Q Open, 2022, **2**, 1–22
https://doi.org/10.1093/qopen/qoac012
Advance access publication date: 8 April 2022
Article

Composting municipal solid waste for agriculture in Northern Ghana: Rural farmers' willingness to pay for compost quality and access attributes

Bunbom Edward Daadi [1,*] and Uwe Latacz-Lohmann [2]

[1]Department of Farm Management & Production Economics, Institute of Agricultural Economics (Institut für Agrarökonomie), Christian-Albrechts University, Kiel, Germany
[2]Department of Farm Management & Production Economics, Institute of Agricultural Economics (Institut für Agrarökonomie), Christian-Albrechts University, Kiel, Germany

*Corresponding author: Department of Farm Management & Production Economics, Institute of Agricultural Economics (Institut für Agrarökonomie), Christian-Albrechts University, Kiel, Germany
Tel: +49(0)431-880-4431/+233 506204990/+4915213850856 (Mobile); E-mail: edwarddaadi@gmail.com; bedaadi@uds.edu.gh or edaadi@ae.uni-kiel.de

Received: July 10, 2021. **Accepted:** March 22, 2022

Abstract

While farmers in rural areas of northern Ghana find it difficult to obtain sufficient organic soil amendments to keep their soil healthy, there is not enough demand for city compost factories attempting to clean cities of organic solid waste to sustain the composting rate at waste-clearing levels. In this study, 398 farmers in rural communities were surveyed in order to estimate the willingness-to-pay for different quality and access attributes of municipal solid waste (MSW) compost and examine how demand for it can be boosted among such farmers. Several specifications of the generalized multinomial logit (G-MNL) model, using farmers' choice data, revealed that the compost quality and market access attributes surveyed in the study significantly affect farmers' decision to buy MSW compost. The results also showed that preferences for the attributes vary widely among the farmers, mainly due to some unobserved personal factors. On average, the empirical estimates indicate that for a 50 kg compost bag, farmers are willing to pay GHS 9.43 for brand/label, GHS 5.76 for pelletized compost, GHS 4.49 for delivery in the community, and GHS 2.49 for sales when they have their cash windfall. Farmers face an average disutility of at least GHS 33.36 for deciding not to buy compost, regardless of its attributes, indicating that besides the attributes captured by the study, other factors important to farmers influence their purchase decisions. Significantly discounted prices together with improved compost quality increase the probability of compost purchase. Thus, overall the findings highlight the need to subsidize MSW compost by more than 50 per cent, to sell it in pelletized form and branded/labelled packages while making it accessible to rural farmers during their cash windfall.

Keywords: Discrete choice experiment, Compost attributes, G-MNL model, Northern Ghana, Willingness-to-pay
JEL codes:Q1, Q2, R2

1. Introduction

The northern part of Ghana has a predominantly agrarian employment structure with a low income-earning capacity among the labour force. The agriculture sector employs approximately 74 per cent of the working population, over 80 per cent of whom are in rural households (Amikuzuno and Donkoh 2012; Government of Ghana 2015). Farmers have a long tradition of subsistence grain production mixed with a few cash-crop enterprises. However, with increasing arable land constraints, farming systems in the area have failed to respond to increasing food demand for the past two decades. One of the reasons for this is soil degradation following continuous exploitation of farmland without fallowing or adequate nutrient replacement (AfDB 2006; Braimoh and Vlek 2006; Agwe *et al.* 2007; Nkonya *et al.* 2015). Semi-arid conditions exacerbate soil degradation by limiting the recovery rate of vegetative cover after human-induced changes, thus slowing the rate of organic matter accumulation in the soil. The result is that soils in the area generally have a low organic matter content (Braimoh and Vlek 2004; Owusu *et al.* 2020).

The blank recommendation of using NPK-based fertilizers as the protocol for field crop production for the past six decades has started to fail due to soil acidification on much of the farmland. Experts emphasize the need for site-specific fertilizer recommendations while encouraging farmers to use organic fertilizers such as compost to physically recondition the soil for improved plant nutrition (Atakora *et al.* 2014). Organic fertilizers provide the essential natural carbon to sustain soil physical, chemical, and biological properties under continuous and intensive cultivation (Vanlauwe 2015; Sudradjat *et al.* 2018). For this purpose, the Ministry of Food and Agriculture (MoFA), in collaboration with non-governmental organizations (NGOs), has been assisting farmers through capacity-building programmes to use organic soil amendments to improve soil conditions. However, the programmes seem to have had a minimal impact on encouraging organic fertilizer use due to a general lack of biomass in the area (GIZ 2013).

Meanwhile, Ghanaian waste management systems in urban centres are characterized by ineffective collection and disposal methods of waste, most of which is biodegradable (Danso *et al.* 2002). City authorities grapple with the sanitation challenges of mounting MSW, 84 per cent of which can be used as organic soil amendments (GIZ 2013; Pradhan *et al.* 2013; Republic of Ghana 2015). This waste usually piles up in cities, looking unsightly and polluting water and air while breeding vectors for diseases such as malaria, typhoid, diarrhoea, cholera, and dysentery (Folefack 2008).

However, the biodegradable components are rich sources of major nutrients usually taken from rural to urban areas. Thus, converting organic waste into agricultural compost for use in rural areas closes the rural–urban nutrient cycle and thus contributes significantly to resolving the challenges of soil depletion. Commercial composting adds value to MSW and thereby improves cost recovery within the waste management sector. It also creates viable businesses with numerous job opportunities (Danso *et al.* 2017).

Besides providing organic fertilizer for farmers, controlled composting of waste from cities reduces the pollution in cities associated with improper waste disposal (Danso *et al.* 2002, 2006; Galgani *et al.* 2014). In particular, Ghana has recognized the roles played by MSW composting in dealing with unsanitary conditions and in strategic policy design for reducing GHG emissions through open landfills (Galgani *et al.* 2014; Republic of Ghana 2015).

Consequently for the last two decades government agencies have focused on creating an enabling environment for the private sector to invest in MSW composting for agricultural use. This push has led entrepreneurs to establish compost factories in collaboration with the main national waste management company Zoomlion Ghana Ltd Like DeCo Compost in Tamale. All such compost stations are located in city suburbs to ensure efficient absorption of the high tonnage (nearly 250 tonnes per day) of waste generated in metropolises (Pradhan *et al.* 2013). However, composting in cities implies that the compost is only physically accessible to urban/peri-urban gardeners rather than to rural farmers who require it in substantial quantities for grain fields (Folefack 2008). Studies (e.g. Danso *et al.* 2006) have shown that composters cannot market their supplies to farmers located beyond a 40 km radius from compost plants without incurring losses due to high distribution costs. However, demand from urban and peri-urban compost users falls short of the quantities required to clear the compost supply when composters are operating at waste-clearing capacities (Danso *et al.* 2006; Folefack 2008; Agyekum *et al.* 2014). Thus, compost stations cut back on production to minimize losses, meaning that the objectives of composting MSW (i.e. sustainable agriculture and environmental management) cannot be achieved in Ghana under free-market conditions (Danso *et al.* 2006).

In 2016, compost producers drew the government's attention to their increasing losses arising from limited demand for compost. They called for the inclusion of organic fertilizer in the national fertilizer subsidy programme to make their compost affordable for resource-poor farmers. Subsequently, the government subsidized the compost price by 50 per cent at some stations, beginning in the 2017 crop season (MoFA 2017). However, this subsidy can increase effective demand only to the extent that users are able to access the input. Extending the compost market to rural farmers will remove access barriers and spur the demand to levels that can stimulate enough MSW composting to achieve its purpose. Hence, there is a need to improve access to rural farm input markets where farmers can physically access the input.

Increasing rural farmers' access to MSW compost implies additional distribution and marketing costs, usually passed on to farmers through pricing. Information about price and other critical attributes to farmers is required to measure potential demand for MSW compost under such conditions. Unfortunately, studies on MSW compost demand in sub-Saharan Africa (e.g. Ampadu 2001; Danso *et al.* 2002, 2006; Folefack 2008; and Agyekum *et al.* 2014, Danso *et al.* 2017; Kuwornu *et al.* 2017) have concentrated on urban/peri-urban users to neglect of countryside farmers. Furthermore, except for Agyekum *et al.* (2014) and Danso *et al.* (2017), such studies in Ghana have generally employed the contingent valuation (CV) method, despite extensive criticism that it overestimates farmers' willingness-to-pay (WTP) (Danso *et al.* 2006). In northern Ghana in particular, there has not been any empirical analysis of rural farmers WTP for MSW compost and its essential attributes. Since rural farmers have not had access to commercial MSW compost, it is unknown what attributes of MSW compost will influence their demand for it. Hence, the need to identify and evaluate the qualities of the input that could attract farmers to buy it before investing in improving their access to it (Agyekum *et al.* 2014).

Thus, by using a discrete choice experiment, this study sought to: (a) estimate rural farmers' WTP for MSW compost through access and relevant quality attributes, and (b) examine how farmers' characteristics relate to variation in the attribute preference. The findings of this study provide useful information to guide investors in the MSW compost sub-sector and highlight the need for the government to intervene in promoting the sector. This study adds spatial and strategic marketing dimensions to the literature on the current debate about closing the rural–urban nutrient cycle in sub-Saharan Africa through waste recycling.

The remainder of this paper is organized as follows: the next section (Section 2) outlines the methodological approach, including sampling, data collection, and exposition on the choice model applied; Section 3 presents the econometric results of the model and its variants, including average WTP estimates from a WTP space specification; and the final section discusses the empirical findings and draws policy conclusions.

2. Data and methodology

2.1 Survey development, discrete choice experiment, and farmer characteristics

The data used for this study were collected through a multistage sampling survey of smallholder maize farmers from fifty-two communities in eight districts of the North East and Upper East Regions of Ghana (Fig. 1). This area was chosen because of its most degraded

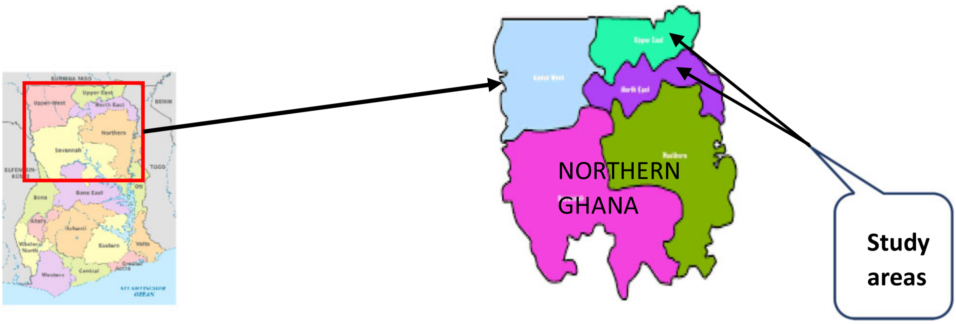


Figure 1. Map of northern Ghana showing the study areas.

Table 1. Compost attributes and levels in the discrete choice experiment.

Attribute	Description of attribute	Levels	Reference level
Form	How the fertilizer has been formed to allow easy application	1. Unpelletized 2. Pelletized	Unpelletized
Brand/label	Whether the bag is branded or not	1. Unbranded bag 2. Branded bag	Unbranded bag
Period of sales	Time of crop season when compost is sold	1. At planting time 2. At preceding crop harvest	At planting time
Delivery point	Where farmers take delivery of the fertilizer they buy	1. At farm input shop 2. In the community	Farm input shop
Price	[a]Price in Ghanaian cedis per 50 kg bag of DeCo MSW compost	1. GHS 15 2. GHS 25 3. GHS 35	Continuous

[a]International currency equivalence: **GHS 6.5 = 1 USD** at the time of the survey.

soil condition in the country. Farmers have received substantial support to use organic soil amendments to improve and sustain soil health. However, organic amendment use among the farmers is being constrained by scarcity of critical biomass for preparing enough organic amendments. Hence, the motivation for this study is to explore the potential to increase MSW compost demand by expanding to market such farmers.

In the North East Region, communities were selected from East and West Mamprusi districts clustered around the Presbyterian Agriculture Station (PAS) at Lagbinsi. The communities chosen for Bunkpurugu and Yunyoo-Nasuan districts were also clustered around Bunkpurugu town. In the Upper East Region, communities in Tempane and Pusiga districts were clustered around Wornyanga, while those for Garu and Binduri districts were centred between Garu and Binduri.

The farmers responded to a two-part structured questionnaire during a personal interview (PI). The first part was a discrete choice experiment that elicited farmers' choices for MSW compost (see Table 1), while the second part sought information on farmers' background characteristics (see Table 3). The hypothetical bags, representing alternatives in the choice experiment, were defined by compost/market access attributes, including its form, the brand/label on packages, the price, the point of compost delivery, and the sales period.

Following Danso *et al.* (2017), the MSW compost attributes in this study were identified and selected in a three-step process. A review of previous empirical studies (e.g. Folefack 2008; Agyekum *et al.* 2014; Bienenfeld 2014; Danso *et al.* 2017; Kuwornu *et al.* 2017) guided the first step for identifying potential attributes. We compiled an initial list of six attributes, including nitrogen-fortified MSW compost from those previous studies. A second-step validation of the attributes through discussions with experts (DeCo Compost, PAS management) revealed that all current MSW compost is nitrogen fertilizer fortified. Hence, only five attributes, including price, were retained. In the third step, information on relevant attributes and their critical levels was obtained through focus group discussions with two farmer groups (Zou 2011; Danso *et al.* 2017; and Ahmed *et al.* 2020). The conversation with farmer representatives revealed that, except for price, each attribute realistically has two qualitative levels. DeCo Compost management provided information on market and price attributes in Tamale.

Considering the prevailing market price, transport costs, and government subsidy price in the cities, three potential price levels were set in the choice experiment. At the time of the survey (May to August 2018), the three price levels reflected the lowest-end price with a 50 per cent government subsidy on the sales price, the market price in cities and the highest-end price made up of the market price plus average transport cost for a bag from the DeCo compost station to communities in the study area. Table 1 shows the MSW compost attributes and their levels for evaluating the utility farmers derive from the input.

For each attribute, some intuitive hypotheses were considered relating to the behaviour of farmers as input users. Generally, pelletizing MSW compost reduces its bulkiness and improves product structure for easy dispensing during application. Pelletized compost is easier to apply with greater precision than powdered or lumped compost (Danso *et al.* 2017; Kuwornu *et al.* 2017), therefore, farmers will prefer pelletized to unpelletized MSW compost. Brands and labels give farmers information about various aspects of the fertilizer, including product identity and nutrient composition, which influence both the descriptive and inferential beliefs about the compost value. Favourable perceptions among farmers about the overall quality of MSW compost in turn influence their purchasing intentions (Larceneux and Carpenter 2008). Thus, farmers are expected to be more likely to buy MSW compost in branded/labelled form than unbranded/unlabelled form (Agyekum *et al.* 2014).

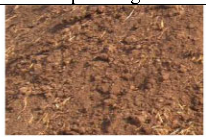
Duflo and Robinson (2011) observed that if fertilizer is offered to farmers during their cash windfall after the preceding crop harvest season, small but time-limiting price discounts could induce sizeable demand increases comparable with a heavy subsidy later on in the farming season. This means that the period after the crop harvest season is a good time for MSW compost sales. Hence, it was hypothesized that farmers prefer to buy MSW compost even at high prices when they have cash from previous harvest sales rather than later on in the farming season.

Deciding on the type of fertilizer, how much of it and where to buy it involves costs. Since farmers always discount future utility, those who plan to use fertilizers defer the decision cost until the last possible moment, irrespective of how small that cost might be (Duflo and Robinson 2011). Danso *et al.* (2006) found that transporting commercial compost from production sites even to urban/peri-urban users limits effective demand for MSW compost among farmers in Ghana. Folefack (2008) reported that the transport cost problem is worse for village farmers and calls for subsidies to boost supply and demand for compost among rural farmers in Cameroon. This means that farmers are more likely to purchase commercial compost if they can obtain it from within their community rather than from somewhere else. Finally, farmers are expected to buy more MSW compost at a lower price than they would at a higher price. Hence, everything else held constant, lower price levels are preferred to higher price levels.

In this multiattribute compost choice experiment the efficiency and accuracy of preferences and the WTP estimates significantly depend on the design used (Kuhfeld *et al.* 1994; Lusk and Norwood 2005; and Street *et al.* 2005). Nevertheless, no single design maximizes efficiency without compromising the attribute orthogonality required for estimation (WHO 2012). To enhance the reliability of estimates, the sequential approach to design was adopted, following Bliemer and Collins (2016) and Bello and Abdulai (2016),

Table 2. Example of choice sets presented to farmers to elicit preferences.

<table>
<tr><td colspan="4">Introduction

Hypothetical bias mitigation (Cheap Talk)
Studies show that people tend to act differently when making hypothetical and real decisions. For example, some people state a price they would pay for an item, but they do not pay the item's price when they see this product in a store. There can be several reasons for this different behaviour. It might be too difficult to measure how buying an item affects the household budget. Another possibility is that it might be challenging for them to visualize themselves getting the product from a grocery store shelf and paying for it. Do you understand what I mean? We want you to behave in the same way you would if you had to pay for the product and take it home. Please consider how much you want the compost bag, comparing the alternatives or constraints that might make you change your behaviour. Please try to put yourself in a realistic situation.</td></tr>
<tr><td>Attribute</td><td>Compost bag "A"</td><td>Compost bag "B"</td><td>Opt-out "C"</td></tr>
<tr><td>Form</td><td>
Unpelletised compost</td><td>
Pelletised compost</td><td rowspan="5">If alternatives A & B are the only options available to me, I will not buy MSW compost</td></tr>
<tr><td>Brand/label</td><td>

Branded/labelled</td><td>
Unbranded/unlabelled</td></tr>
<tr><td>Period of sales</td><td>
At planting time</td><td>
At the preceding crop harvest</td></tr>
<tr><td>Delivery point</td><td>
In the village/community</td><td>
At the nearest input shop</td></tr>
<tr><td>Price</td><td>GHS 35</td><td>GHS 25</td></tr>
<tr><td>Choice</td><td>I will buy ☐</td><td>I will buy ☐</td><td>I will not buy ☐</td></tr>
</table>

International currency equivalence: ***GHS 6.5 = 1 USD*** *at the time of the survey*

International currency equivalence: **GHS 6.5 = 1** USD at the time of the survey.

by first creating an orthogonal fractional factorial design. This initial design was used in a pilot choice experiment to sample twenty members of several farmer groups with whom there were interactions during attribute identification. Conditional logit model preference estimates obtained from the pilot data became Bayesian priors in the design of a final D-efficient experiment to maximize the efficiency and robustness of the final study estimates (Huber and Zwerina 1996; Bliemer and Collins 2016). A D-efficient fractional factorial design from a full factorial with $2^4 \times 3 = 48$ alternative profiles produced six alternative profiles for estimating the attributes' main effects. Two balanced profiles were added for some degree of freedom to test attribute interactions and one dominant profile to check if farmers applied heuristics during choice making. Therefore, a choice experiment with nine choice sets was presented to each respondent to make choices. The last choice set, containing the dominant alternative, was excluded from the analysis. Table 2 provides an example of the choice sets presented to the farmers.

Table 3. Major socioeconomic characteristics of the sample farmers.

Characteristic variable	Mean	Percentage	Min.	Max.	Std. dev.
Gender of household head					
Female (yes = 1/no = 0)	–	21.8			
Male (yes = 1/no = 0)	–	78.2			
Age of household head (number of years)	42.28	–	20	75	14.11
Education of household head (years of formal schooling)	5.21	–	0	22	6.01
Total monthly household income (1000s of GHS)	0.42	–	0.08	2.20	0.29
Household size (number of persons)	6	–	1	20	3.16
Walking distance to the nearest input market (in minutes)	90.03	–	5	190	41.04
Off-farm income job participation (yes/no)					
Yes	–	39.84			
No	–	60.16			
Organic fertilizer experience (yes/no)					
Yes	–	50.4			
No	–	49.6			
Have some means of transport					
None	–	21.68			
Bicycle	–	40.68			
Motorcycle	–	36.52			
Tricycle	–	1.17			

In all, 398 representative households successfully completed the questionnaire, providing data on both socioeconomic characteristics and compost choices. Of the sample farmers interviewed, only eighty-seven (21.8 per cent) were female. More than half of the farmers were between 25 and 60 years old, with an average sample age of 42.28 years. On average, the farmers had 5.21 years of formal education and earned a meagre average monthly income of about GHS 420. Nevertheless, they have to cater for large households of an average of six people. About 40 per cent of them make their income not only from farming, but also through other activities such as craftwork. The farmers generally live about 1.5 hours' walk from the nearest market, facing physical and pecuniary constraints to accessing inputs. Hence, about 50 per cent of them have had to use an organic fertilizer at one time or another. The summary statistics of these characteristic variables are shown in Table 3.

2.2 Conceptual/analytical framework

Following, for instance, Hills *et al.* (2020) and Osburn *et al.* (2020) we analyze the discrete choice data using McFadden's (1974) random utility framework which allows evaluating average utility of choice as well as weights on its attributes. In this context, farmers are expected to maximize the latent utility from their compost bag choices while making trade-offs among the bags' characteristics. Thus, given the attribute profile, we derived and expressed the utility model as a linear function of a farmer's choice. The utility U_{ijt} that a farmer i obtains from choosing an alternative bag j in choice situation t is decomposed into a deterministic part, V_{ijt}, which is observable to the analyst, and a stochastic unobservable part, ε. The function is specified as:

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt}, i = 1, \ldots, \mathrm{N};\ j = 1, \ldots, J, \mathrm{t} = 1, \ldots, \mathrm{T}, \tag{1}$$

where ε_{ijt} is the stochastic error term motivated by heterogeneity in farmers' preferences for attributes unobservable by the analyst (Bello and Abdulai 2016; Osburn *et al.* 2020). The deterministic component V_{ijt} is, in turn, a function of observed compost attributes, $\boldsymbol{X}$, including price, pelletized compost, branded sack, sales at preceding harvest time, and delivery at community sales point of the chosen compost bag. For choice situations in which no compost is chosen (in this case), a dummy variable D_i for an opt-out choice was also included in the function. Thus, U_{ijt} is re-defined as

$$U_{ijt} = \beta_i' \boldsymbol{x}_{ijt} + \alpha_i D_{ijt} + \varepsilon_{ijt}, \tag{2}$$

where β_i is a vector of the utility weights associated with the attribute variables and α_i is the utility farmer i derives from opting not to buy compost. If $prob(U_{ijt} \succ U_{iqt})$ for all $q \neq j$, the probability of farmer i choosing bag j under conditional logit distribution is specified as

$$P_{ijt} = \frac{\exp\left(\beta x_{ijt}\right)}{\sum_{q=1}^{J} \exp\left(\beta x_{iqt}\right)}. \tag{3}$$

The conditional function (3) assumes that ε_{ijt} is an independently and identically distributed type-1 extreme value, meaning no interaction between alternatives in choice situations and that preferences for attributes are homogeneous. These lead to the restrictive, yet often empirically unrealistic, independence of irrelevant alternatives (IIA) assumption (Fiebig *et al.* 2010; Kassie *et al.* 2017). While these assumptions make Equation (3) intuitively desirable at the individual level, they were not valid at the sample level (Ben-Akiva and Bierlaire 1999; Carson and Czajkowski 2014); hence, the need to apply a model that relaxes them to obtain empirically realistic estimates.

We explored the two popular approaches to relaxing the IIA assumption, the latent class model (LCM) and the random parameter logit (RPL) model. Assuming that sample farmers belong to different discrete utility weights classes we applied the LCM models of upto five classes on the data but found not meaningful class (for details, see Zhang and Sohngen 2018). Then, we assumed that the utility weights are continuous variables by specifying the RPL model, permitting weights to vary across farmers in a normal distribution (Rockers *et al.* 2012). In this case, the utility weight β_i for a given attribute, including α_i in (2) becomes $\beta_i = \beta + \eta_i$ (Osburn *et al.* 2020), with the entire function then being (Fiebig *et al.* 2010)

$$U_{ijt} = (\beta + \eta_i)^{\prime X_{ijt}} + \varepsilon_{ijt}, \tag{4}$$

where β is a vector of the attributes' mean utility weights in the population, and η_i is farmer i's specific deviation from the respective means.

The mixing distribution for β_{i} in (4) can be anything, but we specified a multivariate normal distribution following Fiebig *et al.* (2010) and Zhang and Sohngen (2018). However, we were cautious of the fact that the distribution of empirical utility weights obtained by the RPL model often does not approximate normal (Louviere *et al.* 2008; and Fiebig *et al.* 2010). Moreover, preference heterogeneity in most choice contexts is better captured explicitly as scale heterogeneity, where the scale (σ) of the idiosyncratic error term ε_{ijt} is greater for some farmers than others instead of being normalized to one. Scale heterogeneity conditions can take several forms (see Fiebig *et al.* 2010; Kassie *et al.* 2017; Ahmed *et al.* 2020). However, Fiebig *et al.* (2010) and Greene (2018) have shown that all such heterogeneity conditions are nested by the G-MNL model. This currently makes the G-MNL model explorative and very appealing for empirical research (Zhang and Sohngen 2018; and Ahmed *et al.* 2020). Thus, we used the G-MNL model to explore choice data for source(s) of heterogeneity in this analysis (see Gu *et al.* 2013).

2.3 Empirical procedure and econometric model

As already stated above, LCM models with up to five classes gave no meaningful preference class of farmers in this study. However, the Hausman specification test proves that the RPL model is better than the conditional MNL. The data was then explored for sources of preference heterogeneity by fitting the full G-MNL and three of its special cases (see e.g. Fiebig *et al.* 2010 and Hess and Train 2017). Based on three selection criteria (LL, AIC, and BIC), the G-MNL II specification was adopted, and then estimated in the heterogeneity-in-scale setup. Finally, the model was re-cast in WTP space to directly obtain the WTP estimates for compost attributes. The G-MNL model is given as

$$U_{ijt} = [\sigma_i \beta + \gamma \eta_i + (1-\gamma)\,\sigma_i \eta_i]'^{X_{ijt}} + \varepsilon_{ijt}, \tag{5}$$

where parameter γ determines how the standard deviations of the random utility weights are scaled. Usually γ is constrained at between 0 and 1, but Keane and Wasi (2013) argue that there is no reason to do so. Hence, it was allowed to take any value, following Gu *et al.* (2013). However, the explorative data fitting showed that a scaled RPL specification, known as G-MNL-II, best approximates the true data-generating process (Fiebig *et al.* 2010; Kassie *et al.* 2017; Ahmed *et al.* 2020). By this specification, the $\gamma \sim 0$ and standard deviations η of the farmer-specific utility weights of the attributes are scaled proportionally to their mean βs. The individual-specific scaling factor (σ_i) of the idiosyncratic error term is allowed to be a positive log-normally distributed value defined as $\sigma_i = \exp(\bar{\sigma} + \tau\varepsilon_{0i})$, where $\varepsilon_{0i} \sim N(0, 1)$, $\bar{\sigma}$ is a mean parameter of the scale variance, and τ is the coefficient on the unobserved factors influencing scale heterogeneity (ε_{0i}).

To explain this scale variation across farmers, such a scale factor for a farmer at choice scenario t (σ_{it}) was made a function of the farmer's characteristics and some entropy measures of the choice occasion (Fiebig *et al.* 2010; Gu *et al.* 2013). Thus, the choice situation-specific scale, σ_{it}, is expressed as

$$\sigma_{it} = \exp\left(\bar{\sigma} + \theta' z_{it} + \tau\varepsilon_0\right), \tag{6}$$

where z_i is a vector containing interaction terms of choice attributes and farmer characteristics, and θ denotes a set of parameters explaining observed heterogeneity in the scale factor.

Since the integral of the log-likelihood function has no closed form, we evaluated the model using the maximum simulated likelihood (MSL) estimator (with 500 replications) command developed by Gu *et al.* (2013) in Stata. The simulated log-likelihood (SLL) of the estimator is given as

$$SLL\ \ (\beta, \gamma, \tau, \theta,\ \Sigma) = \sum_{i=1}^{N} ln \left\{ \frac{1}{D} \sum_{d=1}^{D} \prod_{t=1}^{T} \prod_{j=1}^{J} \Pr\left(choice_{it} = j|\beta_i^{[d]}\right)^{y_{itj}} \right\}, \tag{7}$$

where $\beta_i^{[d]} = \sigma_i^{[d]}\ \beta + \{\gamma + \sigma_i^{[d]}(1-\gamma)\}\eta_i^{[d]}$ and $\sigma_i^d =\ \exp(\bar{\sigma} + \theta_i + \tau\varepsilon_0^{[d]})$. $\eta_i^{[d]}$ is a k-vector generated from MVN (0, Σ) and $\tau\varepsilon_0^{[d]}$ is an N~(0,1) distributed scalar drawn using Halton and pseudorandom draws, respectively. d = 1, …, D (in this case, D = 500) refers to draws during the simulation. The simulated choice probability, according to Fiebig *et al.* (2010), assumed the form

$$Pr\ \left(choice\ =\ j|X_{it}\right) = \frac{1}{D}\ \sum_{d=1}^{D} \frac{\exp\left(\sigma^d\beta + \gamma\eta^d + (1-\gamma)\,\sigma^d\eta^d\right) X_{ijt}}{\sum_{k=1}^{J} \exp\left(\sigma^d\beta + \gamma\eta^d + (1-\gamma)\,\sigma^d\eta^d\right) X_{ikt}}. \tag{8}$$

This gives the weights of estimated attributes in preference space from which WTP measures are obtained by:

$$WTP_\beta = bootstrap(-\beta[attribute]/(-\beta price])). \tag{9}$$

As stated above, it is empirically appealing to re-parameterize and estimate the G-MNL choice model in WTP space because the coefficients of the attributes in that space are direct and empirically more plausible estimates of WTP than those derived from the utility weights after estimating the preference space (PS) model (Fosgerau 2007; Scarpa *et al.* 2008; Fiebig *et al.* 2010; Hensher and Greene 2011; Kassie *et al.* 2017; Greene 2018; Ahmed *et al.* 2020). Furthermore, WTP estimates obtained from WTP space are better normally distributed than those from the PS specification. Thus, since the G-MNL II model best fitted the empirical data, the model was conveniently recast in the WTP space by constraining $\gamma = \tau = 0$ and normalizing the price coefficient to 1 to obtain the WTP estimates directly (Fiebig *et al.* 2010).

The opt-out decision was captured as a dummy variable labelled NONE, which equals one when a farmer chooses not to buy compost (uses status quo fertilizer type). Since the experiment was unlabelled, values of the opt-out and the constant-utility dummies were zero and one alternate for each observation. This results in perfect negative collinearity between the two dummies. Hence, only one of them (NONE) was estimated in the model.

3. Empirical results

Since G-MNL models allow different specifications to be tested to select the best fit to the data (Fiebig *et al.* 2010), several of them were fitted, including full G-MNL and G-MNL ($\tau = 1$), G-MNL I, and G-MNL II. The G-MNL II model in choice and heterogeneity-in-mean forms produced the best model fit indexes. Thus, that specification was recast in WTP space to directly obtain empirically plausible WTP estimates (Scarpa *et al.* 2008; Fiebig *et al.* 2010; Kassie *et al.* 2017). Here, the G-MNL II model results are presented for compost bag choice, heterogeneity-in-mean preference, and estimates in WTP space. All specifications assumed a theoretically consistent lognormal distribution for price coefficient, but normal distribution for other attributes.

Although the full G-MNL model seemed to have outperformed the others (in terms of LL, Pseudo R^2, and AIC), its γ estimate was not significant, and the estimates were very close to those of the G-MNL II ($\gamma = 0$) specification, which gave the best BIC index. This means that the G-MNL II ($\gamma = 0$) was more realistic and approximated the overall data-generating process better than the full G-MNL. Hence, the results of the restricted G-MNL II ($\gamma = 0$) and its variants are presented below for discussion.

3.1 G-MNL II model results

Table 4 presents the estimation results of the G-MNL II model for three different specifications (PS choice model, scale heterogeneity (SH) model, and WTP space (WTP-S) choice model. Several things should be noted with regard to the estimates, the signs and magnitudes of the estimated coefficients and their standard deviations were pretty robust, with their expected signs across the various specifications. The coefficients were comparable across the specifications regarding the magnitude and direction of influences on farmers' compost choice and significance levels. Consistently, the estimates in all specifications showed that the studied attributes significantly affect a farmer's decision to buy compost. Notably, the mean coefficients of the PS and SH models were almost identical, except for the delivery point attribute and opt-out coefficients, which tended to be lower in the PS model. The third model (WTP-S) with restricted β price = 1 and $\tau = \gamma = 0$ gave higher coefficients, both for mean parameters and standard deviations, because the restriction resulted in direct estimation of the quotients of the weights of the non-price attributes to that of price as measures of WTP for the none-price attributes.

Table 4. G-MNL II ($\gamma = 0$) model estimates for compost choice, scale heterogeneity and WTP.

Variable	PS choice model β	PS choice model S.E	SH choice model β	SH choice model S.E	WTP-S choice model β (β_{WTP})	WTP-S choice model S.E
Mean preference/Mean WTP						
Price	–0.06***	0.01	–0.06***	0.01	1	fixed
Form	0.33***	0.03	0.33***	0.03	5.76***	0.54
Label	0.56***	0.05	0.57***	0.06	9.43***	0.77
Period	0.16***	0.03	0.16***	0.03	2.49***	0.51
Deliv point	0.25***	0.03	0.37***	0.06	4.49***	0.59
None	–1.98 ***	0.13	–1.72***	0.15	–33.36***	1.98
Observed scale heterogeneity (θ)						
Pric*age			0.03	0.05		
Pric*income			–0.09	0.06		
Pric*offfarm			0.20***	0.06		
Pric*edu.			0.14	0.15		
Form*edu.			0.05*	0.03		
Form*income			–0.03	0.03		
Form*offfarm			0.06**	0.03		
Label*edu			0.00	0.04		
Label*offfarm			0.08**	0.04		
Label*orgause			0.03	0.04		
None*income			–0.13*	0.07		
None*offfarm			0.31***	0.07		
None*orgause			–0.14	0.12		
None*transp.			0.31**	0.16		
Period*offfarm			0.08	0.06		
Delivpoint*transp.			–0.20***	0.07		
Delivpoint*Mktdist.			0.08	0.05		
Heterogeneity in mean (η)						
Price	0.04***	0.01	0.04***	0.01	0.00	fixed
Form	0.31***	0.04	0.30***	0.04	5.19***	0.72
Label	0.47***	0.05	0.49***	0.05	8.27***	0.87
Period	0.11**	0.05	0.09	0.06	0.46	1.59
Delivpoint	0.20***	0.06	0.16*	0.10	3.43**	1.05
None	1.42***	0.16	1.33***	0.16	14.13***	1.58
Tau (τ)	0.38***	0.11	0.33***	0.13	0	fixed
Gamma (γ)	0	fixed	0	fixed	0	fixed
Constant (σ)					–2.973***	0.07
No. of Parameters	13		29		11	
LL	–2910.7		–2885.5		–2929.73	
Pseudo R^2	0.25		0.260		0.25	
AIC	5847.3		5829.0		5881.47	
BIC	5942.0		6040.2		5961.57	
Observations	**9,552**		**9,552**		**9,552**	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Other insignificant variables included in the scale heterogeneity function are household location variables and interaction terms of choice attributes with gender and household size. Price coefficient and tau (τ) are constrained at one and zero, respectively, to define the model in WTP space.

The models also revealed substantial heterogeneity around estimated coefficients for all compost attributes, indicating the importance of accounting for variations in preference for MSW compost attributes across farmers (Zhang and Sohngen 2018). Heterogeneity was seen in the significant standard deviations of the vector $\boldsymbol{\eta}$ (heterogeneity of the coefficients) and the scale parameter (τ). It is also worth noting that heterogeneity in preference for the sales period was generally low in all model specifications.

Based on the estimates, a brand/label on compost sacks is the most influential compost attribute affecting farmers' purchasing decisions, followed by a pelletized form of compost. This means that farmers prefer labelled bags with pelletized compost to unlabelled bags with unpelletized compost. In contrast to the anecdotal views of MSW compost producers, these results align with the findings of Agyekum *et al.* (2014) and Kuwornu *et al.* (2017) that these attributes matter for compost demand among farmers in Ghana as well. Even though the average sample farmer cannot read, they associate branded/labelled bags with trusted, high-quality compost and hence obtain an enhanced utility from purchasing such bags. Pelletizing compost also eases and improves dispensing accuracy during compost application. Thus, farmers prefer pelletized to unpelletized compost (Agyekum *et al.* 2014). The other attributes influencing farmers' decisions to purchase compost are the delivery point and the period of compost sales. Farmers prefer having compost delivered in their community rather than collecting it from the nearest input market. Physical access to markets is a challenge because of the poor road network and consequent lack of reliable means of transport. Thus, the opportunity to purchase compost in farmers' communities represents an added value to the compost.

The period when compost is sold, although least significant, is also an important attribute influencing farmers' decision to buy the input. Early sales to farmers during the cash windfall from previous crop harvests will encourage many of them, especially farmers who are 'patient', to purchase compost. These early-season sales will be more attractive if combined with some price discounts (Duflo and Robinson 2011). The coefficient on price is, of course, negative, implying that a higher price reduces farmers' utility from the compost. Thus, as the price per bag increases from the lowest level at GHS 15 to the highest at GHS 35, the likelihood of farmers purchasing MSW compost decreases, other things being constant. Finally, the highly significant negative preference (-1.83, $p < 0.0001$) not to buy compost implies that farmers place an average utility value of up to 1.83 units on MSW compost, which they trade off for status quo soil amendments when they opt not to buy compost regardless of its attributes. They do so probably because of other valuable attributes of the status quo not found in MSW compost (Hills *et al.* 2020). In other words, since the opt-out dummy variable is simply the reverse of the choice decision dummy, the negative preference for opt-out captures (in the reverse direction) the average (constant) utility derived from the MSW compost bag, regardless of any attribute.

Figure 2 shows the increased probabilities resulting from improved levels of the compost attributes from their reference levels and in combination with a price at a 50 per cent subsidy. The graph shows that a compost price subsidy of 50 per cent combined with improved levels in non-cost attributes increases the compost uptake rate by between 53 per cent (with transport costs covered) and 88 per cent (with labelled compost bags). At that subsidized price, offering pelletized compost, selling during farmers' cash windfall, and delivering compost in their community will increase the uptake rate by 85, 83, and 84 per cent, respectively. This indicates how much a subsidy, together with improved compost qualities and market access, can impact MSW compost uptake among rural farmers.

3.2 Attribute preference heterogeneity and indicators

The heterogeneity-in-mean preference specification explored sources of heterogeneity using farmer characteristics and their interaction terms with choice attributes as potential moderators $\boldsymbol{Z}_i$ of the heterogeneity function given in Equation (6). The results are presented in column three of Table 4. As noted above, the standard deviations of attributes' preferences and the error scale parameter are significant. These reveal substantial heterogeneity across individual preferences for the attributes, except for the sales period.

Gender, age, household size, organic fertilizer use experience, and the distance between a household and the nearest input market were found not to influence preference

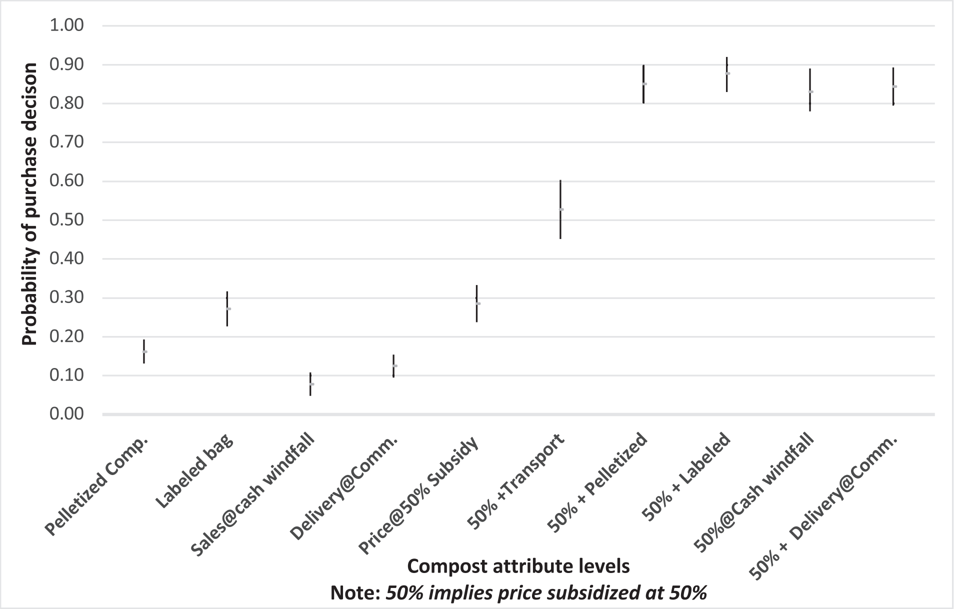


Figure 2. Marginal probabilities of uptake with attributes level changes.

heterogeneity. In contrast, education, income, off-farm job participation, and transport ownership significantly explained scale variations around average preferences for attributes. The number of years of formal education that a farmer had also determined the variation around the mean preference for pelletized compost. Farmers with many years of formal education are more interested in pelletized compost than those with few years of formal education. Household income explains the variation around the average level of preference for not buying compost. High-income households prefer to buy compost more than low-income households. It means that the unobserved compost attributes that lead farmers to opt out of compost purchases are less critical to farmers with high household income than to those with a low income.

Off-farm job participation significantly explains the variation in preference for compost price, pelletized form, brand/label, and unobserved attributes. All other attributes held constant, farmers who have an off-farm income prefer these traits more than those without off-farm income sources. The variation around the mean preference for compost delivery point is explained by transport ownership. Farmers who own a means of transport such as a bicycle, motorbike or tricycle tend to care less about taking delivery of compost in the community. This makes sense because those farmers can afford to transport their compost from the input market, and thus trade off delivery in the community for other attributes such as a lower price. Transport ownership also positively explains the variation around mean preference not to buy compost. This means that transport owners prefer some compost attributes not elicited in this study more than those who do not have transport. Lastly, heterogeneity-in-mean preference models showed the presence of unobserved heterogeneity around the attributes, except for sales period.

3.3 Farmers' willingness-to-pay for MSW compost attributes

The G-MNL-II model in the last column of Table 4 gives the marginal values or WTP for improved levels of compost attributes estimated in WTP space (Scarpa *et al.* 2008; Fiebig *et al.* 2010; Hensher and Greene 2011; Kassie *et al.* 2017; Greene 2018; and

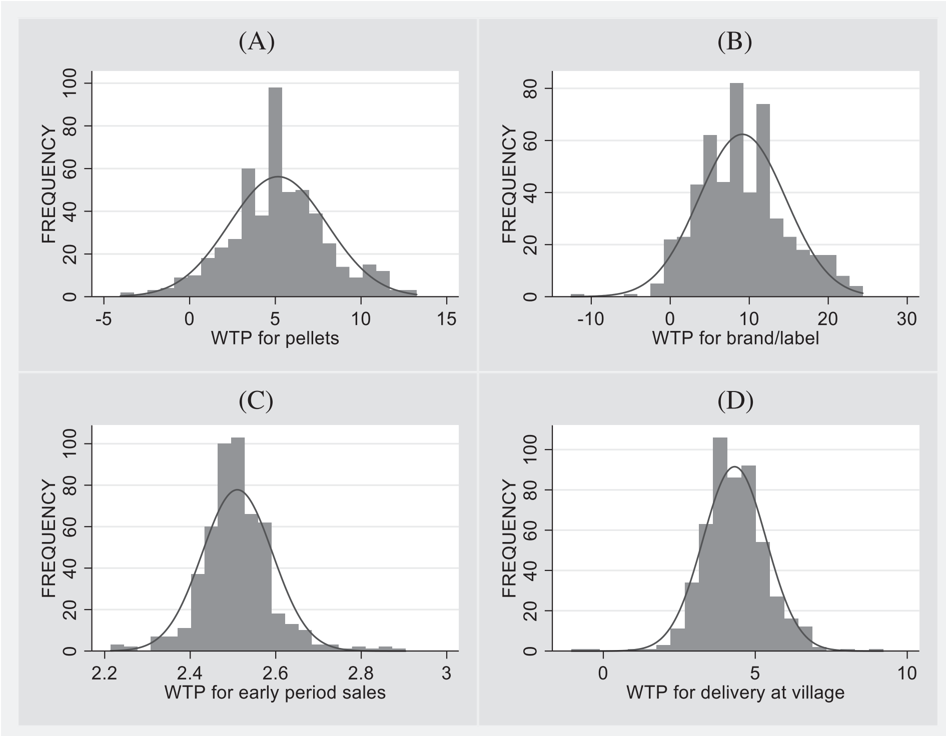


Figure 3. Distributions of farmer-specific WTP for MSW compost attributes.

Ahmed *et al.* 2020). These WTP estimates represent additional prices that farmers are prepared to pay for the improved attributes, such that their utility, and for that matter the choice probability, remains unchanged. In other words, the WTP reflects the monetary values or premiums to be paid for improvement in the attributes.

These WTP estimates show that farmers in the study area value brand/label more than any other elicited attributes. This is followed, in order, by a pelletized form of compost, compost delivery to the farmers' village and sales in cash windfall periods. However, there is an average disutility valued at GHS 33.35 for a decision to buy a bag of compost. This indicates that at GHS 33.35 per bag of MSW compost, an average rural farmer is undecided about purchasing MSW compost and will opt out of buying it, regardless of the attribute profiles, if the price rises further.

The mean WTP estimates indicate that farmers are willing to pay a premium for a brand/label that is 1.69 times what they are willing to pay for pelletized compost, double the premium for delivery in the community, and four times that of early sales (during the cash windfall). This shows the relative importance of branding/labelling in attracting farmers to buy the compost.

Figure 3 shows the distribution of farmer-specific WTP for each of the attributes. Brand/label (b) has the most widely distributed farmer-specific WTP estimates, followed by pelletized form (a) with the most significant deviation. Few farmers (3 per cent) showed a negative WTP for these attributes, which means that for those farmers, compost pelletizing and branding combine with a negative implicit price to maintain utility from compost choices. The next attribute with significantly varying WTP estimates is the point of delivery. Except for two farmers, the WTP for delivery in farmers' communities is positive, ranging from 0.84 to 9.21 Ghanaian cedis. The WTP estimates for early-period sales (c) are entirely positive, ranging narrowly from 2.2 to 2.9 Ghanaian cedis per compost bag. With a spread of a 1.5-cedis interval, the standard deviation around the mean (GHS 2.49) is not significant. Thus, WTP for sales during the cash windfall seems fixed among the sample farmers.

4. Discussion and conclusions

The Ministry of Food and Agriculture, in collaboration with NGOs, is striving to build farmers' capacity to produce and use organic soil amendments in northern Ghana, while MSW compost producers in cities lack effective demand for their products. In order to continue clearing public waste from cities through composting, these composters need to expand their market base by reaching out to the rural farming population. Successful marketing of MSW compost to rural farmers requires knowledge about WTP. Farmers' willingness to pay for compost attributes essentially governs their attraction to the inputs. Therefore, it is vital to elicit such attributes and determine the implicit prices that farmers are prepared to pay.

A discrete choice experiment was used to elicit preferences for access and quality attributes of a hypothetical MSW compost. The G-MNL model was applied to quantify the implicit prices that farmers are willing to pay for the attributes. Different model specifications consistently showed that the attributes elicited in the study were significant determinants of farmers' decisions to buy compost, with bag brand/label being the most preferred attribute. However, preference for the attributes varied widely across individual farmers, except for the period/time of sales.

On average, the farmers trade off utility valued at GHS 33.36 not to buy MSW compost. This utility, which is captured by the WTP for opt-out, is equivalent in absolute value to the average premium a farmer places on an MSW compost bag, regardless of its attributes. The amount was significant and very close to the producer price at the factory. It was also an indication that some vital status quo fertilizer attributes not included in the survey influence farmers to opt out when MSW compost price equals or exceeds GHS 33.36 (Hills *et al.* 2020). There was no further information supporting any immediate reason for this result. However, this finding is at variance with city user-focused studies such as Danso *et al.* (2002 and 2006) that urban waste compost demand could be low due to the availability of cheaper yet nutrient-rich alternative soil amendments. In this case, there are no cheaper alternatives in the study area for rural farmers. The disutility value being about half the price of subsidized mineral fertilizer may indicate that farmers contrast the expected utility from MSW composts with that of mineral fertilizer.

This study provides useful insights for compost business managers on 'how', 'when', and 'where' to offer the input so that rural farmers are attracted to buy it. Specifically, the findings have implications for marketing solid waste-based compost from city-based factories in Ghana. When designing their marketing strategies, compost manufacturers need to consider rural farmers' preferences for MSW compost quality and access. Attracting farmers to purchase compost means increased use of organic fertilizer and, consequently, improved soil health, crop yields and, for that matter, farmers' income and food security.

The study revealed that a key strategy for attracting rural farmers to MSW compost is to offer pelletized compost in branded packages made available to the farmers in their communities when they have the cash to buy. This strategy should be supported by a subsidized price much lower than the market price. However, compost producers cannot offer significant price cuts if they need to recover costs and remain in production. Thus, the situation calls for a much larger government subsidy than that currently given by the National Fertilizer Subsidy Programme. Extra subsidies on organic fertilizers over mineral fertilizers could offset the higher distribution costs (Folefack 2008).

Given the high average disutility associated with the decision not to buy compost and the very low literacy rates among farmers, the importance of branding/labelling could be decisive. At first sight, farmers might associate brands/labels with a reputation for quality. If so, branding/labelling becomes a valuable marketing tool for the initial purchase (uptake) decisions. If this is true, farmers may avoid making subsequent purchases unless their initial compost purchases prove valuable to them. Therefore, efforts should be made to improve the overall attractiveness of compost through the other attributes, especially pelletizing it and delivering it to farmers' communities.

The attributes examined in this study only allowed farmers' economic preferences to be assessed. Further studies could consider the role of communication strategies in promoting use of the input.

Supplementary material

Supplementary data are available at *Q Open* online.

Acknowledgments

The authors are very grateful to DAAD for a scholarship that enabled the first author to study and conduct this research. We also acknowledge the invaluable contribution of all anonymous reviewers to improve this paper by reviewing and providing valuable comments.

Farmers in the operational areas of the Presbyterian Agriculture Station (PAS) participated in this study with the permission and assistance of their management. The authors are therefore grateful to the management of PAS in Garu, Langbinsi, Sandema, and Tamale for their wonderful support in sampling study participants and facilitating data collection. The authors also acknowledge DAAD's role in providing a scholarship with which the first author studied and conducted this research.

Funding

Funding for this publication is provided by the Deutsche Forschungsgemeinschaft (DFG)-OA Fund of the Christian-Albrechts University of Kiel (CAU).

Data availability

This study surveyed farmers in PAS Ghana's project areas with the permission of the project's management under the condition that no third party accesses the data without consent of the management. Therefore, the data that support findings of this study cannot be made public but can be obtained from the corresponding author upon reasonable request (i.e. seeking permission through Presbyterian Agriculture Station -PAS, Ghana).

References

AfDB. (2006) 'Abuja Declaration on Fertilizer for the African Green revolution', Africa Fertilizer Summit, Abuja Nigeria, June 9-13.

Agyekum E.O., Ohene-Yankyera K., Benard K., Simon, C.F. and Robert C.A. (2014) 'Willingness to Pay for Faecal Compost by Farmers in Southern Ghana', *Journal of Economics and Sustainable Development,* 5:18–25.

Agwe J., Morris M. and Fernandes E. (2007) 'Africa's Growing Soil Fertility Crisis: What Role for Fertilizer?', *Agricultural and Rural Development Notes, 21*. World Bank, Washington, DC.

Ahmed J., Tefera, T. and Kassie G.T. (2020) 'Consumers Preference and Willingness to Pay for Enriched Snack Product Traits in Shashamane and Hawassa Cities, Ethiopia', *Agricultural and Food Economics,* 8: 1–20. Retrieved from https://doi.org/10.1186/s40100-020-00157-1.

Amikuzuno J., and Donkoh S. (2012) 'Climate Variability and Yields of Major Staple Food Crops in Northern Ghana', *African Crop Science Journal,* 20: 349–60.

Ampadu H. (2001) *Willingness to Pay for Compost from Urban Waste by Farmers of Different Urban and Peri-urban Farming Systems in the Greater Accra Region*. Unpublished M.Phil Thesis Submitted to Faculty of Agriculture, (University of Ghana, Legon). Retrieved from http://ugspace.ug.edu.gh/bitstream/handle/123456789/7953/WILLINGNESS.

Atakora W., Fosu M., Safo E., Tuffour H. and Tetteh F. (2014) 'Response of Maize Growth and Development to Mineral Fertilizer and Soil Characteristics in Northern Ghana', *International Journal of Advance Agricultural Research* 2:67–76.

Bello M., and Abdulai A. (2016) 'Impact of Ex-ante Hypothetical Bias Mitigation Methods on Attribute Non-Attendance in Choice Experiments', *American Journal of Agricultural Economics* 98: 1486–506.

Ben-Akiva M. and Bierlaire M. (1999) 'Discrete Choice Methods and their Applications to Short Term Travel Decisions', In Hall R.W. (eds.) *Handbook of Transportation Science*, *International Series in Operations Research & Management Science*, 23. Springer, Boston, MA. Retrieved from https://doi.org/10.1007/978-1-4615-5203-1 2.

Bienenfeld J.M. (2014) 'Consumer Willingness to Pay for Organic, Environmental and Country of Origin Attributes of Food Products', *Unpublished PhD Dissertation*, The Ohio State University, Ohio.

Bliemer M.C.J., and Collins A.T. (2016) 'On Determining Priors for the Generation of Efficient Stated Choice Experimental Designs', *Journal of Choice Modelling,* 21:10–4.

Braimoh A.K. and Vlek P.L.G. (2006) 'Soil Quality and Other Factors Influencing Maize Yield in Northern Ghana', *Soil Use and Management*. 22: 165–71. Retrieved from https://doi.org/10.1111/j.1475-2743.2006.00032.x.

Braimoh A.K. and Vlek P.L.G. (2004) 'The Impact of Land-Cover Change on Soil Properties in Northern Ghana', *Land Degradation & Development,* 15: 65–74. Retrieved from https://doi.org/10.1002/ldr.590.

Carson R.T. and Czajkowski M. (2014) 'The Discrete Choice Experiment Approach to Environmental Contingent Valuation', In Hess S. and Daly A (ed.) *Handbook of Choice Modelling*', Lansdown Road, Cheltenham UK, 15: 202–35.

Danso G., Fialor S.C. and Drechsel P. (2002) 'Farmers Perception and Willingness to Pay for Urban Waste Compost in Ghana', In Almorza D., Brebbia C.A., Sales D. and Popov V. (Ed.) *Waste Management and the Environment*', pp. 231–41. WIT Press, Ashurst Lodge, Southampton, SO40 7AA, UK.

Danso G., Drechsel P., Fialor S. and Giordano M. (2006) 'Estimating the Demand for Municipal Waste Compost via Farmers' Willingness-to-Pay in Ghana', *Waste Management,* 26: 1400–9. Retrieved from https://doi.org/10.1016/j.wasman.2005.09.021.

Danso G.K., Otoo M., Ekere W., Ddungu, S. and Madurangi G. (2017) 'Market Feasibility of Faecal Sludge and Municipal Solid Waste-Based Compost as Measured by Farmers' Willingness-to-Pay for Product Attributes: Evidence from Kampala, Uganda', *Resources,* 6: 1–17. Retrieved from https://doi.org/10.3390/resources6030031.

Duflo E.K.M. and Robinson J. (2011) 'Nudging Farmers to Use Fertilizer : Theory and Experimental Evidence from Kenya', *American Economic Review*, 101: 2350–90. Retrieved from https://doi.org/10.1257/aer.101.6.2350.

Fiebig D.G., Keane M.P., Louviere J. and Wasi N. (2010) 'The Generalized Multinomial Logit Model: Accounting for Scale and Coefficient Heterogeneity', *Marketing Science*, 29: 393–421. Retrieved from https://doi.org/10.1287/mksc.1090.0508.

Folefack A.J.J. (2008) 'Factors Influencing the Use of Compost from Household Waste in the Centre Province of Cameroon', *Journal of Human Ecology,* 24: 77–83. Retrieved from https://doi.org/10.1080/09709274.2008.11906103.

Fosgerau M. (2007) 'Using Nonparametric to Specify a Model to Measure the Value of Travel Time', *Transportation Research Part A: Policy and Practice.,* 41: 842–56.

Galgani P., Van Der, V.E. and Korevaar G. (2014) 'Composting, Anaerobic Digestion, and Biochar Production in Ghana. Environmental—Economic Assessment in the Context of Voluntary Carbon Markets', *Waste Management,* 34: 2454–65.

GIZ. (2013) 'Sustainable Waste Management and Organic Fertilizer Production for Smallholder Farmers', *Environment—Ghana* (December 2013).

Government of Ghana. (2015) *Spatial Development Framework for The Northern Savannah Ecological Zone (2015-2035)*, Volume 1 . Republic of Ghana (Accra, Ghana.)

Greene W.H. (2018) *Econometric Analysis*, eighth edition. pp. 855–5. Uttar Pradesh: Pearson India Education Services Pvt pp. 854–5.

Gu Y., Hole A.R. and Knox S. (2013) 'Fitting the Generalized Multinomial Logit in Stata', *The Stata Journal: Promoting communications on statistics and Stata*, 13: 382–97. https://doi.org/10.1177/1536867×1301300213.

Hensher D.A. and Greene W.H. (2011) 'Valuation of Travel Time Savings in WTP and Preference Space in the Presence of Taste and Scale 'Heterogeneity', *Journal of Transport Economics and Policy*, 45:505–25.

Hess S. and Train K. (2017) 'Correlation and Scale in Mixed Logit Models', *Journal of Choice Modelling,* 23:1–8. Retrieved from https://doi.org/10.1016/j.jocm.2017.03.001.

Hills K., Yorgey G. and Cook J. (2021) 'Demand for Bio-Based Fertilizers from Dairy Manure in Washington State : A Small-scale Discrete Choice Experiment', *Renewable Agriculture and Food Systems*,36, First view, pp.207–14. Retrieved from https://doi.org/10.1017/S174217052000023X.

Huber J. and Zwerina K. (1996) 'The Importance of Utility Balance in Efficient Choice Designs', *Journal of Marketing Research*, 33: 307–17.

Kassie G.T., Abdulai A., Greene W.H., Shiferaw B., Abate T., Tarekegne A. and Sutcliffe C. (2017) 'Modeling Preference and Willingness to Pay for Drought Tolerance (DT) in Maize in Rural Zimbabwe', *World Development*, 94: 465–77.

Keane M. and Wasi N. (2012) 'Comparing Alternative Models of Heterogeneity in Consumer Choice Behaviour', *Journal of Applied Econometrics,* 28:n/a-. Retrieved from https://doi.org/10.1002/jae.2304.

Kuhfeld W.F, Tobias, R.D. and Garratt M. (1994) 'Efficient Experimental Design with Marketing Research' Applications', *Journal of Marketing Research*, 31: 545–57. Retrieved from https://doi.org/10.2307/3151882.

Kuwornu J.K.M., Narh Jnr A.B., Egyir I.S., Onumah E.E. and Gebrezgabher S. (2017) 'Willingness to Pay for Excreta Pellet Fertilizer: Empirical Evidence from Ghana', *Acta agriculturae Slovenica,* 109: 165–73. https://doi.org/10.14720/aas.2017.109.2.14.

Larceneux F. and Carpenter M. (2008) 'Third-party Labelling and the Consumer Decision Process: The Case of the PGI European' Label', *HEC Research Papers Series*, 891. HEC Paris, Retrieved from https://econpapers.repec.org/paper/ebgheccah/0891.htm.

Louviere J.J., Street D., Burgess L., Wasi N., Islam T. and Marley A.A.J. (2008) 'Modelling the Choices of Individuals Decision-makers by Combining Efficient Choice Experiment Designs with Extra Preference 'information', *Journal of Choice Modelling,* 1: 128–64.

Lusk J.L. and Norwood F.B. (2005) 'Effect of Experimental Design on Choice-based Conjoint Valuation Estimates', *American Journal of Agricultural Economics*, 87: 771–85.

McFadden D. (1974) Conditional Logit Analysis of Qualitative Choice Behaviour', In: Zarembka P. (ed.) *Frontiers of Econometrics*, pp. 105–42. Academic Press, New York.

MoFA. (2017) *Ghana National Fertilizer Subsidy Program for 2017/18 Crop Season. Ministry of Food and Agriculture*, Ghana, Accra.

Nkonya E., Mirzabaev A. and von Braun J. (2015) 'Economics of Land Degradation and Improvement: An Introduction and Overview', In Nkonya, E., Mirzabaev, A., and von Braun, J. (eds.), *Economics of Land Degradation and Improvement—A Global Assessment for Sustainable Development*. Cham: Springer, doi: 10.1007/978-3-319-19168-3_3.

Osburn M., Holcomb R.B. and Neill C.L. (2020) 'Masked Heterogeneity in Aggregation: Incorporating Beliefs and Geographic Information into Consumer Willingness to Pay for State Brands', *Journal of Agricultural and Applied Economics*, 52, 527–44, first view article. Retrieved from https://doi.org/10.1017/aae.2020.17.

Owusu S., Yigini Y., Olmedo G.F. and Omuto C.T. (2020) 'Spatial Prediction of Soil Organic Carbon in Ghana Using Legacy Data', *Geoderma*, 360(Article 114008). Retrieved from https://doi.org/10.1016/j.geoderma.2019.114008.

Pradhan S.K., Opuni S.C., Fosu, M. and Dreschsel P. (2013) 'Municipal Waste Management Challenges and Opportunities in Tamale, Ghana', *A paper presentation at the 36th WEDC International Conference*, Nakuru, Kenya.

Republic of Ghana. (2015) *Intended Nationally Determined Contribution (INDC) and Accompanying Explanatory Notes*. Ghana's INDC submitted to UNFCC under the Paris Agreement (Accra Ghana, pp. 2–8.

Rockers P.C., Jaskiewicz W., Wurts L., Kruk M.E., Mgomella G., Ntalazi F. and Tulenko K. (2012) 'Preferences for Working in Rural Clinics Among Trainee Health Professionals in Uganda: A Discrete Choice Experiment', *BMC Health Services Research*, 12: 212.

Scarpa R., Thiene M. and Train K. (2008) 'Utility in Willingness to Pay Space: A Tool to Address Confounding Random Scale Effects in Destination Choice to the Alps', *American Journal of Agricultural Economics*, 90: 994–1010. Retrieved from https://doi.org/10.1111/j.1467-8276.2008.01155.x.

Street D.J., Jordan L.B. and Louviere J. (2005) 'Quick and Easy Choice Sets: Constructing Optimal and Nearly Optimal Stated Choice 'Experiments', *International Journal of Research in Marketing*, 22: 459–70. Retrieved from https://doi.org/10.1016/j.ijresmar.2005.09.003.

Sudradjat S., Hidayat Y., Purwanto O.D. and Apriliani S. (2018) 'Inorganic and Organic Fertilizer Packages for Growth Acceleration and Productivity Enhancement on a Four-Year-Old Mature Oil Palm', *IOP Conference Series: Earth and Environmental Science*, 196: 012004.

Vanlauwe B. (2015) 'Time to End the False Debate of Organic vs Mineral Fertilizer', *Devex*. Retrieved from https://www.devex.com/news/authors/bernard-v-1103750.

WHO. (2012) '*How to Conduct a Discrete Choice Experiment for Health Workforce Recruitment and Retention in Remote and Rural Areas: A User Guide with Case Studies*'. World Health Organization Press, 20 Avenue, Appia, 1211 Geneva. Retrieved from https://www.who.int/hrh/resources/DCE_UserGuide_WEB.pdf.

Zhang W. and Sohngen B. (2018) 'Do U.S. Anglers Care About Harmful Algal Blooms? A Discrete Choice Experiment of Lake Erie Recreational Anglers', *American Journal of Agricultural Economics*, 100: 868–88. Retrieved from https://doi.org/10.1093/ajae/aay006.

Zou N. (2011) *Canadian Consumers Functional Food Choices: Labelling and Reference-dependent Effects*, PhD Dissertation, University of Saskatchewan, 2011. Retrieved from Harvest: https://harvest.usask.ca/handle/10388/etd-06072011-194119.

Appendix

Appendix 1. Stata code used to produce the analysis presented in this paper

```
/* Statistical software: stata */
/* version 15.1 */
use 'G:\CHOICE ANALYSIS_ARNE\DATA ANALYSIS\FINAL_CHOICE1.dta', clear
*Do the Hausman test for IIA*
****************************************
quietly mlogit ybchosin price form label period delpoint none if attention = = 1
est store full
quitely mlogit ybchosin price form label period delpoint none if alti! = 1 & attention = = 1
est store part1
hausman part1 full
************************************
/* Latent class models */
lclogit ybchosin price form label period delpoint none if attention = = 1, group(cs) id(respid) nclasses(2) membership(gender age edu income offfarm///
orgause pric_age pric_income pric_offfarm form_edu form_incom form_offfarm label_edu label_offfarm label_orgause none_incom none_offfarm///
none_orgause none_trans p_offfarm del_trans del_dist)
lclogit ybchosin price form label period delpoint none if attention = = 1, group(cs) id(respid) nclasses(3) membership(gender age edu income offfarm///
orgause pric_age pric_income pric_offfarm form_edu form_incom form_offfarm label_edu label_offfarm label_orgause none_incom none_offfarm///
none_orgause none_trans p_offfarm del_trans del_dist)
lclogit ybchosin price form label period delpoint none if attention = = 1, group(cs) id(respid) nclasses(4) membership(gender age edu income offfarm///
orgause pric_age pric_income pric_offfarm form_edu form_incom form_offfarm label_edu label_offfarm label_orgause none_incom none_offfarm///
none_orgause none_trans p_offfarm del_trans del_dist)
```

```
lclogit ybchosin price form label period delpoint none if attention = = 1, group(cs) id(respid) nclasses(5) membership(gender age edu income offfarm///
orgause pric_age pric_income pric_offfarm form_edu form_incom form_offfarm label_edu label_offfarm label_orgause none_incom none_offfarm///
none_orgause none_trans p_offfarm del_trans del_dist)
*********************Do the Hausman test for RP Model fit */**********************************
xtlogit ybchosin price form label period delpoint none if attention = = 1, fe/* consistent specification*/
est store fixed
xtlogit ybchosin price form label period delpoint none if attention = = 1, re/* efficient and consistent specification */
est store rand
hausman rand fixed, sigmaless constant
***********************************************************************
/*CONDITIONAL/FIXED-EFFECTS LOGIT MODEL*/
clogit ybchosin price form label period delpoint none if attention = = 1, group(cs)
/* MIXLOGIT PREFERENCE SPACE CHOICE MODEL*/
global randvars 'price form label period delpoint none'
mixlogit ybchosin if attention = = 1, group(cs)id(respid)rand($randvars) ln(1) nrep(500) burn(5000)seed(5000)
***********************************************************************
/**G-MNL CHOICE MODELS**/
global randvars 'price form label period delpoint none '
crossfold gmnl ybchosin if attention = = 1, group(cs)id(respid)rand($randvars) nrep(500) seed(5000)/* Full GMNL*/
outreg2 using choices2.xml, dec(3) replace
estat ic
global randvars 'price form label period delpoint none '
gmnl ybchosin if attention = = 1, group(cs)id(respid)rand($randvars) gamma(1) nrep(500) seed(5000)/* GMNL-I */
outreg2 using choices2.xml, dec(3) append
estat ic
constraint 1 [tau]_cons = 1
matrix start = 0,0,0,0,0,0,0,0,0,0,0,0,1,0
global randvars 'price form label period delpoint none'
gmnl ybchosin if attention = = 1, group(cs)id(respid)rand($randvars) constraint(1)from(start, copy) difficult nrep(500)seed(5000)/* GMNL-Tau = 1*/
outreg2 using choices2.xml, dec(3) append
estat ic
global randvars 'price form1 label period delpoint none'
gmnl ybchosin if attention = = 1, group(cs)id(respid)rand($randvars) gamma(0) nrep(500) seed(5000)/* GMNL-II (results reported) */
outreg2 using choices2.xml, dec(3) append
estat ic
****************************** predicting probabilities****************************************
gmnlpred probs1 if price = = 35|label = = -1|form = = 1|period = = -1|delpoint = = -1|none = = 0/*probability of buying pelletised compost bag at market price*/
gmnlpred probs2 if price = = 35|label = = 1|form = = -1|period = = -1|delpoint = = -1|none = = 0/*probability of buying labeled compost bag at market price*/
```

gmnlpred probs3 if price = = 35|label = = -1|form = = -1|period = = 1|delpoint = = -1|none = = 0 /*probability of buying compost bag during cash windfall at market price*/
gmnlpred probs4 if price = = 35|label = = -1|form = = -1|period = = -1|delpoint = = -1|none = = 0/*probability of buying compost bag delivered at community at market price */
gmnlpred probs5 if price = = 25|label = = -1|form = = -1|period = = -1|delpoint = = -1|none = = 0/*probability of buying compost bag at 50 per cent subsidy*/
gmnlpred probs6 if price = = 15|label = = -1|form = = -1|period = = -1|delpoint = = -1|none = = 0/*probability of buying compost bag at 50 per cent price + transport cost subsidy*/
gmnlpred probs7 if price = = 25|label = = -1|form = = 1|period = = -1|delpoint = = -1|none = = 0/*probability of buying pelletised compost bag at 50 per cent price subsidy*/
gmnlpred probs8 if price = = 25|label = = 1|form = = -1|period = = -1|delpoint = = -1|none = = 0/*probability of buying a labeled compost bag at 50 per cent price subsidy*/
gmnlpred probs9 if price = = 25|label = = -1|form = = -1|period = = 1|delpoint = = -1|none = = 0/*probability of buying compost bag at 5 per cent subsidy + during cash winfall*/
gmnlpred probs10if price = = 25|label = = -1|form = = -1|period = = -1|delpoint = = 1|none = = 0/*probability of buying a compost bag at 50 per cent subsidy + delivery at community*/
/*marginal probability graph*//* graph predicted probabilities using HIGH-LOW-CLOSE CHART in excell*/
****
/*G-MNL HETEROGENEITY-IN-MEAN PREFERENCE MODELS */
global randvars ‘price form label period delpoint none ’
gmnl ybchosin if attention = = 1, group(cs)id(respid)rand($randvars) het(pric_age pric_income pric_offfarm form_edu form_incom///
form_offfarm label_edu label_offfarm label_orgause none_incom none_offfarm none_orgause none_trans p_offfarm del_trans del_dist)nrep(500) seed(5000)/* Full GMNL*/
outreg2 using choices.xml, dec(3) append
estat ic
global randvars ‘price form label period delpoint none ’
gmnl ybchosin if attention = = 1, group(cs)id(respid)rand($randvars) gamma(1)het(pric_age pric_income///
pric_offfarm form_edu form_incom form_offfarm label_edu label_offfarm label_orgause none_incom none_offfarm none_orgause none_trans p_offfarm////* GMNL-I */
del_trans del_dist)nrep(500) seed(5000)
outreg2 using choices.xml, dec(3) append
estat ic
global randvars ‘price form label period delpoint none’
gmnl ybchosin if attention = = 1, group(cs)id(respid)rand($randvars) gamma(0) het(pric_age pric_income///
pric_offfarm form_edu form_incom form_offfarm label_edu label_offfarm label_orgause none_incom none_offfarm none_orgause none_trans p_offfarm///
del_trans del_dist)nrep(500) seed(5000)/* GMNL-II (results reported) */
outreg2 using choices.xml, dec(3) append
estat ic
matrix start = 0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1
constraint 1 [tau]_cons = 1
global randvars ‘price form label period delpoint none’

```
gmnl ybchosin if attention = = 1, group(cs)id(respid)rand($randvars) constraint(1) from(start, copy) het(pric_age pric_income///
pric_offfarm form_edu form_incom form_offfarm label_edu label_offfarm label_orgause none_incom none_offfarm none_orgause none_trans p_offfarm///
del_trans del_dist)nrep(500) seed(5000)/* GMNL-Tau = 1*/
outreg2 using choicemodels.xml, dec(3) append
estat ic
/* GMNL models in WTP space */
gen cons = 1
constraint 1 [Mean]price = 1
constraint 2 [tau]_cons = 0
matrix start = 1,0,0,0,0,0,0,0,0.1,0.1,0.1,0.1,0.1
global randvars 'form label period delpoint none'
gmnl ybchosin price if attention = = 1, group(cs)id(respid) rand($randvars) het(const) constraint(1 2)from(start, copy) nrep(500) gamma(0) seed(5000)/*G-MNL II in WTP space(results reported) */
gmnlbeta form label1 period1 delpoint1, saving('stata data filename') noscale/* obtain and save farmer-specific WTPs as data*/
/* use the data to graph wtp distributions*/
histogram form, color(blue per cent100) frequency normal xtitle(WTP for pellets)ytitle(FREQUENCY)
graph save WTPform
histogram label, color(blue per cent100)frequency normal xtitle(WTP for brand/label)ytitle(FREQUENCY)
graph save WTPlabel
histogram period, color(blue per cent100)frequency normal xtitle(WTP for early period sales)ytitle(FREQUENCY)
graph save WTPperiod
histogram delpoint, color(blue per cent100)frequency normal xtitle(WTP for delivery at village) ytitle(FREQUENCY)
graph save WTPdelpoint
graph combine WTPform.gph WTPlabel.gph WTPperiod.gph WTPdelpoint.gph
```