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Heterogeneous demand for soybean quality

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Abstract

Agricultural commercialisation is a critical pathway for economic development in Sub-Saharan Africa (SSA). However, the lack of market information may impede this development. To the best of the authors' knowledge, this is the first paper to examine market information and preferences for soybean quality in a developing-world context. We seek to understand the nature of information markets associated with the nascent soybean trade in Sub-Saharan Africa in order to inform the market and policy of previously unknown key marketing information. The research involves a discrete choice experiment with 228 buyers of soybean involving five key soybean quality attributes. The sample represents three distinct classes of buyer/traders: wholesalers, processors and retailers. Traders significantly discount the price of soybean attributes such as off-colour, small grain size, low oil levels and high contamination with foreign material, such as stones. Foreign material ranks highest of the attributes that we examined, in terms of the discount level, at 22%. The study finds significant preference heterogeneity among traders, explained partly by the socioeconomic and trade characteristics of the respondents. We identified three distinct classes of traders per the latent class logit (LCL) results, namely 'high price discounters', 'big bean supporters', and 'oil sceptics'. Our findings improve soybean market information, transparency and signalling. This will lead farmers to be more efficient and allow policymakers to understand better how the market actually prices grain at the farm gate.

Key words: soybean; trade; choice experiment; latent class; willingness to pay

1. Introduction

Over the last 20 years, soybean has been the fastest growing broad land crop in terms of land under cultivation, outpacing the number two and three crops, viz. rice and maize, by one-third (Tamimie & Goldsmith 2019). Soybean's growth results from the rise in incomes and the change in diets and food consumption patterns as a result of shifts to animal-sourced and processed foods. While global demand has risen rapidly, farmers in Sub-Saharan African (SSA) and the rural economy have not benefited. To date, less than 0.5% of the world's soybean production originates from SSA, excluding South Africa. As a result, and relevant to this manuscript, regional policymakers and development operatives in Africa now are looking to develop local soybean value chains as a way to increase economic development and reduce the imports of food oil and livestock feeds (TechnoServe 2010).

The introduction of a new commercial crop like soybean involves new market interactions as farmers move beyond traditional subsistence crops to increase incomes and exit poverty traps. Commercial crops may challenge smallholders as they navigate new norms associated with commercial value chains (Tamimie & Goldsmith 2019).

Commercialisation by definition involves an interaction between producers and buyers, but is particularly relevant with respect to the subject of this manuscript, viz. soybean. Soybean is a non-native, non-staple crop; while having many uses, it requires processing prior to use, and is predominately used as a livestock feed. Thus, farmers must sell their soybean to buyers such as traders, grain aggregators, soybean processors or local retailers for use downstream by livestock producers or food manufacturers.

Fundamental to this commercial transaction is the definition of quality by the buyer, and the discounting that results when grain fails to meet the expected standard. In developed-country settings, grain standards are well defined (see Grain Inspection, Packers and Stockyards Administration [GIPSA] 2004). However, in developing country settings, especially with new commercial crops like soybean, standards are not legally defined, or enforced even if defined. This makes it difficult for the market in general, and farmers in particular, to elicit trader preferences in the market, given both the number of trade-relevant soybean attributes and the diversity of trader types (wholesalers, retailers and processors). Our research question involves measuring and ordering these quality attributes. Our research fills the information void by eliciting the stated preferences of soybean buyers, which heretofore were unknown.

Specifically the study employs choice experiment to elicit traders' preferences for soybean attributes. Our method allows buyers to reveal the economic value of the grain and the underlying quality attributes. The research aims to improve the symmetry of quality information across the soybean transaction interface so that farmers, industry, and policymakers understand how buyers define quality and discount the soybean they purchase. Once knowing how traders buy soybean, farmers can then improve their quality and make sound investments to raise their prices received and reduce the uncertainty they face in the marketplace.

This study contributes to the agricultural commercialisation literature on competitiveness, market integration, price discounting and quality standards in the developing world. While much research has surveyed farmers about their preferences with respect to the grains they produce (see Hoffman & Gotubu 2014; Kadjo *et al*. 2016), there have been only a few studies of buyers (see Kamara *et al*. 2014; Jones *et al*. 2016). To the best of the authors' knowledge, no buy-side study involves soybean. The study hypothesises and tests the following: (1) significant differences exist in the level of discounts across key soybean attributes; and (2) significant differences exist in the level of discounts across buyer types operating in the soybean value chain. The study extends the literature by using preference-elicitation methods (latent class model) to quantify buyer willingness to pay (WTP) for improved soybean trade attributes. Secondly, the study contributes to the literature on traders' preferences regarding soybean commercialisation in terms of price discounting. Thirdly, the study explores preference heterogeneity across buyer types, given that their preferences may differ significantly depending on the demands of their customers. A greater symmetry of market information will result from the findings, which will benefit farmers, policymakers and development practitioners by improving soybean market performance and reducing pricing uncertainty and inefficiencies.

2. Background: Soybean commercialisation in Ghana

Ghana has achieved a compound annual growth rate of 16% in soybean production over the period 2002 to 2014, but still remains one of the region's smaller producers, with yields at less than 1 000 kilograms per hectare (Lee 2019). Growth in the aggregate soybean supply since 2008, now at about 150 000 MT per year (Figure 1), results from extensification and not from the use of improved technologies or greater factor productivity, hence the low yields. Domestic demand is over and above the domestic supply, thus prices are favourable (Martey *et al*. 2019). The poultry industry utilises about 75% of the total soybean demanded annually in the form of soybean meal as the protein base for feed (Gage *et al*. 2012). High demand for soybean in the consumption regions requires oilseed and feed processors to import significant levels (60%) of both soybean and soybean meal respectively to supplement the local supply (see Pradhan *et al*. 2010; Gage *et al*. 2012; Eshun *et al*. 2018).

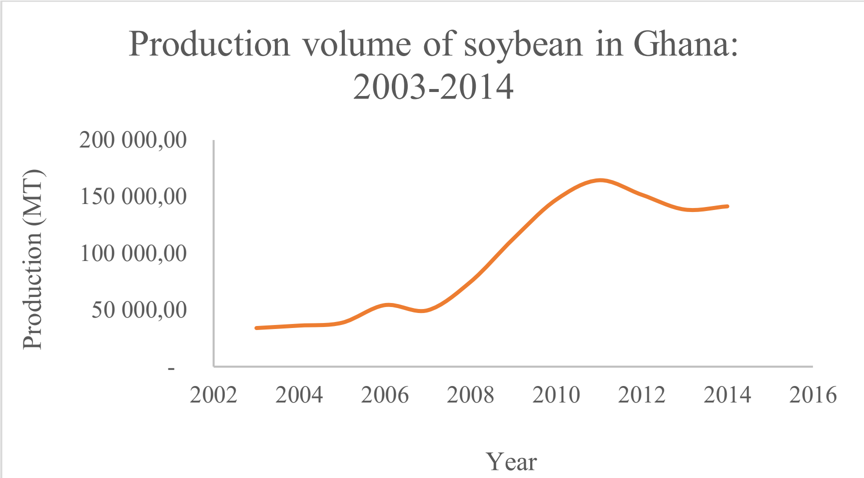

Figure 1: Soybean annual production, 2003 to 2014

Northern Ghana serves as the centre of production for Ghana, while utilisation takes place in the central and southern regions (Pradhan *et al*. 2010; Gage *et al*. 2012). The soybean marketing system in Ghana (Figure 2) consists mainly of actors that serve as intermediaries between northern producers and central and southern customers. About 90% of the soybean traded is purchased from northern Ghana, while the remaining originates from the Ashanti Region of Ghana (Martey *et al*. 2019).

Most of the processing capacity is located in the middle belt of Ghana. Processors buy as much soybean as they can at harvest time to ensure more stable meal prices to poultry (Gage *et al*. 2012). Processors employ purchasing agents who buy directly from the producers in northern Ghana. These arrangements incur lower costs (search, negotiation and transportation) relative to buying from either wholesalers, NGOs, government institutions or the World Food Programme. Two types of wholesalers, itinerant and resident, serve as intermediaries between wholesalers from the south and farmers in the north. The itinerant wholesalers from the south also sell to processors. Itinerant wholesalers aggregate soybean from different farm locations in northern Ghana. The resident wholesalers buy soybean from farmer-based organisations (FBOs), or from individual farmers located within the same village or in close proximity. Comparatively, itinerant wholesalers incur higher transaction costs (searching, bargaining, transportation, aggregation and storage) than resident wholesalers (negotiation, storage and transportation) because they lack the tacit knowledge of the region and incur higher transport and storage costs. As a result, itinerant costs of goods sold are higher, and these are passed along to southern buyers. While resident wholesalers benefit from lower costs, they lack the tacit knowledge and market linkages of southern buyers, and thus face weaker demand and overall lower prices.

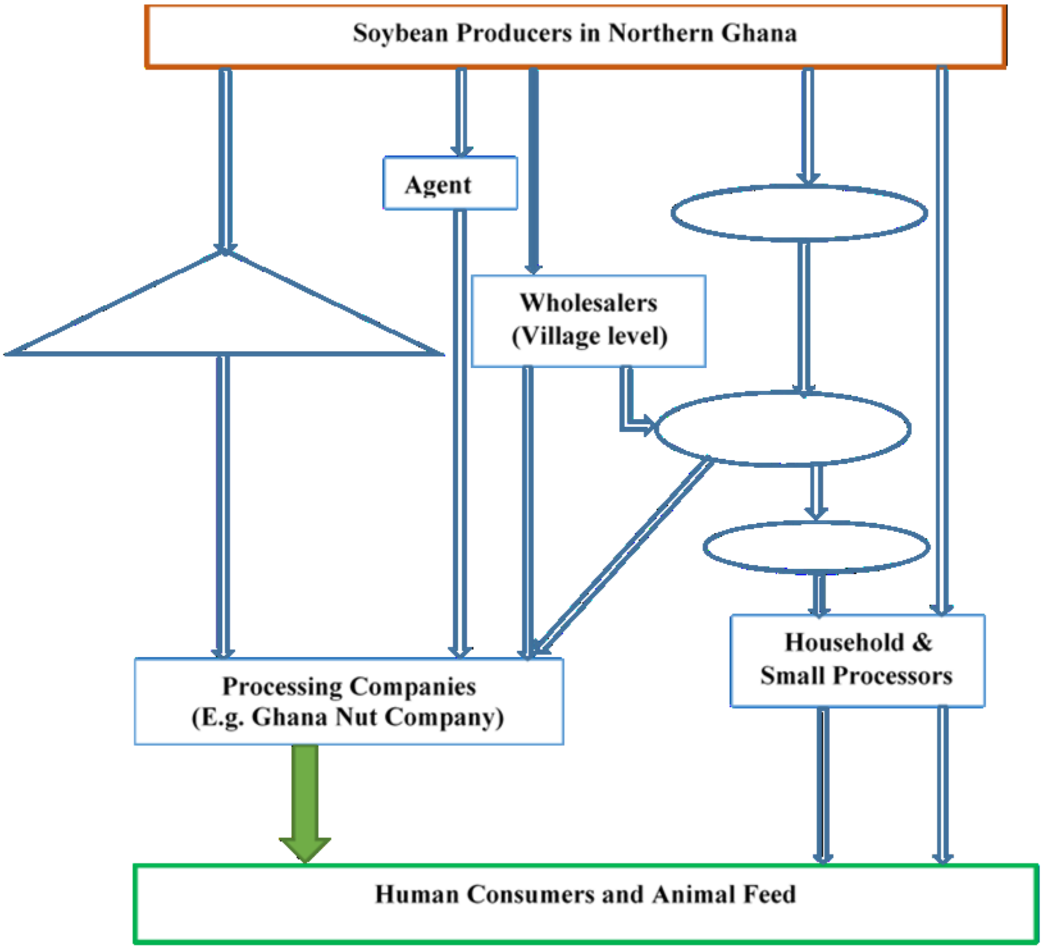

Figure 2: Soybean marketing distribution channel

While the dominant market structure is highly competitive, there are low-level non-verbal contractual arrangements entered into by both itinerant and resident wholesalers that cannot be enforced legally, but are based entirely on trust. Reneging can occur on these soft contacts due to the non-binding nature of the agreement as farmer information improves about the state of the harvest and prices paid elsewhere, for example when supply becomes short and prices rise.

Processors in the central part of the country sit at the end of the chain, buying grain directly, or buying from wholesalers, and then transforming that grain into meal and oil for human food and livestock feed markets. Processors then purchase from these wholesalers or rely on their own agents. Small-scale or local processors in northern Ghana buy a small proportion of national output to process into products such as 'dawadawa' (a local seasoning used in preparing dishes) and kebabs (Dogbe *et al.* 2013). Local retailers in the north, mostly women, will also purchase soybean directly from producers or from resident wholesalers, and sell soybean to households and small-scale processors. Trade preferences will likely differ among the various trader types, as they differ in terms of scale, procurement practice and customer base.

In Ghana there is significant uncertainty about the quality attributes available in the market. Grain sampling and attribute measurement takes place by visual assessment, and not by objective physical or chemical analyses that are common within developed-country grain markets. Thus, grain quality information is imperfect due not only to poor measurement, but also to power asymmetry across the buy-sell interface. Buyers, for example, could take advantage of cash-short farmers whose product offer is undifferentiated. The imbalance of power, opportunism among agents, and imperfect information create a poor information market, where farmers try to sell inferior grain as a superior product, and buyers over identify grain quality flaws to achieve higher levels of discounts.

3. Experimental design

3.1 Selection of attributes

We selected the five market attributes of soybean, namely colour, size, foreign matter (FM), variety (a proxy measurement of oil content) and price. A literature search, consultation with experts and focus group discussions informed the different levels of each attribute to be presented to the traders during the choice experiment (Table 1). We employed only a few attributes in the choice set. This allowed buyers to make an actual choice by reducing or eliminating the tendency to ignore one or more of the attributes in the experiment, referred to as attribute non-attendance (ANA) (Hensher & Greene 2010).

Table 1: Trade attributes levels and description

Attribute	Levels			Preference/Description
	1	2	3	
Colour	Light brown	Deep brown		• A bright colour (deep brown) is preferred. • A dull-coloured soybean is perceived to be mouldy.
Size	Small	Big		• A bigger grain is preferred to smaller grains. • A smaller quantity of bigger grains is required to fill a bag (104 kg). • Larger grains yield higher levels of meal and oil per ton of raw material.
Foreign matter	Stone free	Stones		• Stone-free soybean is preferred. • Soybean with stones affects the crushing and drying process and may lead to damaged equipment and the discoloration of grains.
Variety	'Jenguma'	'Salintua I'	'Salintua II'	• 'Jenguma' is preferred. • Common knowledge associates high yield with 'Jenguma. • Yields are high. • 'Jenguma also is resistant to early shattering and thus has lower levels of FM.
Price	GH¢170	GH¢200	GH¢230	• The value is per bag (104 kg). GH¢200 is the expected market price for quality soybean

3.1.1 Colour

The colour of soybean serves as a sign of healthy grain. Traders consider discoloration in soybean to indicate damaged soybeans (Guinn 2002). Poor drying conditions or storage at high levels of moisture often lead to discoloration. Brightly coloured soybean is a preferred trait according to 73% (166) of the sampled traders. Smallholders experience a lack of improved storage and threshing equipment, which in turn leads to poor grain quality, particularly off-colour, cracks and breaks, and high levels of foreign matter. Most farmers in Ghana manually thresh soybeans and then store them in improvised storage structures with little temperature control or air movement. Poor storage leads to high levels of mould and a subsequent change in colour. However, soybean that is adequately dried and well stored has a higher rate of colour retention (deep brown) and attracts relatively higher prices.

3.1.2 Size

Buyers looking to supply soybean for processing into soybean meal for poultry feed prefer a larger soybean because of the higher yield of meal. Trade occurs by weight, thus smaller grain size produces less meal output from the standard 104 kg bag used in Ghana.

3.1.3 Foreign matter

Foreign materials (FM) are "… materials which readily passes through an 8/64 inch (3.2 mm), round-hole, perforated sieve and any material other than soybean remaining atop the sieve" (Guinn 2002). The contamination of soybean with foreign materials occurs through poor harvest management, manual threshing, and challenging transportation infrastructure. The removal of FM from the grain can also be labour intensive. Traders primarily discount soybean with high levels of foreign matter because higher levels result in less grain (protein and oil) per ton of purchase. In addition, the presence of foreign material affects drying and storage efficiency, the quality of processed products such as oil and protein meal, and the wear and tear on processing equipment.

3.1.4 Oil

Processors and traders do not focus on agronomic or harvest performance, but instead value oil content (in Ghana), which is in high demand for human consumption. Processors do not test their inbound grain for oil, thus do not know the oil levels of Ghana's four national varieties, or of the grain they buy, until the grain has been aggregated in the plant. Of specific interest in this study is a better understanding of buyers' willingness to pay/discount for higher/lower oil content in the soybean they buy. We presented buyers in the experiment with three varieties of soybean with three levels of oil: 'Jenguma' – high oil content; 'Salintua I' – low oil content; and 'Salintua II' – very low oil content.

3.1.5 Price

Three levels of prices were specified: GH₵[1]170, GH₵200, and GH₵230 per bag (104 kg), or US$298/MT, US$351/MT and US$404/MT respectively.[2] Trade experts in the soybean business informed the choice of these prices. The prices reflect the different level of soybean attributes and market prices across the three regions. For example, soybean that satisfies all the required attributes, such as 'Jenguma' (high oil content), which is deep brown, big and stone free, attracts a price of GH₵230 (US$404/MT), whereas soybean that falls short of these qualities attracts a relatively lower price (GH₵170 (US$298/MT) and GH₵200 (US$351/MT).

3.2 Design of choice sets

We used the OPTEX procedure in SAS to establish the optimal experimental design using the attributes and levels previously described. With three attributes varying across two levels each, and two attributes varying across three levels, there were 72 ($3^2 * 2^3$) possible combinations of attributes and their levels. We used a D-optimal design with a modified Federov search algorithm, with a full-factorial design constituting the candidate set. A total of 18 choice sets (row) were generated and put into three blocks, with each block consisting of six choice sets. We randomly assigned each participant in the choice experiment to a block provided them with six independent choice sets. Figure 3 provides an example of one of the choice set scenarios, with illustrations to accommodate different levels of literacy among the participants.

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[1] GH₵ represents Ghana cedi; exchange rate is US$1 = GH₵ 4.361 (Source: Bank of Ghana, 2017)
[2] Price at the time, according to Esoko (2019), was GH₵200.

Please check (✓) the option (A, B or C) that you would be most likely to choose

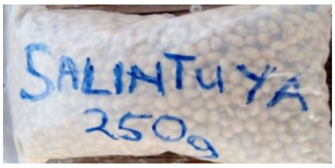
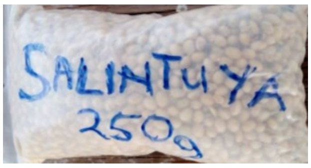
Market attributes	Option A	Option B	Option C
Colour	Deep brown 	Deep brown 	Light brown 
Size	Small 	Small 	Big 
FM	Not sorted 	Not sorted 	Sorted 
Variety	Salintua 1 (Low oil content) 	Salintua 2 (Very low oil) 	Jenguma (High oil content) 
Price per bag (104 kg)	GH₵170	GH₵200	GH₵200
I will choose…	☐	☐	☐

Figure 3: Example of choice set presented to survey respondents

3.3 Study area and sampling design

The Guinea and Sudan Savannah agroecological[3] zone of Ghana, consisting of the Northern, Upper East and Upper West regions, served as the study site. Soybean is a relatively new crop in Ghana and cultivated mostly by smallholder farmers under rain-fed conditions (Akramov & Malek 2012). The Upper East, Upper West, Northern, Brong-Ahafo and Volta regions are the major soybean production areas in Ghana (SRID 2012), but Northern region alone contributes about 70% (49 950 ha) of national soybean area and about 66% of national (76 000 ha) production (SRID 2012). Field sizes average about 0.8 hectares.

[3] Currently, the Guinea and Sudan Savannah agroecological zone consists of five regions, but at the time of the survey (2016) the zone consisted of three regions.

Three broad categories of traders, as defined previously, characterise the soybean trade in northern Ghana – wholesalers (itinerant and resident), processors and retailers. Wholesalers are individuals or organisations who buy large quantities of soybean from different sources to resell either to processing firms or regional markets. Processors are individuals or private firms that buy soybean from wholesalers or directly from farmers. Retailers are traders (largely dominated by women) who engage in smaller volumes of soybean trade and sell directly to 'pure' consumers.

The target survey population was soybean traders in northern Ghana who have engaged in soybean trade for at least a year (Table 2). The study comprised a sample of 228 traders. The identification of traders began with the consultation of key stakeholders in the soybean value chain, such as research institutions, NGOs, producer organisations and trade groups. We used a multistage sampling technique to sample wholesalers or aggregators, processors and retailers. In the first stage, the study purposively selected nine districts based on the volume of soybean produced and traded. The second stage of sampling was based on clustering of the traders, such that wholesalers, processors and retailers are represented within each cluster. In the third stage, we randomly selected wholesalers, processors and retailers from the clusters. In aggregate, 85 wholesalers, 48 processors and 95 retailers were sampled within the Guinea and Sudan Savannah agroecological zone of Ghana. The traders in our sample reported purchases of 4 517 tons in the Northern region, 1 963 tons in the Upper West, and 398 tons in the Upper East (Figure 4).

Table 2: Distribution of sampled traders by region

Regions	Districts	Aggregators	Processors	Retailers	Total
Northern	4	33	27	46	106
Upper East	3	22	10	30	62
Upper West	2	30	11	19	60
Total	9	85	48	95	228

Note: The total number of different categories of traders across each specific region is the horizontal summation excluding the districts, while the vertical summations are the specific trader types summed over the three regions.

4. Data and descriptive statistics

4.1 Data

Data for the analysis arose from two sources: first, a survey of traders about their practices and preferences, which then informed the choice experiment. Both the survey and the experiment, which were conducted by trained enumerators, took place in 2017 (June to July). Grain harvest normally takes place in November, while planting occurs in July. Thus, the setting for the data collection was late in the season, when grain stocks are relatively low and grain prices are relatively high.

Enumerators interviewed aggregators (wholesalers), processors and retailers using a pretested questionnaire. Interviews took place at different times of the day and days of the week, depending on respondent availability. About 3% of the traders declined to participate due to their busy schedules and were replaced with other traders from our sample frame. Enumerators scheduled interviews, which allowed for enumeration efficiency. Some of the information captured in the data include demographics and trade characteristics, such as the type of soybean-trading business, quantity, sources and period of purchases, trading partners, price, preferred soybean attributes, and transaction-related costs. The survey provided information on how traders discount the price of soybean when the grain fails to meet the required preferred traits, such as colour, size and foreign matter.

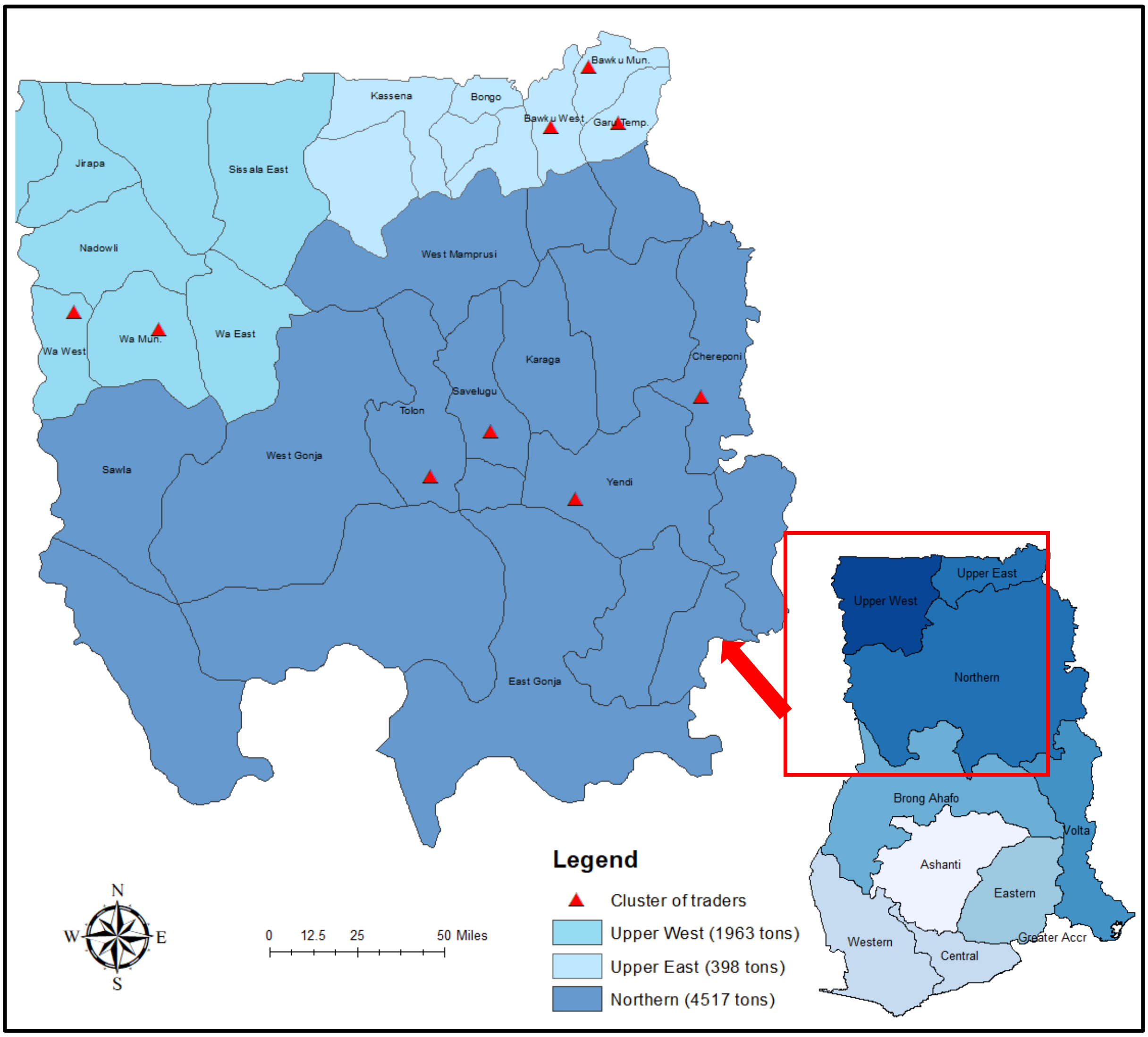


Figure 4: Regional volume of soybean purchased by sample traders in northern Ghana

Data from the choice experiment reflects the traders' preferences and WTP for soybean traits. All buyers who participated in the survey also participated in the choice experiment. Each trader had the opportunity to make six choices of a preferred trade attribute among alternatives, with corresponding WTP. This brought the total observations to 1 368 (228 respondents * 6 choices). Strategies employed by the enumerators to minimise the issue of attribute non-attendance (ANA) included effective articulation of the purpose and steps in the experiment and its end use, testing the understanding of the respondents, and pausing at regular intervals when the respondents became distracted. Finally, a unique trader identification number linked the respondent's survey with the responses.

4.2 Descriptive statistics

Over 85% of the sample were women, and 100% of the retailers were women (Table 3a). The average age of a trader was 43 years, they were married and had approximately two years of formal education, while aggregators had slightly more than two years of formal education. The results indicate a statistically significant difference in the education of aggregators and retailers, at the 1% level of significance (Table 3b). Traders had varying levels of annual purchase volumes of soybean: aggregators purchased 54 414 kg; processors purchased 37 231 kg; and retailers purchased 4 895 kg. There was a statistically significant difference in the annual volume of soybean purchased between the aggregators and retailers (Table 3b).

The sampled traders bought soybean from three main sources: farmers, farmer organisations, and itinerant traders or 'middlemen'. On average, traders buy 88 bags and 56 bags of soybean from farmers during the post-harvest period (December through May) and pre-harvest period (June through November), respectively. Results indicate that traders buy 30 bags and 7 bags of soybean from farmer organisations during the post and pre harvest periods respectively, and 38 bags and 47 bags of soybean from itinerant traders during the same periods (Table 3a). The results suggest that traders generally rely on itinerant traders for soybean supply during pre-harvest, when supply is generally low. Consistent with the fact that aggregators annually procure significantly larger volumes of soybean retailers, the study records a similarly statistically significant difference in the quantity of soybean purchased in both the post and pre-harvest periods. However, no significant difference exists between aggregators and processors or between retailers and processors in terms of seasonal purchases (Table 3b).

Table 3a: Summary statistics by trader type

Variable	**Aggregator (N = 85)**		**Retailer (N = 95)**		**Processors (N = 48)**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
Age of respondent (number)	43.14	9.00	43.22	10.01	41.90	10.09
Gender of respondent (1 = Male, 0 = Female)	0.18	0.38	0.00	0.00	0.10	0.31
Marital status (1 = Married, 0 = Single)	0.91	0.29	0.91	0.29	0.94	0.24
Number of years of education (years)	2.52	3.42	1.13	2.66	1.81	4.21
Total purchased from all sources (kg)	54 414	204 323	4 895	8 598	37 231	233 825
Farmer						
Purchase soybean from farmer (1 = Yes)	0.92	0.28	0.92	0.28	0.73	0.45
Quantity purchased – postharvest period (bags)	185.90	633.08	17.02	25.79	109.92	573.64
Length of postharvest (months)	4.38	3.07	5.76	15.94	3.00	1.28
Quantity purchased preharvest period (bags)	91.93	225.74	17.53	33.26	116.62	623.84
Length of preharvest (months)	8.41	1.35	8.61	1.59	8.99	1.26
Farmer organisation/cooperative						
Purchased soybean from farmer organisation (1 = Yes)	0.07	0.26	0.01	0.10	0.02	1.40
Quantity purchased postharvest period (bags)	583.06	1 658.00	0.56	1.59	750.00	1 061.0
Length of postharvest (months)	4.50	2.17	7.000	0.00	3.00	0.00
Quantity purchased preharvest period (bags)	111.50	199.01	3.000	0.00	900.00	0.00
Length of preharvest (months)	7.17	2.04	5.000	0.00	9.000	0.00
Itinerant traders						
Purchased soybean from farmer organisation (1 = Yes)	0.490	0.500	0.45	0.50	0.46	0.50
Quantity purchased postharvest period (bags)	125.62	347.23	16.94	30.36	97.53	406.80
Length of postharvest period (months)	4.95	3.53	5.60	3.77	4.00	2.58
Quantity purchased preharvest period (bags)	143.33	388.21	17.50	35.81	185.33	831.89
Length of preharvest (months)	7.42	2.70	6.72	3.26	8.30	1.96

Table 3b: Difference in mean test by trader type

Variable	Aggregator – Retailer (N = 180)		Aggregator – Processor (N = 133)		Retailer – Processor (N = 143)	
	Diff.	***P* value**	**Diff.**	***P* value**	**Diff.**	***P* value**
Age of respondent (number)	-0.08	0.96	1.25	0.46	1.33	0.46
Gender of respondent (1 = Male, 0 = Female)	0.17	0.00	0.07	0.27	-0.10	0.00
Marital status (1 = Married, 0 = Single)	0.00	0.99	-0.03	0.53	-0.03	0.52
Number of years of education (years)	1.39	0.00	0.705	0.30	-0.69	0.24
Total quantity of soybean purchased from all sources (kg)	49 519	0.02	17 183	0.66	-32 336	0.18
Farmer						
Purchased soybean from farmer	0.00	0.96	0.19	0.00	0.19	0.00
Quantity purchased postharvest period (bags)	155	0.01	86	0.41	-69	0.18
Length of postharvest (months)	1.38	0.45	1.37	0.01	2.75	0.31
Quantity purchased preharvest period (bags)	68	0.00	-1	0.99	-69	0.21
Length of preharvest (months)	0.20	0.39	-0.58	0.04	-0.38	0.21
Farmer organisation/cooperative						
Purchased soybean from farmer organisation	0.06	0.04	0.05	0.22	-0.01	0.62
Quantity purchased postharvest period (bags)	62	0.27	30	0.71	-31	0.16
Quantity purchased preharvest period (bags)	8	0.18	-11	0.50	-19	0.16
Itinerant traders						
Purchased soybean from farmer organisation	0.04	0.58	0.04	0.69	-0.01	0.95
Quantity purchased postharvest period (bags)	59	0.03	18	0.72	-41	0.17
Length of postharvest (months)	0.65	0.43	0.95	0.26	1.60	0.08
Quantity purchased preharvest period (bags)	60	0.04	21	0.77	-81	0.17
Length of preharvest (months)	0.70	0.30	0.90	0.17	-1.60	0.04

Note: Difference (Diff.) is specified as the difference in the means of the trader type (e.g. Aggregator – Retailer reads as mean of aggregator minus mean of retailer)

Processors were willing to pay as much as GH₵156 (US$36), followed by retailers, who were willing to pay GH₵154 (US$35), and the aggregators, at GH₵150 (US$34) (Table 4). The colour of soybean was a desirable attribute among all trader types, given that more than 70% of the sample reported a high preference for the colour attribute. Deep brown soybean is usually the preferred trait. Aggregators paid the lowest price (GH₵124 or US$28) if farmers were unable to meet the desired colour attribute, followed by processors (GH₵129 or US$30) and retailers (GH₵135 or US$31). Retailers were more flexible in their choice of soybean attributes. The results show that processors had the lowest rejection rate of soybean if farmers were unable to meet the colour preference.

Table 4: Preferences for soybean attributes by trader status

Trader preferences	Aggregator (N = 85)		Retailer (N = 95)		Processor (N = 48)	
	Mean	SD	Mean	SD	Mean	SD
Amount paid for all attributes (GH₵)	149.710	43.420	154.470	43.950	156.250	40.300
Colour						
Interested in colour (1 = Yes, 0 = No)	0.760	0.420	0.720	0.450	0.710	0.460
Satisfied with colour (1 = Yes, 0 = No)	0.520	0.500	0.490	0.500	0.480	0.500
Rejected light brown soybean (1 = Yes, 0 = No)	0.660	0.480	0.620	0.490	0.710	0.460
Paid less for light brown (1 = Yes, 0 = No)	0.760	0.430	0.670	0.470	0.600	0.490
Amount for light brown (GH₵)	124.310	41.080	134.840	43.680	128.790	52.140
Size						
Interested in size (1 = Yes, 0 = No)	0.730	0.450	0.660	0.480	0.790	0.410
Satisfied with size (1 = Yes, 0 = No)	0.600	1.150	0.450	0.500	0.480	0.500
Rejected small size (1 = Yes, 0 = No)	0.600	0.490	0.540	0.500	0.570	0.500
Paid less for small size (1 = Yes, 0 = No)	0.690	0.460	0.630	0.480	0.580	0.500
Amount for small size (GH₵)	120.088	41.440	133.250	44.680	127.310	49.640
FM						
Interested in FM (1 = Yes, 0 = No)	0.960	0.190	0.960	0.200	1.000	0.000
Satisfied with standard (1 = Yes, 0 = No)	0.850	0.360	0.830	0.400	0.920	0.280
Rejected FM (1 = Yes, 0 = No)	0.860	0.350	0.790	0.410	0.810	0.390
Paid less for FM (1 = Yes, 0 = No)	0.920	0.280	0.800	0.400	0.770	0.420
Amount for FM (GH₵)	122.690	37.940	129.800	38.710	129.310	41.780
Oil content						
Interested in oil content (1 = Yes, 0 = No)	0.650	0.480	0.550	0.500	0.500	0.510
Satisfied with standard (1 = Yes, 0 = No)	0.440	0.500	0.330	0.470	0.330	0.480
Rejected low oil content (1 = Yes, 0 = No)	0.620	0.490	0.480	0.500	0.380	0.490
Paid less for low oil content (1 = Yes, 0 = No)	0.590	0.500	0.550	0.500	0.380	0.490
Amount for low oil content (GH₵)	119.270	43.020	125.280	50.660	122.730	57.190

Note: SD means standard deviation

Size was preferred more by the processors (79%) and aggregators (73%) than by the retailers (66%). Similarly, discounting the price for the inability to meet the desired size attribute (big size) was more evident among aggregators and processors than among retailers. Aggregators paid the lowest price (GH₵120 or US$28) to farmers for supplying soybean grain of a smaller size. However, processors (GH₵127 or US$29) and retailers (GH₵133 or US$31) paid a little above the value paid by the aggregators. FM was the most undesirable soybean attribute among all traders. The results show that more than 90% of the traders preferred soybean without FM. Regarding price discounting for soybean containing FM, the aggregators paid the lowest price (GH₵123 or US$28), while the processors (GH₵129 or US$30) and retailers (GH₵130 or US$30) paid marginally above the price offered by the aggregators.

The results show that both the processors and retailers had the same preference for oil content, while the aggregators recorded the highest preference level (65%). Retailers paid the highest (GH₵125 or US$29) for the inability to satisfy the desired attribute (high oil content), while processors (GH₵123 or US$28) and aggregators (GH₵119 or US$27) discounted the price more than did retailers.

5. Empirical methodology

5.1 Econometric models

The underlying theoretical framework for modelling preference-elicitation studies hinges on two main theories: random utility theory (McFadden 1973) and Lancaster theory of value (Lancaster 1966). Choice modelling based on Lancastarian consumer theory allows the researcher to estimate marginal values for attributes of specific goods or services, including non-market goods and services

(Lusk & Shogren 2007). The random utility framework postulates that an individual chooses among alternatives based on the utility associated with that choice.

Given that traders are also consumers, the study modelled their behaviour in the context of utility maximisation, where the expected profit from trade is maximised by choosing a combination of trade attributes among a set of possible alternatives subject to transaction costs (transportation, negotiation, search and storage). Assuming that the expected utility of trader i choosing a soybean trade alternative j is defined as:

$$EU_{ij} = V\left(X_j, Z_{ij}\right) + \varepsilon_{ij}, \tag{1}$$

where X_j is a vector of soybean attributes associated with alternative j (colour, size, varieties, FM and price); Z_{ij} is a vector interaction between trader-specific characteristics (socioeconomic and trade characteristics) and choice variables; and ε_{ij} is the random error term that is unobserved by the researcher. Following the above expression, a trader i presented with G alternatives contained in set S will choose j if, and only if, the utility of choosing j is greater than the expected utility from any other alternative k (EU_{ik}):

$$EU_{ij} = V\left(X_j, Z_{ij}\right) + \varepsilon_{ij} > EU_{ik} = V(X_k, Z_{ik}) + \varepsilon_{ik} \quad \forall j \neq k; j, k \in S \tag{2}$$

The individual trader choice is considered to be random due to the unobserved error component, thus making the random utility the probability ($P(k)$) of making an alternative decision among a set of alternatives. The probability that a trader chooses option j, given all other alternatives in S, is argued to be the same as the probability that the subjective expected utility of alternative j is greater than that of any other alternative in the choice set.

$$Prob\left(V_{ijt} = 1\right) = Prob\left(X'_{ijt}\beta + \varepsilon_{ijt} > X'_{ikt}\beta + \varepsilon_{ikt}\right) \, for \; all \; k \in S, \forall \; k \neq j \tag{3}$$

$$Prob\left(V_{ijt} = 1\right) = Prob\left(\varepsilon_{ikt} < X'_{ijt}\beta + \varepsilon_{ijt} - X'_{ikt}\beta\right) \, for \; all \; k \in S, \forall \; k \neq j \tag{4}$$

On the assumption that $\varepsilon_{i1t}, \varepsilon_{i2t}, \ldots, \varepsilon_{iGt}$ are an identically and independently distributed (iid) extreme value (Train 2009), the probability of observing alternative j selected over all other alternatives, conditional on the observed levels of the attribute vector for all alternatives in the choice set S, is expressed as:

$$Prob\left(V_{ijt} = 1 | X'_{i1t}, X'_{i2t}, \ldots, X'_{iGt}, \beta\right) = \frac{\exp\left(X'_{ijt}\beta + \eta Q_{ijt}\right)}{\sum_{k=1}^{G} \exp\left(X'_{ikt}\beta + \eta Q_{ikt}\right)}, \tag{5}$$

where Equation (5) represents the conditional logit (CL) model, which is estimated using the maximum likelihood estimation; Q_{ijt} is an alternative specific constant (ASC), which takes a value of one for the status quo (preferred soybean attributes) and zero otherwise, with an associated coefficient η. The CL model assumes that preference structures are homogeneous across traders. This may not necessarily hold true, given that individual characteristics are likely to explain a portion of the preferences traders have toward soybean attributes.

Using Equation (5), the N vector of parameters $\beta = (\beta_1, \beta_2, \ldots., \beta_N)$, representing tastes and preferences over the N attributes, can be interpreted as marginal utilities, and the ratio of any two of such marginal utilities is the marginal rate of substitution of one for the other. Assuming the coefficient on the Nth attribute is price, say β_N (marginal disutility of price), then the willingness to pay for a specific attribute (also called marginal rate of substitution) is estimated as:

$$WTP = -\frac{\beta_n}{\beta_N}, \quad n \in [1, N-1], \tag{6}$$

where β_n is the estimated parameter for the nth attribute. Following the argument of Ward *et al.* (2014), the negative sign implies that the marginal utility of income is the negative of the marginal disutility of cost, which ensures that the marginal utility for desirable (undesirable) attributes is positive (negative).

The study assumes that soybean traders are heterogeneous and their preferences for trade attributes may also be heterogeneous. A more frequent way of evaluating preference heterogeneity is the estimation of a random parameters logit (RPL) model that allows random taste variation within a sample based on a specified distribution (McFadden & Train, 2000). To allow for preference heterogeneity across traders, individual-specific characteristics, Z, were interacted with alternative-specific attribute levels X. Based on Train (2009), the unconditional choice probability that individual i chooses alternative j within the choice set S in situation t is given by:

$$Prob\left(V_{ijt} = 1 | X'_{i1t}, X'_{i2t}, \dots, X'_{iGt}, \Theta\right) = \int \frac{\exp\left(X'_{ijt}\beta_i + \eta Q_{ijt} + \lambda Z_i X_j\right)}{\sum_{g=1}^{G} \exp\left(X'_{igt}\beta_i + \eta Q_{igt} + \lambda Z_i X_g\right)} f(\beta|\Theta) d\beta, \tag{7}$$

where vector Θ refers collectively to the parameters characterising the distribution of the random parameters (e.g. mean and covariance of β), which the researcher can specify. This allows the researcher to estimate a distribution of preference parameters for each individual.

A normal distribution is specified for each of the attributes, since it is more flexible and allows for both negative and positive coefficients for a given attribute. Secondly, it is difficult to decide on the signs on each of the trade attributes under consideration. The study implements parameterisation of the coefficient on price (Carson & Czajkowski 2013), which is accomplished by specifying the coefficient on the negative of price as log-normally distributed with zero variance. However, all the coefficients corresponding to the constant and all other attributes vary normally. The RPL was estimated using simulated maximum likelihood with 1 000[4] Halton draws. Following Hole (2007), the confidence intervals for each of the attribute WTP was estimated using the delta method.

To complement the RPL estimation and gain a deeper understanding of preference heterogeneity across traders, the study employed the latent class logit (LCL) model. Preferences for trade attributes may differ significantly among the traders, given that the sample consists of three types of traders, and their individual characteristics are likely to influence preferences for certain characteristics of soybean traits. According to Swait (1994), the LCL framework assumes that individuals are members of a group with unique preferences, independent of the choice problem being examined. Assuming H classes in the population, and individual i belonging to class $h (h = 1, \dots, H)$, the indirect utility function can be expressed as:

$$U_{ji|h} = X'_{ji}\beta_h + \varepsilon_{ji|h}, \tag{8}$$

where β_h is the vector of preferences parameters for class h, X'_{ji} is a vector of individual alternative specific characteristics, and $\varepsilon_{ji|h}$ is the random portion of utility for individual i of class h. Socioeconomic, location and trade characteristics determine the selection of respondents into a specific class. The probability of individual i selecting alternative j depends partially on the respondent's specific class within the population. Preference parameters varying by class are as follows:

[4] This is based on the recommendation by Bhat (2001).

$$P_{i|h}(j) = \frac{\exp(X_j'\beta_h)}{\sum_{i=1}^{J} \exp(X_s'\beta_h)} \tag{9}$$

Following Holmes and Adamowicz (2003), the logit model identifies the class membership as follows:

$$P_{ih} = \frac{\exp(Z_j'\gamma_h)}{\sum_{h=1}^{h} \exp(Z_j'\gamma_h)}, \tag{10}$$

where γ is a vector of parameters and Z is as defined previously. The Bayesian information criterion (BIC) and Akaike information criterion (AIC) inform the choice of classes (Swait 1994). Equations (9) and (10) are combined to obtain the joint probability of individual i belonging to class h and selecting alternative j as:

$$P_i(j) = \sum_{h=1}^{H}[P_{i|h}(j)P_{ih}] = \sum_{h=1}^{H}\left(\frac{\exp(R_j'\gamma_h)}{\sum_{h=1}^{h}\exp(R_j'\gamma_h)}\right)\prod_{s=1}^{S}\left(\frac{\exp(X_{jis}'\beta_h)}{\sum_{i=1}^{J}\exp(X_{jis}'\beta_h)}\right) \tag{11}$$

The basic model specification (CL model) indicated that none of the attributes deviated from the *a priori* expectation. This indicates an absence of attribute non-attendance (ANA) in the choice of soybean attributes by the traders. Within the framework of LCL, the average marginal willingness to pay (MWTP) for one unit of improvement in any of the attributes is estimated as follows:

$$MWTP = -\left(\frac{\beta_{\widehat{attribute}} + \sum_{d=1}^{D}\lambda_{id}W_d}{\beta_{\widehat{cost}} + \sum_{d=1}^{D}\theta_{id}W_d}\right), \tag{12}$$

where W represents the fraction of the study area population that falls into each of the d socioeconomic, location and trade characteristics, and all other parameters previously defined hold. Equation (12) shows the adjusted average MWTP that corrects for the potential differences in survey respondents not being representative of the demographic characteristics of the study area in general (Han *et al*. 2008). We finally computed the MWTP for each class 1 through H, using the coefficient from equation (12), as:

$$MWTP = -\left(\frac{\beta_{\widehat{attribute}}}{\beta_{\widehat{cost}}}\right) \tag{13}$$

6. Results and discussion

6.1. Random parameter logit results

Table 5 presents the random parameter logit results. Columns (1) and (2) show the RPL estimates without and with correlations between attributes respectively. The traders associate high disutility for soybean with FM. The significant and positive ASC suggests that the respondents, relative to the other choices (options 1 and 2), prefer the status quo (quality soybean). This indicates that most of the traders gain more utility from buying the ‘Jenguma’ soybean variety (high oil content) with a deep brown colour, bigger size and no FM.

Table 5: Random parameter logit (RPL) results

Variables	**RPL – No correlation Coefficient (Std. error)**	RPL – Correlation Coefficient (Std. error)
ASC	**11.429*** (0.819)**	12.203*** (1.102)
$\ln\beta(-\text{Price})$	**-2.862*** (0.066)**	-2.786*** (0.085)
Colour (1 = light brown and 0 = deep brown)	**-0.673*** (0.161)**	-0.541** (0.253)
Size (1 = small and 0 = big)	**-0.536*** (0.161)**	-0.572*** (0.212)
Variety 2 (1 = 'Salintua I' and 0 = 'Jenguma')	**-0.009 (0.169)**	-0.044 (0.204)
Variety 3 (1 = 'Salintua II' and 0 = 'Jenguma')	**-0.723*** (0.212)**	-0.685*** (0.264)
FM (1 = stone and 0 = stone free)	**-2.933*** (0.271)**	-3.176*** (0.355)
Non-random parameters		
Residence of trader (1 = Northern)	**0.845*** (0.233)**	0.954*** (0.269)
Gender of trader (1 = Male)	**-0.643 (0.438)**	-0.596 (0.475)
Years of formal education (years)	**-0.063* (0.036)**	-0.065* (0.039)
Itinerant traders supply soybean (1 = Yes)	**0.447** (0.215)**	0.420 (0.259)
Standard deviations		
ASC	**0.744*** (0.162)**	1.442 (2.153)
Colour (1 = light brown and 0 = deep brown)	**0.387 (0.382)**	1.025 (2.950)
Size (1 = small and 0 = big)	**0.923*** (0.271)**	1.438 (3.578)
Variety 2 (1 = 'Salintua I' and 0 = 'Jenguma')	**0.412 (0.507)**	0.887 (1.467)
Variety 3 (1 = 'Salintua II' and 0 = 'Jenguma')	**1.214*** (0.297)**	1.446 (4.138)
FM (1 = stone and 0 = stone free)	**1.771*** (0.337)**	2.051 (2.295)
Number of observations	**1 368**	1 368
AIC (BIC)	**2 001 (2 090)**	1 998 (2 197)
Log likelihood	**-983.6**	-961.1

Notes: Random parameters logit model estimated using NLOGIT 5.0 based on 1 000 draws for simulated maximum likelihood. The coefficient on the interaction term is not reported. The log normal distribution is imposed on the price variable, but the standard deviation is restricted to zero. *** $\rho < 0.01$; ** $\rho < 0.05$; * $\rho < 0.1$

The log-likelihood (LL) and AIC values reported in Table 5 justify the use of RPL to model the traders' preferences for soybean quality. Furthermore, the RPL specification with correlation among attributes (Column 3) is the best option, given that it has relatively lower LL and AIC. However, the results of the RPL (Column 2), which do not allow for correlation among attributes, have reasonably lower standard deviations of the attributes relative to the RPL results with correlation among attributes. Following the advice of Revelt and Train (1998) on the choice of 'best' model, the study utilised the RPL results without correlation for discussion purposes. The choice is justified given that the choice experiment was designed to allow for minimum correlation between the attributes.[5]

[5] The results show that five out of the 15 attribute interaction terms were significant. The results are not reported in the interest of brevity, but are available upon request.

The significance of the standard deviations of the attributes in the RPL result (Column 2) suggests preference heterogeneity in the traders' choice of size, variety (oil content) and FM. The significance of the standard deviation of the ASC shows a violation of the independence of irrelevant alternatives (IIA) assumption, therefore the use of RPL is appropriate in relaxing this assumption. The coefficient and sign on the colour attribute indicate that traders prefer a deep brown soybean. Similarly, the sign on the size and attributes of variety 3 shows that traders prefer a large grain size and dislike the 'Salintua II' variety (very low oil content). Comparatively, the magnitude of the coefficient on FM attributes is higher relative to all the other attributes. The sign indicates that traders dislike soybean containing foreign materials.

The socioeconomic, region-specific and trade control variables were included in the RPL model to account for a portion of the variation in the preference heterogeneity among traders. Traders in the Northern region of Ghana are more likely to compromise on the quality of soybean purchased relative to traders in the Upper East and West regions of Ghana. This is consistent with the information generated from the trader survey, where traders in the Northern region explained that they valued quality soybean but failure on the part of farmers to meet these requirements did not lead to rejection of the entire lot, just a price discount. Highly educated traders are less likely to buy low-quality soybean from farmers. Traders who buy soybean from itinerant traders are more likely to buy low-quality soybean. Aggregating soybean from different sources also is likely to reduce the quality.

Traders associate negative WTP with all the attributes, and by doing so are discounting the prices paid to farmers with increasing levels of the negative attributes, such as small versus large or higher levels of FM (Figure 5). The results show a wide variation in WTP across traders for FM, followed by variety 3 ('Salintua II'/very low oil) and size. Comparatively, traders are willing to pay less for FM relative to variety 3 ('Salintua II'/very low oil) and size. For the size attribute, the distribution of traders willing to pay above and below the mean WTP is almost the same, but differs significantly for FM, in which case most of the traders were willing to pay less above the mean WTP. These findings about foreign matter relative to oil level and grain size are important. They nicely reflect the ordering processors use in terms of what drives their discounting schedules. Of course, it is important to restate that we did not evaluate moisture, which we know is also very important for buyers. The results indicate little variation in the WTP for the colour attribute. In summary, the distribution of traders' WTP for soybean attributes illustrates that traders are willing to discount price for failure to satisfy the base level of preferred soybean attributes.

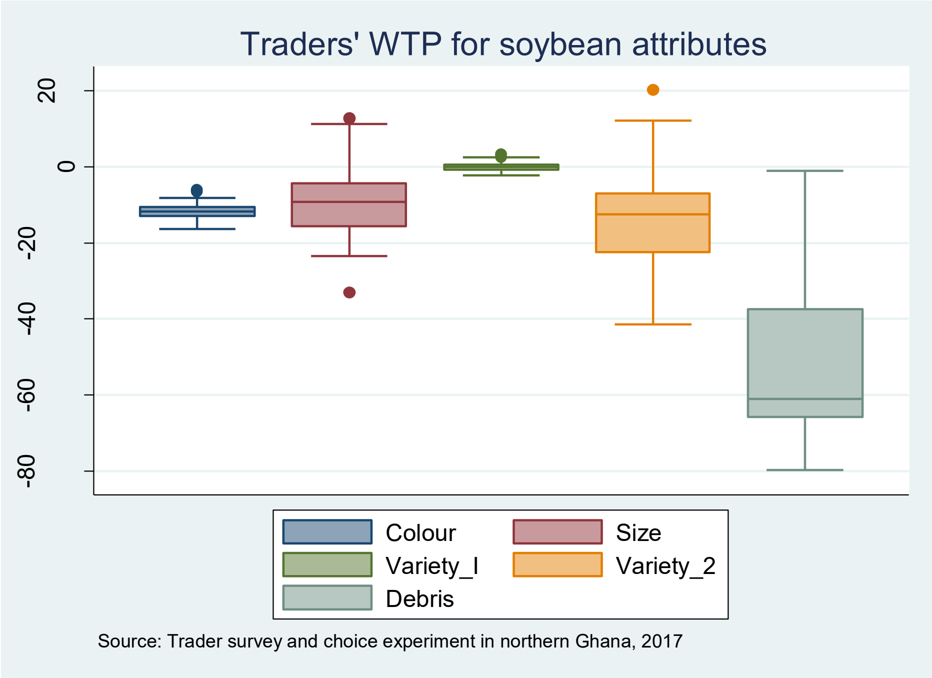


Figure 5: Distribution of WTP for soybean attributes

6.2 Preference heterogeneity by trader type

Table 6 shows that variations exist in the WTP across trader types. The results indicate variation in the valuation of the different soybean trade attributes among the different traders. Generally, traders were willing to discount the price of a bag of soybean for failure to satisfy the preferred attributes. For instance, attributes such as FM, low oil (variety 3 – 'Salintua II'), size and colour are the most valuable attributes for all the traders. The results show that processors value colour, size and oil level more than do aggregators and retailers. However, aggregators recorded the lowest mean WTP for soybean that contains foreign materials. By comparing retailers and aggregators, we find that the former are very interested in the size and oil level relative to the aggregators. Retailers value the colour attribute more than do aggregators.

Table 6: Mean willingness to pay by trader type

	All sample (N = 228)	Aggregators (N = 85)	Retailers (N = 95)	Processors (N = 48)
	Mean WTP	**Mean WTP**	**Mean WTP**	**Mean WTP**
	(95% CI)	**(95% CI)**	**(95% CI)**	**(95% CI)**
Colour	-11.789 (-26.358, 2.925)	-9.824 (-29.039, 9.392)	-15.480 (-23.504, -7.456)	-15.494 (-16.009, -14.978)
Size	-9.297 (-38.586, 20.586)	-5.604 (-25.883, 14.675)	-13.626 (-22.087, -5.166)	-14.088 (-48.334, 20.159)
Variety 2	0.019 (-6.232, 6.774)	2.568 (1.756, 3.380)	-5.636 (-10.514, -0.759)	-3.255 (-17.617, 11.107)
Variety 3	-12.777 (-49.295, 24.300)	-1.527 (-2.340, 32.633)	-4.495 (-6.553, -2.437)	-22.839 (-24.097, -21.582)
FM	-51.725 (-97.698, -3.731)	-66.502 (-122.171, -10.833)	-60.749 (-137.346, 15.847)	-46.829 (-90.751, -2.907)
ASC	200.225 (178.065, 222.385)	194.678 (175.091, 214.264)	74.617 (73.830, 75.405)	214.010 (193.482, 234.539)

Notes: Mean WTP is calculated from the random parameter logit model using NLOGIT 5.0 based on 1 000 draws for simulated maximum likelihood. The exchange rate used is US$1 = GH₵4.36067 (Source: Bank of Ghana 2017). The numbers in parentheses are 95% confidence intervals. Confidence intervals were calculated based on the delta method.

The study investigated the existence of significant heterogeneity in the demand for soybean attributes by plotting the WTP against the percentage of traders. Demand for soybean is generally negative for about 80% of the sample, but variations exist in terms of the magnitude of demand across soybean attributes and trader types (Figure 6). A bag of soybean that contains foreign particles is the most discounted attribute for traders, and it dominates all other attributes across sample and trader types. This finding is consistent with Kumar and Kalita (2017), who found that foreign matter in the grain is one of the most significant grain quality attributes that (negatively) influence farmers' crop revenue. Comparatively, colour is a highly valued attribute for the processors, and for retailers who engage directly with consumers. Similarly, size is highly valued (upper 18%) by processors relative to aggregators and retailers. This makes sense, as processors directly understand the correlation between soybean grain size and plant operating efficiency when producing meal and oil inside their facilities.

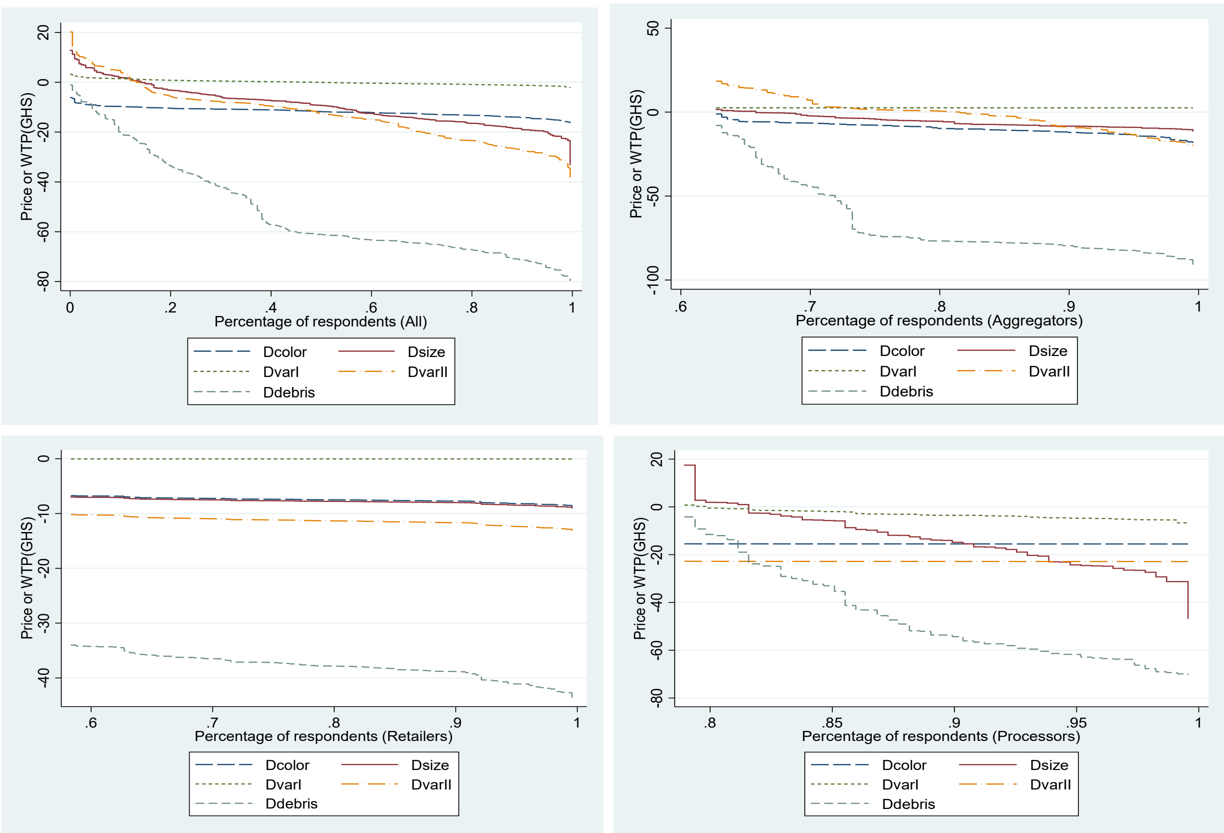


Figure 6: Demand for improved soybean trade attributes

6.3 Latent class model results

Consistent with the hypothesis of preference heterogeneity, the LCL model suggests three (3) classes of traders based on the AIC and BIC results: 'high price discounters', 'big bean supporters', and 'oil sceptics' (Table 7). The same set of covariates used in the RPL model were also included in the LCL model. Determinants of class membership for the other classes are interpreted with respect to Class 3, 'oil sceptics'. All the coefficient estimates of the attributes had the expected sign, with the exception of the coefficients on varieties 2 and 3 (medium and low oil) for Class 2 ('big bean supporters'), and the coefficients on size and variety 2 (medium oil) for Class 3 ('oil sceptics'). Traders in all three classes were willing to pay the highest discounts for a bag of soybean that contains foreign materials (Table 8).

Table 7: Latent class model results

	High price discounters	Big bean supporters	Oil sceptics
Variables	Class 1 Coefficient (Std. error)	Class 2 Coefficient (Std. error)	Class 3 Coefficient (Std. error)
ASC	15.382*** (1.972)	11.314*** (2.441)	7.737*** (1.056)
lnβ(−Price)	0.084*** (0.011)	0.041*** (0.010)	0.040*** (0.005)
Colour (1 = light brown and 0 = deep brown)	-0.293 (0.274)	-1.764*** (0.592)	-0.456** (0.205)
Size (1 = small and 0 = big	-0.198 (0.263)	-2.482*** (0.719)	0.082 (0.268)
Variety 2 (1 = 'Salintua I' and 0 = 'Jenguma'	-0.443 (0.286)	0.052 (0.527)	0.662** (0.275)
Variety 3 (1 = 'Salintua II' and 0 = 'Jenguma')	-0.934*** (0.339)	0.448 (0.756)	-0.684** (0.288)
FM (1 = stone and 0 = stone free)	-3.603*** (0.435)	-4.217*** (1.018)	-0.450* (0.232)
Class membership parameters			
Residence of trader (1 = Northern)	1.672*** (0.363)	0.165 (0.522)	0.759** (0.361)
Gender of trader (1 = Male)	0.063 (0.468)	-0.084 (1.189)	-1.775*** (0.654)
Years of formal education (years)	0.002 (0.044)	0.031 (0.139)	-0.143*** (0.049)
Buy from itinerant traders (1 = Yes)	0.280 (0.960)	-0.987* (0.541)	0.696** (0.347)
Latent class probabilities	0.536*** (0.062)	0.173*** (0.052)	0.291*** (0.0520
Posterior membership	94%		
Log likelihood	-945.513		
AIC	2 003		
Number of observations	1 368		

Notes: Latent class logit model estimated using NLOGIT 5.0 based on 1 000 draws for simulated maximum likelihood. *** ρ < 0:01; ** ρ < 0:05; * ρ < 0:1.

Table 8: Traders' marginal willingness to pay by class

	High price discounters	Big bean supporters	Oil sceptics
Attributes	Class 1 Mean WTP (95% CI)	Class 2 Mean WTP (95% CI)	Class 3 Mean WTP (95% CI)
Colour	-3.488 (-8.324, 1.348)	-43.024 (-53.990, -32.059)	-11.400 (-21.783, -1.017)
Size	-2.353 -8.619, 3.913)	-60.537 (-74.404, -46.669)	2.050 (-11.025, 15.125)
Variety 2	-5.273 (-11.721, 1.175)	1.268 (-11.888, 14.425)	16.550 (3.196, 29.904)
Variety 3	-11.119 (-17.616, -4.622)	10.927 (-3.287, 25.140)	-17.100 (-30.484, -3.716)
FM	-42.893 (-48.258, -37.528)	-102.854 (-112.939, -92.769)	-11.250 (-22.517, 0.017)

Notes: Mean WTP is calculated from the random parameter logit model using NLOGIT 5.0 based on 1 000 draws for simulated maximum likelihood. Confidence intervals are calculated based on the delta method. Exchange rate is US$1 = GH₵4.361 (Source: Bank of Ghana 2017).

6.3.1 Class 1, the 'high price discounters'

This class constitutes the largest share, with 54% of decision makers. Members of Class 1 were labelled as 'high price discounters' on the basis of the price coefficient. All the traders in Class 1 recorded the highest discounted price for foreign matter and low oil levels. 'High price discounters' paid GH₵11 (US$0.03) or 6% less and GH₵43 (US$0.09) or 22% less to buy 'Salintua II', the variety with the lowest oil, and soybean with foreign material respectively.

Traders in the Northern region of Ghana were more likely to belong to Classes 1 ('high price discounters') and 3 ('medium oil supporters'). 'High price discounters' have a strong preference for the entire set of soybean quality attributes (positive and significant ASC). However, they are indifferent with respect to colour and size. This class of decision makers also has a higher preference for high oil levels, namely the 'Jenguma' variety.

6.3.2 Class 2, 'big bean supporters'

Members of Class 2 are the smallest group, constituting 17% of the decision makers. They are indifferent about soybean oil levels, but discount the most for grain size among the three classes, hence the name 'big bean supporters'. Class 2 buyers are less likely to buy from itinerant traders. 'Big bean supporters' offer a statistically significant higher price discount for a supplier's inability to meet the desired size (big) and colour (deep brown) attributes relative to the other two classes.

6.3.2 Class 3, 'oil sceptics'

Traders in Class 3 represent the second largest group, with 29% of the traders. They are characterised as having mixed preferences regarding soybean – for both medium oil over high oil, but also high oil over low oil. This suggests they are sceptical or uncertain about the importance of oil content, hence the name. Whereas Class 2 members have a high preference for size attributes, Class 3 differs significantly, as the coefficient differs and is not significant. They recorded the highest price discount (GH₵17) for buying variety 3 than any other class.

In sum, the study supports both proposed hypotheses: 1) that significant discounting as to quality takes place, even though discount schedules are not explicit or formalised; and 2) that significant differences exist across types of buyers. Traders pay attention to attributes such as FM, colour and size, as revealed by their willingness to discount the price offered to customers for supplying soybean that does not meet the preferred standards. For example, traders discount the price of a bag of soybean by GH₵44 (US$0.10) or 22%, GH₵13 (US$0.03) or 7%, and GH₵11 (US$0.02) or 6% for an inability of the soybean offered to meet the required minimum allowable levels of foreign matter FM, colour quality, and size respectively (Table 9). Farmers and other organisations that supply soybean to these traders lose significant revenue when delivering a product that is unable to meet the traders' standards. Sources of product inferiority range from poor agronomic practices (weed management and timely harvesting) to poor postharvest practices (threshing, winnowing, transportation and storage). However, traders are willing to pay GH₵202 or US$445 per metric ton (full price) for a bag of high-oil 'Jenguma' soybean that has a large grain size, a deep brown colour and is free from foreign materials.

Table 9: Traders' marginal willingness to pay

	Latent class logit model
	Mean WTP (95% CI)
Colour	-12.630 (-20.141, -5.120)
Size	-11.138 (-20.700, -1.575)
Variety 2	2.209 (-7.409, 11.827)
Variety 3	-9.046 (-18.882, 0.791)
Debris	-44.058 (-51.957, -36.159)

Notes: Mean WTP is calculated from the random parameter logit model using NLOGIT 5.0 based on 1 000 draws for simulated maximum likelihood. Confidence intervals are calculated based on the delta method. Exchange rate is US$1 = GH₵4.361 (Source: Bank of Ghana 2017).

7. Conclusions

The results of the study show both specificity in quality discounting by traders and evidence of heterogeneity in traders' preferences for grain quality. For suppliers, this means that real revenue losses occur when delivering poor quality. However, buy-side preferences are not transparent and consistent across purchasers. The lack of objectivity and consistency with respect to quality standards, and the resulting information asymmetry, create market inefficiencies, as pricing signals are obtuse.

The results of the LCL model reveal three (3) classes of traders, namely 'high price discounters', 'big bean supporters' and 'oil sceptics', based on heterogeneity tied to the socioeconomic and trade characteristics of the traders. High price discounters report the highest coefficient on the price discount variable, while big bean supporters record the largest coefficient on the size attribute. Oil sceptics were unclear on their valuation of oil as a trade attribute.

Five main conclusions arise from the results. First, soybean traders clearly discount for poor quality. Second, they are clear about what attributes are important, viz. colour, size, oil level and foreign matter. We cannot say traders do not discount for other attributes as well, such as moisture, lot size, hilum colour, etc., as we only tested four attributes. Third, discounts are significant, as much as 22%. Fourth, foreign matter presents the greatest concern for traders. Fifth, traders, depending if they are an aggregator, retailer or processor, vary significantly in their discounts.

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