LR) to the attributes, then we expect the interaction terms to be significant. The results in Table 5 show that only two of the interaction terms (*medium cultivar* and *mechanical weeding*) are significant in ML-SAI model (Model 4) and three in GML-SAI (Model 5); *rice–fallow system*, *double rice cropping* and *positive risk*. This implies that with these exceptions, the stated level of attribute importance does not manifest in different preferences.

A validity check using isolated coefficients for significant interaction terms give an indication of whether attributes were really associated with low rankings. If the isolated coefficients are significant, then the results are counter intuitive (high ranking instead of low ranking), and if the isolated coefficients are not significant, then attributes were indeed associated with low rankings. We observed some of the isolated coefficients[3] are significant (mechanical weeding under the PS model and rice–fallow

[3]Results are not reported here, but are available upon request.

Table 5
Model estimates for PS and WS model with SAI interaction

	Model 4-ML Correlated SAI			Model 5-GML Correlated SAI		
	Baseline coefficient High rankers		SAI interaction Low rankers	Baseline coefficient High rankers		SAI interaction Low rankers
Attributes	Mean γ_0	SD γ_0	Mean γ_1	Mean γ_0	SD γ_0	Mean γ_1
Gross margin	0.57^{l}***	1.44***	−0.06	1(fixed)	–	−0.23
	(0.19)	(0.15)	(0.43)		–	(0.38)
Yield	0.03***	–	−0.01	0.01***	–	0.00
	(0.01)	–	(0.01)	(0.00)	–	(0.01)
Labour	−0.02***	–	0.00	0.00	–	0.00
	(0.01)	–	(0.00)	(0.00)	–	(0.00)
Early cultivar[b]						
Medium cultivar	0.02	–	−0.48*	−0.03**	–	−0.07
	(0.15)	–	(0.28)	(0.01)	–	(0.16)
Late cultivar	−0.12	–	−0.06	−0.06**	–	0.00
	(0.14)	–	(0.28)	(0.02)	–	(0.15)
Manual weeding[b]						
Mechanical weeding	−0.48***	–	0.56**	−0.02*	–	0.15
	(0.15)	–	(0.23)	(0.02)	–	(0.15)
Chemical weeding	0.46	–	−1.60	0.03***	–	−0.30
	(0.42)	–	(1.41)	(0.02)	–	(0.29)
Rice–vegetable system[b]						
Rice–fallow system	-0.02^{n}	0.47***	0.03	0.03**	0.06***	−0.15*
	(0.18)	(0.11)	(0.22)	(0.01)	(0.01)	(0.08)
Double rice system	0.03	–	0.30	0.01	–	0.30**
	(0.21)	–	(0.21)	(0.03)	–	(0.13)
SQ risk	-0.58^{n}	1.27***	0.16	0.70	0.66***	0.16
	(0.48)	(0.23)	(0.14)	(0.54)	(0.18)	(0.14)
Negative risk	-0.72^{n}***	0.67***	0.03	−0.14***	0.11***	−0.02
	(0.08)	(0.09)	(0.05)	(0.01)	(0.01)	(0.04)
Positive risk	-0.40^{n}***	0.44***	0.07	−0.18***	0.16***	0.06*
	(0.08)	(0.06)	(0.05)	(0.02)	(0.02)	(0.04)
SQ	-5.49^{n}***	3.93***		−12.62***	8.72***	
	(1.21)	(0.90)		(2.53)	(1.92)	
Scale parameter (tau)				2.56***		
				(0.30)		
Log likelihood	−2,483.30			−2,456.78		
P > chi	0.00			0.00		
N	11,016			11,016		
NP	46			42		

Notes: Standard deviation is not reported for the interaction terms because they were assumed to be fixed. b = base for dummy coding, l = lognormally distributed, n = normally distributed, N = number of observations, NP = number of parameters, standard errors in parentheses and ***, **, * represents significant at 1%, 5% and 10%, respectively. Covariance matrix in online Appendix S2.

system, double rice cropping and positive risk) under the WS model, a clear indication that these attributes were highly ranked (considered) by the low rankers. This reveals some inconsistencies in stated ranking information as has been reported by previous analysis (Balcombe *et al.*, 2014).

We also observe a 16% reduction in the magnitude of the scale parameter, a clear indication of an improvement in the consistency of choices made when extra information on the importance of attributes is accounted for. In terms of magnitude of coefficients, we do not observe much variation in both models, a finding that is consistent with previous studies (Balcombe *et al.*, 2014).

4.3. Comparison of WTP estimates

The WTP estimates were derived using simulation techniques where individual specific values are conditioned on individual choices. We therefore obtained distributions of WTP from the distributions of non-monetary coefficients to monetary coefficient using 10,000 draws in the calculation. The results are reported in Table S3 in online Appendix S3. We observe that respondents associate positive value with *yield* and *double cropping system* and negative value with *labour, mechnical weeding* and *medium cultivar* in Model 2. In Model 4 where we accounted for the effect of SAI on marginal utilities, we find the yield attribute is highly valued, but a negative value is associated with *labour*, *mechnical weeding* and *risk*.

For WS models, with the exception of *rice–fallow system* that is considered important in Model 5, a positive value is associated with *yield* and *chemical weeding* and negative value with *labour, risk* and *medium cultivar*. Overall, there is consistency in the results across models with respondents' preference for *yield* and negative value associated with *labour* and various *risk* specifications. The estimates also indicate a high standard deviation in PS model*s* compared with WS models for random parameters, suggesting WTP values are more varied and therefore less reliable. However, accounting for SAI generally reduces the level of variability of the WTP estimates in the PS models, but induces equivalent or slightly higher standard deviations in WS models.

The variation in the distribution of the simulated WTP estimates generated from Models 2–5 is best observed through a graphical display. We do this by plotting kernel smoothing densities with cross validated bandwidth using the SM package in R (Bowman and Azzalini, 1997) for a subset of the attributes, specifically the risk attribute. Figures 3 and 4 show the distributions for positive risk (PR) and negative risk (NR) for the PS and WS models as well as the SAI effect on those distributions. While PS and WS indicate the random parameter component of the model (without SAI effect), PS-SAI and WS-SAI include SAI effect. Generally, we observe that SAI does not have a substantial effect on the distributions of the PS and WS models (Figure 3).

However, Figure 4 shows distributions are highly skewed in the PS models compared with WS models that have a tighter distribution with low variance. WS-SAI distributions are similarly better than the PS-SAI distributions. These findings confirm the superiority of WS models in producing more reliable WTP estimates, at least in our sample data.

We conducted a Kolmogorov-Smirnov test to verify whether the variations in the distributions are statistically significant. The results (online Appendix S4) indicate

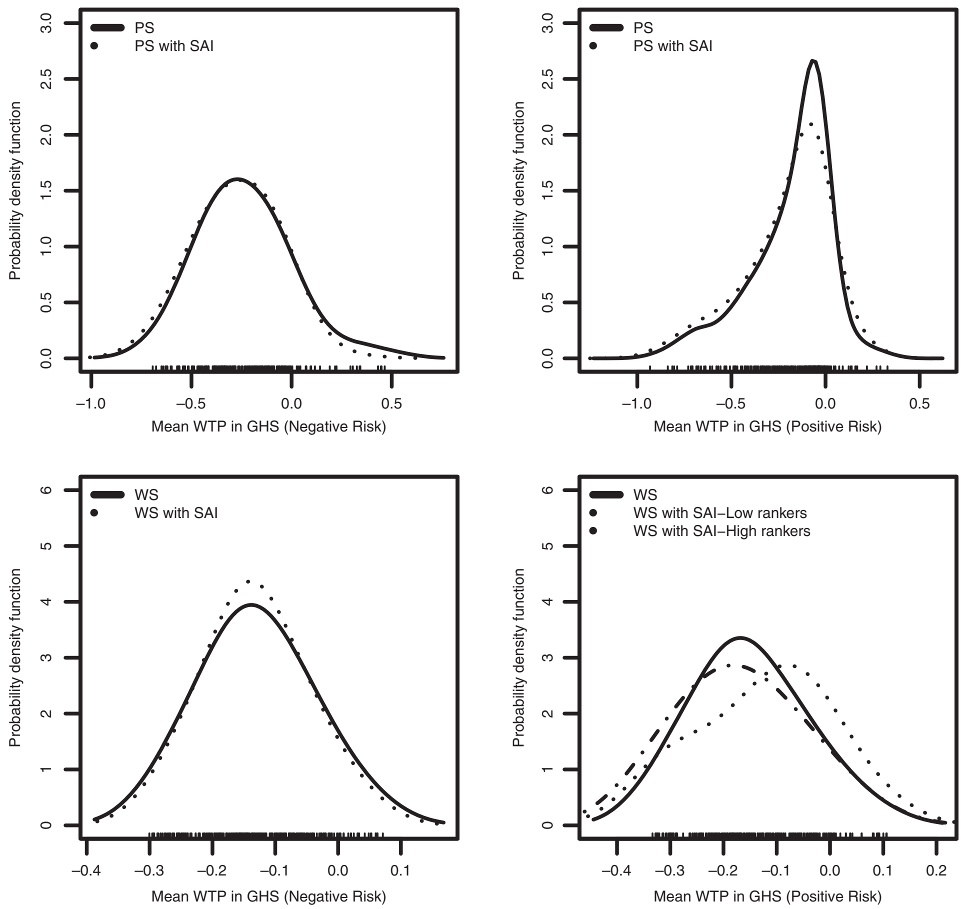

Figure 3. Distribution of willingness to pay (WTP) for negative and positive risk for Models 2 and 4 (top) and 3 and 5 (bottom).

that there are significant differences in the WTP distributions. However, we failed to reject the null hypothesis of equal distribution between the negative risk attribute, with and without SAI information in both PS and WS models.

A further graphical synthesis (Figure 5) for negative risk (NR) and positive risk (PR) attributes using notched boxplot indicate a clear variation in the distribution of the PS and WS models, with PS exhibiting a wide variability and thus, less reliable WTP estimates. With the inclusion of SAI (NR-WS-SAI, PR-WS-SAI), we still observe that the distribution of WTP is smaller in the WS model compared with the PS model.

Finally, we demonstrate variation in preferences according to SAI rankings using positive risk attribute. Figure 6 shows that marginal coefficients are affected by the perceived level of importance of an attribute and failure to account for this variation may affect the estimated WTP values.

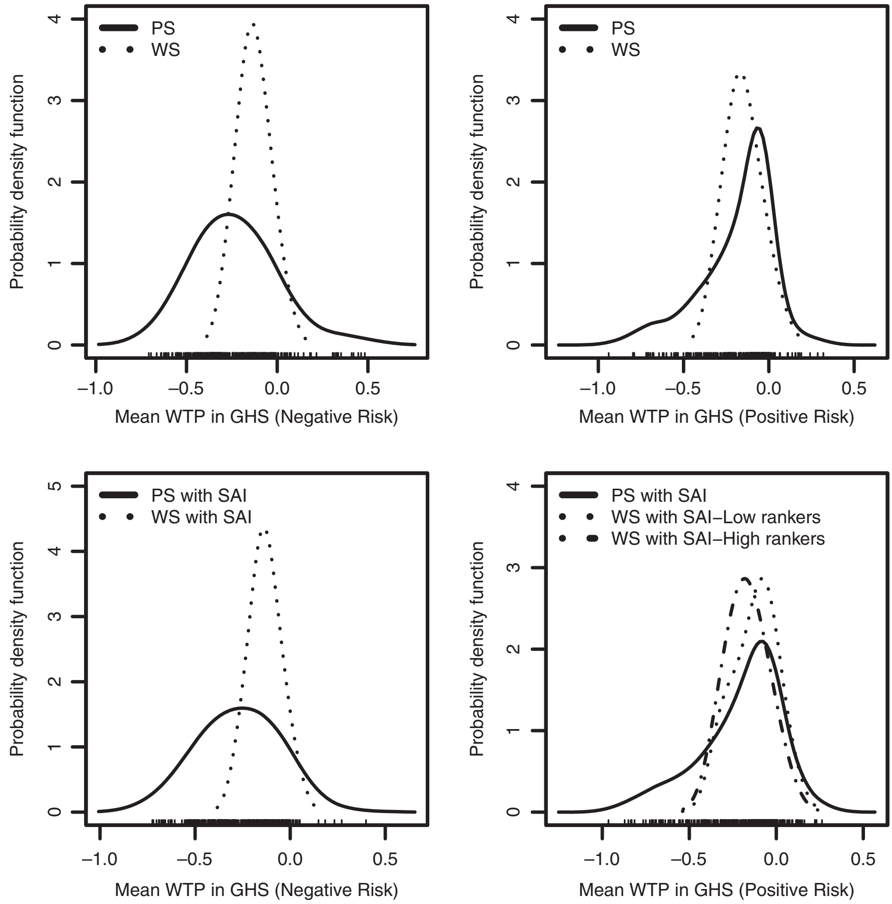

Figure 4. Distribution of willingness to pay (WTP) for negative and positive risk for Models 2 and 3 (top) and 4 and 5 (bottom).

4.4. Model comparison

To examine the goodness of fit of our estimated models, we report the model selection statistics often applied in empirical applications (Hole and Kolstad, 2012) in Table 6. These relate to Akaike Information Criteria (AIC) and the Bayesian Information Criteria (BIC), Adjusted McFadden R^2 and the difference in magnitude of BIC values. We observe from Table 6 that within the preference space, Model 2 provides the best fit in terms of Adjusted McFadden R^2 and information criteria signifying that preference heterogeneity is important when examining farmers' preferences.

Accounting for the effect of SAI (Model 4) however seems not to have an effect on model performance as revealed by both the BIC and the difference in magnitude of BIC. Within the WS models, Adjusted McFadden R^2 indicates no gain in fit between Model 3 and Model 5, however, the BIC and difference in BIC indicates that Model 3 is better. Across all models, we find that Model 3 fits our data best, indicating that the WS model outperforms the PS model in our application. This finding is consistent with Scarpa *et al.* (2008) and Rose and Masiero (2009).

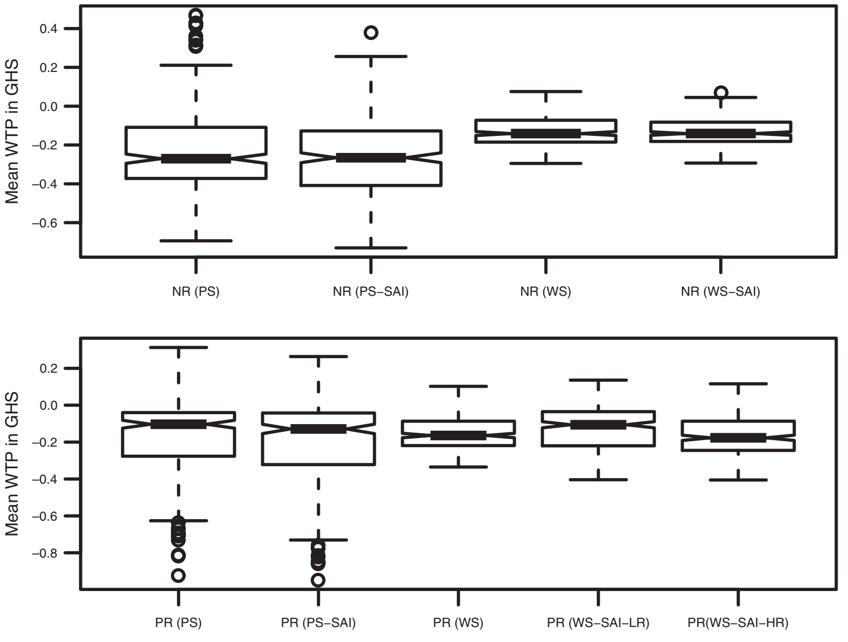

Figure 5. A graph for positive risk (PR) and negative risk (NR) WTP distribution for Models 2–5.

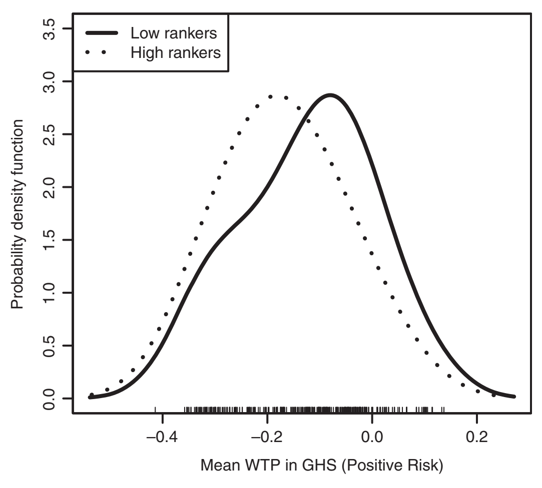

Figure 6. Comparison of willingness to pay (WTP) by different stated attribute importance ranks for positive risk.

5. Conclusions

We investigate farmers' choice of rice production practices in Ghana using a DCE. Specifically, we contrasted two flexible discrete choice approaches (willingness to pay space (WS) and preference space (PS) models). We further accounted for the effect of

Table 6
Model comparison

Model	LL	NP	AIC	BIC	Adjusted McFadden R^2
Model 1	−2,989.50	13	6,005.10	6,099.99	0.26
Model 2	−2,491.85	34	5,051.71	5,300.15	0.37
Model 3	−2,465.45	30	4,988.92	5,200.83	0.38
Model 4	−2,483.30	46	5,058.59	5,394.72	0.37
Model 5	−2,456.78	42	4,995.56	5,295.15	0.38

	Diff BIC ($BIC_1 - BIC_2$)	Remarks
Model 1 vs. Model 2	799.84	Model 2 is preferred
Model 2 vs. Model 3	99.33	Model 3 is preferred
Model 2 vs. Model 4	−94.57	Model 2 is preferred
Model 2 vs. Model 5	5.00	Model 5 is preferred
Model 3 vs. Model 4	−193.89	Model 3 is preferred
Model 3 vs. Model 5	−94.33	Model 3 is preferred
Model 4 vs. Model 5	99.56	Model 5 is preferred

Notes: Decision criteria: if $BIC_1 - BIC_2 < 0$, then Model 1 is preferred and if $BIC_1 - BIC_2 > 0$, then Model 2 is preferred (Long and Freese, 2006).

farmers SAI ranking information on the estimated willingness to pay estimates (WTP).

The results from the PS model show farmers value high yield and early cultivars but show a disutility for labour and higher risk levels. The WS model revealed similar preference patterns for the technology attributes. The similarity in the results indicates consistency of the two models in predicting farmers' preferences for technology or production practice characteristics. However, we find less variability in WTP estimates derived from the WS model, suggesting that the WTP estimates are much more reliable than those estimated using the PS model. Again, we found the WS model produced tighter distributions for the WTP values, excluding extremely large or small estimates, a finding that confirms other results in the literature.

Further, the inclusion of SAI data in the PS and WS models did not produce much difference in the WTP estimates. However, SAI integration produces a better distribution for the WTP values under the WS model compared with the PS model, reflecting the generation of the WTP values. Within the PS model, WTP is derived as a ratio and, depending on the distributions of the monetary attribute, draws obtained can either be high or low, which in turn can affect the distributions of the WTP values including the generation of extreme WTP estimates.

From a policy perspective, farmers' preferences for higher returns and low risk technologies give an indication that technologies with these characteristics may speed adoption. The finding in relation to labour requirements, though not surprising, highlights the need for better focus on an effect that might have not received adequate attention in the past. Developing country agriculture is generally considered as a production system characterised by surplus labour and it has been widely argued that technologies need to be labour intensive to succeed. However, these findings highlight the importance of considering a wider set of parameters in the design and promotion of new technologies, including sensitivity to labour requirements.

Methodogically, PS models are considered as superior to WS models in terms of model performance. However, previous empirical applications (i.e., Scarpa *et al.*, 2008; Rose and Masiero, 2009) show that WS models can perform better than PS models. A critical question for research analysts is whether to opt for model performance (provided by PS) or more reliable WTP estimates (provided by WS). Our findings contribute to the ongoing debate about the appropriate model for estimating WTP values. Our results provide further support for WS over PS models when accounting for preference and scale heterogeneity. That is, if one accounts for both sources of heterogeneity, the WS model can be better statistically and yield more reliable WTP estimates.

Supporting Information

Additional Supporting Information may be found in the online version of this article:

Appendix S1. Question to assess respondents' perception of the level of attribute importance.

Appendix S2. Covariance matrix from estimated models.

Table S1. Covariance matrix of the random coefficients – Model 2 and Model 4.

Table S2. Covariance matrix of the random coefficients – Model 3 and Model 5.

Appendix S3. Willingness to pay estimates for alternative models.

Table S3. WTP estimates for correlated ML and GML models (per 1,000 Ghana Cedis) based on individual parameters.

Appendix S4. Results of Kolmogorov -Smirnov test of equality of distribution of estimated models.

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