Willingness to pay for postharvest technologies and its influencing factors among smallholder mango farmers in Kenya

by Esther Mujuka, John Mburu, Ackello Ogutu, and Jane Ambuko

Willingness to pay for postharvest technologies and its influencing factors among smallholder mango farmers in Kenya

Esther Mujuka [1, *], John Mburu[1], Ackello Ogutu[1] and Jane Ambuko[2]

[1]Department of Agricultural Economics, University of Nairobi, P.O Box 29053, Nairobi, Kenya;

[2]Department of Plant Science and Crop Protection, University of Nairobi, Kenya.

Corresponding author: Department of Agricultural Economics, University of Nairobi, P.O Box 29053, Nairobi, Kenya: Tel: +254 725 639 180: *Email address:* *esthermujuka@gmail.com*

Willingness to pay for postharvest technologies and its influencing factors among smallholder mango farmers in Kenya

Abstract

Achieving global food security for the nearly 10 billion people by 2050 remains a key policy challenge. There is need to reduce postharvest losses, estimated at 30% globally and higher in fruits in Kenya. Reduction of these losses require adoption of acceptable postharvest technologies. Thus, this study sought to assess the acceptability of brick coolers, charcoal coolers and solar driers among smallholder mango farmers in Kenya. Multistage sampling technique was used to select 320 respondents in Embu and Machakos Counties. A double hurdle model was used to estimate WTP for these technologies and the conditioning factors. The farmers' probability to pay was positively influenced by marital status, initial bid, agricultural group membership, market access and income from mangoes. Gender negatively and positively influenced the probability to pay in Embu and Machakos, respectively. Further, the initial bid, agricultural group membership and income from mangoes positively influenced the WTP amount. Experience, credit access, market access, land tenure and age negatively influenced WTP amount. Results revealed that the WTP for the postharvest technologies were lower than the market prices. Thus, the government should spur demand through short term price subsidies.

Keywords: WTP, postharvest loss, postharvest technology, double hurdle, Kenya.

1. Introduction

A key global policy challenge is ensuring food security for the nearly 10 billion people by the year 2050 (FAO, 2020). Agricultural research has historically focused on increasing productivity with little emphasis on minimization of post-harvest losses. Globally, annual postharvest losses are estimated at US$ 1 trillion (FA0, 2015). This is the case despite the high incidences of food insecurity that are expected to rise with population growth. Postharvest losses are higher in horticulture due to their perishability. In developing countries and at the micro level, both quantitative and qualitative postharvest losses occur during harvesting, storage, processing, packaging, transportation and marketing (Kader, 2009; Hodges et al., 2011). Lack of postharvest technologies and poor infrastructure lead to quantitative and qualitative postharvest losses at all stages of fruit and vegetable supply chains in Kenya (FAO, 2014).

Most of the world's population growth is expected from sub-Saharan Africa (SSA) where about 200 million people are food insecure. In Kenya, fruits are valued at about KES 60.7 billion (USD 0.6 billion) and domestically this accounts for about 26 percent of the value of horticultural produce (HCD, 2017). The horticultural sector is considered befitting to smallholder farmers since the required land and labor are low (Andrea, 2012). According to FAO (2017), the prevalence of undernourishment over the period 2014-2016 was approximately 20% of the total population in Kenya. With respect to production and acreage, the mango (Mangifera indica, Linn) is an important fruit in Kenya as it is the second largest after the banana (HCD, 2017). Mango is rich in thiamine, niacin, calcium, iron and the protein content in it surpasses that in all other fruits except avocado (Griesburg, 2003).

Mango prices vary based on varieties. However, mangoes are sold at an average farm gate price of KES 25 (USD 0.25) per kg (Musyoka et al., 2020). At low farm gate prices, middlemen maximize their profits by higher margins. This relegates mango farmers to mere price takers due to their lack of capacity to store and process their mangoes for extended shelf life and higher margins. The domestic market for fresh fruit currently constitutes the biggest market for mangoes accounting for 99% (695,888 MT) of the total mango production, while the export market accounts for a meagre 1% that is valued at approximately KES 1.4 billion (USD 14 million) per year (HCD, 2017).

Investment in postharvest loss reduction technologies is a cost effective pathway (Kitinoja, 2013) for ensuring food and nutritional security. A study on the potential economic impact of investment in postharvest technologies among mango farmers in Embu County in Kenya, found that the investment was worthwhile (Mujuka et al., 2019). The NPV, IRR and BCR were estimated at US $ 1.3 billion., 28% and 4.29, respectively. Further, postharvest technologies eliminate wastage of scarce resources in the production of food that would otherwise be lost (GIZ, 2013). According to the FAO and the World Bank, the postharvest sector requires about half of the USD 940 billion required for hunger eradication in SSA. The resolute efforts to halve the postharvest losses have also been demonstrated by the United Nation's Sustainable Development Goal (SDG 12.3) and the African Union Agenda 2063. Simple and effective evaporative cooling technologies (Shitanda et al., 2011) such as zero-energy brick coolers and charcoal coolers can thus be used to minimize postharvest losses thereby improving farm incomes. Solar driers reduce postharvest losses through drying of fruits and vegetables into more shelf stable products such as mango leather and mango crisps which fetch higher prices (Steve,2010).

Charcoal coolers and zero energy brick coolers are off-grid evaporative cooling technologies which are appropriate for smallholder farmers without access to electricity (Ambuko et al. 2017). Further, they are constructed from locally available materials making them accessible to resource-poor smallholder farmers. Evaporative cooling is appropriate for minimization of postharvest losses in horticulture at collection points and at the retail level. Solar driers rely on direct sun radiation and work based on the resulting greenhouse effect. They have three main components which are; a drying chamber for drying food, a solar collector that heats the air, and an airflow system. Solar driers can dry horticultural produce increasing shelf life by up to one year. Globally, these technologies are not new but their adoption is limited in Kenya. A number of initiatives such as the University of Nairobi's postharvest project seek to create awareness and provide these technologies to smallholder farmers in Embu and Machakos Counties. However, their acceptability as well as farmers' adoption capacity are not known. Therefore, this study sought to estimate the value of the mean willingness to pay (WTP) and the influencing factors in order to demonstrate the acceptability of the postharvest loss reduction technologies, and guide pricing decisions and product development.

2. Approaches in estimation of WTP

The two general approaches used to estimate WTP are the indirect and direct measurements. The indirect approach examines real-world decisions that occurred previously and involve trade-offs between money and expected outcomes while the direct measurement of WTP involves survey methods to elicit stated monetary values for non-market goods and services (O'Brien and Viramontes, 1994). The indirect approach employs data collected on observed behavior while the direct approach involves interviewing individuals to establish the value one is willing to pay for a hypothetical market good (Whittington et al., 1990). In economics, the direct approach is contingent valuation (CV). This method is termed as "contingent" because it involves provision of a hypothetical good or service by the researcher (Arrow et al., 1993) with the purpose of eliciting individual's WTP. It has utility for use in this study since it is based on stated preference for nonmarket goods and services.

2.1 Contingent Valuation Method (CVM)

Contingent valuation method is a value elicitation approach that is survey-based and involves systematically interviewing respondents in order to estimate their WTP for either a proposed policy or program for development interventions (Kwak, 2013). Goods being tested are evaluated by receptors on relevance that will increase effectiveness and value (Mwaura et al., 2010). This often consists of presenting the individual under survey with one or several prices that she can either accept to pay or not, thus leading to interval data on WTP (Fernandez et al., 2004). The CV method of measuring WTP was employed in the current study. This is because this study involves a hypothetical market transaction for which there is need to elicit individual's WTP. The advantages of CVM over indirect methods are twofold. First, it allows both use and non-use values while apart from involving weak complementarity assumptions, the indirect methods only cover use value. Secondly, CVM addresses WTP question through theoretically sound monetary measures of utility change unlike the indirect methods (Perman et al., 2003).

The estimation of WTP depends on how the information on WTP is elicited (Umberger et al., 2009). There are different elicitation methods undertaken in a CVM study, including open ended format through which the respondent provides a point estimate of their WTP; Dichotomous or Discrete Choice CVM through which stylized questions are asked to respondents who simply answer with a yes or no; payment cards through which respondents choose a WTP point estimate (or a range of estimates) from a list of predetermined values by the researcher and displayed on a card and lastly bidding games that to start with, involve asking respondents whether they would accept an initial bid price for the good. For the latter, the initial bid price is increased or decreased depending on the responses, with bidding process stopping at the point of convergence which is a point estimate of WTP (Haab and McConnell, 2002).

Bidding game ensures respondents carefully consider their options before stating the amount they are willing to pay (Willis, 2002). However, it is susceptible to 'Yea saying', which is a type of bias that occurs when a respondent replies 'yes' to the WTP question whether or not they are actually WTP (Ready et al., 1997). This would amount to inflated mean WTP estimates (Ternent and Tsuchiya, 2013). Starting point bias among individuals without definite preferences for the good or service and consequently no definite idea of their maximum WTP, may consider the initial bid as suggestive of the true value of the respective good or service (Whitehead, 2002).

According to Boyle et al. (1988) between iterative bidding, payment cards and dichotomous cards (DC) none is a superior value elicitation method. Consequently, the current study used iterative bidding games. Further, there is evidence that they capture the upper limit of the price that respondents are WTP (Wattage, 2002) thus measure the complete consumer surplus (Cummings et al. 1986). The monotonous small regular increment of the amounts offers the respondent leeway to turn down the bid amount contrary to a double-bound DC format where the bids are doubled or halved (Venkatachalam, 2004). To get realistic WTP estimates, the proposed technologies were clearly described to the respondent (Bateman et al., 2002).

3 Theoretical Framework

The random utility theory or model (RUM) underpins the concept of WTP. The total amount of money that people are willing to give up (WTP) (Arrow et al., 1993) for postharvest storage technologies subject to the expected utility can be used to derive compensated market demand for these interventions in order to detect the point on the demand curve that maximizes profit that often is not essentially the mean value. The consumer will not be WTP if the utility he/she expects to realize is lower than the money foregone and hence will not express interest in a commodity/service and vice versa (Herriges et al., 2004). The maximum WTP is considered as an expression of an individual's values about a good or service (Herriges et al., 2004).

Assuming that the utility derived from postharvest technologies is given as Uiq, A mango farmer will decide on whether or not to pay for postharvest technologies depending on the relative utility levels associated with the two choices. The probability that postharvest technology will be chosen is given by

$$P(y_i = q) = P\left(U_{iq} \geq U_{ir} \,/\, X, \emptyset\, r = q\right) = P(\mathcal{E}_{iq}\text{-}\mathcal{E}_{ir}) \leq X_{iq}{}'\beta_q - X_{iq}{}'\beta_r \,/\, X, \emptyset\, r \neq q \quad (1)$$

Where y_i is the observed outcome for the i^{th} observation. i=1 ….. N indexes the mango farmer, q=1 and r =1….r are the alternatives under consideration and $\mathcal{E}$ are the random errors. The difference in the utilities, Vi of adoption and non-adoption are unobserved,

$$Vi = Uiq - Uir \quad (2)$$

The household decision is taken as a binary outcome such that

$$q_i \in q = \{1\, if\, V > 0, 0\, if\, V \leq 0\} \quad (3)$$

Since utility is unobservable, choices are based on preferences and what is not chosen is influenced by random factors (McFadden, 1974). Producers' WTP for non market goods has been demonstrated to be significantly lower than current technology prices (Hudson and Hite, 2003; Atreya, 2007). Extensive economic literature highlight factors that influence WTP, some of which will be used in this study.

4. Empirical model

The first hurdle relating to the WTP for postharvest technologies was modelled as a probit regression as follows:

$$w* = v_i'\alpha + \varepsilon_i$$

$$w_i = 1 \text{ if } w_1{}^* > 0 \text{ and } w_i = 0, \text{ if } w_1{}^* \leq 0$$

$w*$ is a latent variable representing WTP for postharvest technologies which assumes a value of 1 and 0 otherwise, v is a vector of non-linear variables that explain the WTP decision. α represents a vector of parameters and $\varepsilon_i$is the error term assumed to be independent with a normal distribution and constant variance.

The second hurdle which relates to the WTP amount is a truncated regression (at zero) and which is expressed as:

$$w_{amt} = m_i'\beta + \mu_i$$

$$w_{amti} = w_{amt} * if\ w_{amt} *> 0\ and\ w_{amt} * = 0\ if\ otherwise$$

w_{amt} is the observed WTP amount for postharvest technologies, m is a vector of variables explaining the WTP amount, β is a vector of parameters and $\mu_i$is the randomly distributed error term.

5. Materials and Methods

5.1 Study Area

This study was carried out at Karurumo and Masii Locations of Embu and Machakos Counties, respectively. These two Counties contribute about 23% of the total mango production in Kenya (HCD, 2017). Mango production is the mainstay for farmers in the County. Embu County lies between latitude 0°8′ - 0°50′ South and longitude 37°3′ - 37°9′ East. The agro ecological zones in Embu County range from high altitude (LH1) to upper midland zone (UM4). The temperatures at the County range from 12°C in July to 30°C in March with a mean average of 21°C. The area has bimodial rainfall. The October-December short rains provide between 1,200 - 1,850 mm while the March - June long rains provide between 850 and 1,850 mm of annual rainfall. Other major crops grown in the County are tea, cassava, coffee, dairy, millet, and horticultural crops. Machakos lies between latitudes 0º45'- 1º31' South and longitudes 36°45' - 37°45' East. The county has an altitude of 1000 - 1600 meters above sea level. It has semi-arid areas (Mua, Iveti and parts of Mwala) receiving rainfall of 250- 650 mm per annum and arid areas (Yatta and parts of Mwala) receiving rainfall of 150- 250 mm per annum with high temperatures. It borders Nairobi and Kiambu counties to the West, Embu to the North, Kitui to the East and Makueni to the South. Fruits, vegetables, maize and drought-resistant crops such as sorghum and millet do well in the County.

5.2 Sampling procedure and data collection

A multi-stage sampling procedure was employed in the selection of 320 farmers following Cochran (1963). Systematic random sampling technique was used to select farmers in Karurumo and Masii Locations of Machakos and Embu Counties, respectively. These Counties were purposively selected as a follow up of the yield wise project which had earlier been implemented for proper agronomic practices in a bid to reduce preharvest losses. Primary data was collected between June - July 2018 from face-to-face interviews using a semi-structured questionnaire. Data collected included socio-economic characteristics of the farmers and their WTP for brick cooler, charcoal cooler and solar drier.

Structured questionnaires with open and closed ended questions were administered to the farmers to gather primary data. Protest answers were judged by first asking the respondents whether they would be willing to pay for each of the postharvest technologies and if no, the reasons why they were not willing to pay any amount were captured. To elicit WTP, the respondents were asked whether they would be WTP each of a series of amounts that ascended or descended from a specified starting point (initial bid). The iterative process eventually arrived at the respondent's maximum WTP. Respondents were asked the following questions in the case of a charcoal cooler, brick cooler and solar drier respectively. “Would you be willing to pay KES 10,000 (USD 100) to construct $1M^3$ of charcoal cooler with a capacity of 163 mango pieces? Would you be willing to pay KES 20,000 (USD 200) to construct $1M^3$ of brick cooler with a capacity of 150 mango pieces? Would you be willing to pay KES 25,000 (USD 250) for $1M^3$ of tunnel solar drier with a drying capacity of 40 mango pieces? If a farmer response was a YES to the initial bid amount, an increment of USD 200, was offered in the case of charcoal cooler until the maximum amount the farmer would be willing to pay was attained. In the case of brick cooler and solar drier, if a farmer response was a YES to the initial bid amount, an increment of USD 500, was offered until the maximum amount the farmer would be willing to pay was attained. If the farmer response was a NO to the initial bid, equal decrements of USD 200 (charcoal cooler) and USD 500 (brick cooler or solar drier) were used until the amount the respondent would be willing to pay was revealed. This would be the maximum amount the respondent would be willing to pay.

5.3 Methods of data analysis

In modeling determinants of WTP, existence of zero values of WTP suggest that the dependent variable exhibits properties of a corner solution variable (Wooldridge, 2010). This implies that the use of ordinary least squares method would be biased. The Tobit model is based on a very restrictive assumption (Carroll et al., 2006) that the decision on whether or not to pay and how much are made jointly. Thus, similar factors affect the two decisions. However, the decision to pay precedes that on the level of payment and hence the explaining variables at the two levels may differ (Liebe et al. 2010). An alternative to the Tobit model is the Probit - Tobit model whose estimates involve determining the probability of participation (ρ) and non-participation (1- ρ) (Deaton and Irish, 1984). This model seems appropriate but the unique value of the ρ parameter for all individuals limits it.

The Heckman correction method (1979) allows for better estimators by correcting the self-selection bias induced by the corner solution. The Heckman and the double-hurdle are both two-stage models. However, Heckman assumes the absence of zero observations after the first hurdle is passed. In this case, the double-hurdle model is more appropriate (Lera-López et al., 2014). The model accounts for the possibility that zeros are due to non-participation in the market for reasons that may not be economic. The double-hurdle model assumes that determinants of participation and expenditure decisions are allowed to differ and emanate from two different choices. However, biased estimators may be as a result of nonnormality of the data (Box and Cox, 1964). To address this, a Box-Cox variant of the double-hurdle model in which the dependent variable is transformed by a change in variable is used.

The dependent variable was empirically measured by the maximum WTP for the postharvest technologies. The independent variables were selected based on literature. *Experience* measured as a continuous variable was the number of years the respondent had been engaged in mango production; *Gender* was a dummy variable equal to 1 if the respondent is male, 0 otherwise; *Marital status* was a dummy variable equal to 1 if the respondent was married, 0 otherwise; *Initial bid amount* was a dummy variable equal to 1 if the respondent said yes to the initial bid amount, 0 otherwise; *Credit access* was a dummy variable equal to 1 if the household accessed credit within the last one year, 0 otherwise; *Agricultural Group membership* was a dummy variable equal to 1 if the respondent belonged to an agricultural related group, 0 otherwise; *Market access* was a dummy variable equal to 1 if the respondent had access to markets, 0 otherwise; *Tenure* was a dummy variable equal to 1 if the household enjoyed formal land tenure, 0 otherwise; *AGE* measured as a continuous variable was the age of the respondent in years.

6. Results and discussion

6.1 Data description

Summary descriptive statistics show that respondents had experience in mango production as indicated by an average of over 9 years in mango production (Table 1). It was therefore expected that these respondents would make informed decisions in a bid to reduce postharvest losses. Results revealed that mango production is dominated by elderly married men. It was however surprising that their access to credit was consistently low in both Counties. This can be attributed to the informal land tenure system that poses a challenge in securing credit. Access to agricultural extension services and belonging to agricultural group were also consistently low. Consequently, the level of awareness on the postharvest technologies was low. However, the level of market access and income per season were high. Most respondents expressed willingness to pay for charcoal cooler that was more affordable than the zero-energy brick cooler and solar drier.

Table 1: Selected summary statistics of respondents

Variables	Embu County n=160		Machakos County n= 160	
	Mean	**Std. Deviation**	**Mean**	**Std. Deviation**
Experience (Years)	10.92	6.90	9.25	5.74
Gender (% Male)	0.84	0.36	0.82	0.39
Marital Status (% Married)	0.78	0.42	0.79	0.41
Credit access (% Yes)	0.08	0.26	0.03	0.16
Agricultural group membership (% Yes)	0.22	0.42	0.16	0.37
Agricultural extension access (% Yes)	0.43	0.50	0.34	0.47
Market access (% Yes)	0.78	0.42	0.81	0.39
Land tenure (% Formal)	0.77	0.42	0.43	0.50
Age of household head (Years)	58.09	14.71	60.51	13.93
Awareness on postharvest technologies (% Yes)	0.62	0.49	0.45	0.50
WTP for charcoal cooler (% Yes)	0.71	0.45	0.81	0.40
WTP for brick cooler (% Yes)	0.50	0.50	0.61	0.49
WTP for tunnel solar drier (% Yes)	0.48	0.50	0.48	0.50
Income from mangoes per season (USD)	548.67	1084.63	402.53	638.28

Source: survey data, 2018

6.2 Estimation of mean WTP for postharvest technologies

Results show that the mean WTP amount in Embu and Machakos Counties, respectively was on average 35%, 58% and 60% lower than the market price of the charcoal cooler, zero energy brick cooler and tunnel solar drier (Table 2). Producers' WTP has been demonstrated to be significantly lower than market prices (Channa, 2019). This is often the case when there is lack of prior awareness of the proposed technologies as was the case in this study. However, farmers in Machakos County were willing to pay 17% more than farmers in Embu County for the tunnel solar drier. This is attributable to the higher temperatures in Machakos County and market access. This finding is supported by Maalouf and Chalak (2019) who found that farmers with access to wholesale market have a significantly higher willingness to pay for postharvest technologies.

Table 2: Mean WTP for postharvest technologies

Postharvest technologies	Mean WTP (USD)		Market price (USD)
	Embu	Machakos	
Charcoal cooler ($1M^3$)	67.19	62.80	100
Zero energy brick cooler ($1M^3$)	93.67	76.11	200
Tunnel solar drier ($1M^3$)	92.24	108.22	250

Source: Computed from survey data, 2018

6.3 Factors influencing farmers' WTP for postharvest technologies

Since the independent variables of the probit model are non-linear, the coefficients are not directly interpreted. Marginal effects are therefore reported at the means for individual independent variable (Table 3). The farmers' probability to pay for the postharvest technologies was significantly and positively influenced by marital status, initial bid, agricultural group membership, market access and income from mangoes. Marital status positively influenced

WTP for charcoal cooler at five percent in Embu. Married people driven by their social responsibility would likely be more responsive to innovations to increase their productivity so as to be able to cater for the family (Elemasho et al., 2017). This finding is also recorded by Vilane et al. (2012) who found that adoption of a postharvest technology was mainly by married people. Gender significantly influenced probability to pay for postharvest technologies negatively and positively in Embu and Machakos, respectively. This result corroborates with the findings of Mukarumbwa et al. (2017) that while gender was found to positively influence the number of postharvest practices adopted, marginal effect results suggested that female heads of households would adopt an extra unit of postharvest practices. It is possible that gender roles could come to play as the technologies involve cleaning and grading of fruits before arranging them in crates.

Table 3: Factors influencing farmers' WTP for postharvest technologies

Independent Variables	Embu County						Machakos County					
	First Hurdle			**Second Hurdle**			**First Hurdle**			**Second Hurdle**		
	Prob. WTP			**WTP Amount**			**Prob. WTP**			**WTP Amount**		
	dy/dx			**Coefficient**			**dy/dx**			**Coefficient**		
	CC	**BC**	**SD**	**CC**	**BC**	**SD**	**CC**	**BC**	**SD**	**CC**	**BC**	**SD**
Experience	0.005	0.01	-0.0027	-263.60*	43.70	-137.97	-0.00016	-	0.0045	-70.38	-87.61	-
Gender	-0.33**	-0.38**	-0.20	-223.35	1704.81	-	0.2271	0.187*	0.2179**	1658.80	1830.87	7828.34
Marital Status	0.28**	0.16	0.13	-919.79	-2130.25	-	-0.2254	-	-	-14.39	-	-
Initial bid	0.23***	0.48***	-	12671.58***	15009.27***	22189.1***	1.0675	-	-	8982.02***	13287.16***	52083.37***
Credit Access	0.10	0.118	0.05	-6241.45**	-1666.74	2278.82	-0.0406	0.35	-	1718.86	-	-
AGM	0.12	0.121	0.17*	5461.25***	1026.47	6056.22**	0.0703	-	0.0552	977.50	-	-
Market access	0.19**	-0.01	0.08	-1461.93	-804.37	-6040.75**	0.1184*	0.19*	0.1516	-900.81	-	-9163.35
Tenure	-0.07	-0.004	-0.056	2987.73	-1100.32	-769.06	-0.0857	-	-0.0382	-1732.35***	-	10375.21
Age	0.002	-0.002	-	-142.10**	-31.88	-109.88	0.000038	0.0033	0.0045	21.54	30.49	-266.71
Mango income (ln)	0.03***	0.03**	0.038***	74.66	-66.58	-135.40	0.0324***	0.0158	0.018	190.78*	-	3437.60*
Constant	-			9342.92	10411.92	7051.18	-	0.771		777.274	2624.59	-35327.69
Number of observations				160	160	160				160	160	160
Log likelihood				-1138.48	-833.45	-867.101				-1206.71	-960.878	-938.98
Wald chi2				32.85	28.08	14.56				22.94	10.37	12.27
Prob > chi2				0.0003	0.0018	0.0684				0.011	0.0654	0.092

*, ** and *** denote statistical significance at 10%, 5% and 1% respectively

CC: Charcoal Cooler, BC: Brick Cooler, SD: Solar Drier

AGM: Agricultural group membership

The WTP amount for postharvest technologies was positively and significantly influenced by the initial bid, agricultural group membership and income from mangoes. However, experience, credit access, market access, land tenure and age significantly influenced WTP amount negatively. These results contradict literature that suggest that household characteristics have no influence on WTP amount for postharvest technologies (Channa, 2019). Initial bid amount positively influenced the WTP amount for the postharvest technologies at one percent in both Counties. This is consistent with the work of Migwi (2016) who found that an increase in the initial bid amount occasioned an increase in the household mean WTP for agricultural technology. Agricultural group membership positively influenced WTP amount for postharvest technologies in Embu only. This conformed to the apriori expectation that organized farmers are empowered and therefore possess higher bargaining power for cost-effective technologies. As expected, income from mango production positively influenced the WTP amount. This is because farmers with higher incomes have higher purchasing power.

Experience of mango farming negatively influenced WTP amount for charcoal cooler in Embu County at 10%. A one year experience is likely to reduce the amount a household is willing to pay by KES 264 (USD 2.64). This result is in line with findings of Maalouf and Chalak (2019) who found that experience significantly influences WTP amount for postharvest technologies negatively. A plausible explanation is that experienced farmers devise mechanisms for reduction of postharvest losses over time. Credit access negatively influenced the amount farmers were willing to pay for charcoal coolers in Embu only. This contradicts a priori expectation and the findings of Owach, (2017) that WTP for improved postharvest structures is influenced positively by credit access. This can be explained by the fact that farmers allocate agricultural credit to non-farm activities with higher rates of return (Alabi et al., 2014).

The WTP amount for solar drier was negatively and significantly influenced by market access in Embu. A possible reason is that the market for the value added products made from the solar driers is not yet fully developed in the research area. Land tenure negatively influenced the WTP amount for charcoal cooler at 1% in Machakos County. This is attributable to the uncertainty resulting from tenure insecurity in the study area. This result is at variance with findings of Bokusheva (2012) that acquisition of a postharvest storage technology is influenced by ownership of land. Age negatively influenced the amount a farmer was willing to pay for charcoal cooler in Embu and was statistically significant at 5%. The result showed that an increase in the age of a farmer by 1 year reduced their WTP amount by KES 142 (USD 1.42). Younger farmers are risk loving and this result is consistent with the findings of Elemasho et al. (2017).

7. Conclusions and policy implications

This study employed a double hurdle model to estimate WTP for postharvest technologies such as zero energy brick coolers, charcoal coolers and solar driers among smallholder farmers in Embu and Machakos Counties of Kenya. These are proven technologies that are common across the world but have limited adoption in Kenya. Marital status, initial bid, agricultural group membership, market access and income from mangoes significantly and positively influenced probability to pay for the postharvest technologies. Probability to pay for postharvest technologies was significantly influenced by gender negatively and positively in Embu and Machakos, respectively. Charcoal coolers that are cheaper than the more efficient zero energy brick coolers and solar driers were found acceptable. Factors that were found to positively and significantly influence the WTP amount for postharvest technologies were initial bid, agricultural group membership and income from mangoes. On the flipside, experience, credit access, market access, land tenure and age significantly influenced the WTP amount negatively. Further, we found low access to agricultural extension services and awareness on the postharvest technologies. The estimated WTP amount for all the postharvest technologies suggested that most of the farmers would prefer the technologies to be offered at lower than the current market prices. Short term price subsidies could spur awareness of these postharvest technologies and their eventual adoption. Credit access was found to negatively influence WTP amount for postharvest technologies. The government and other stakeholders need to invest in measures that would make credit work for value addition in mangoes. Such measures would include discouraging credit diversion to other agricultural activities and peer-peer supervision of credit use and repayment in order to ensure efficient utilization in post harvest loss-reduction technologies. Farmers who operate under informal land tenure systems were not willing to pay for postharvest technologies. The government needs to strengthen tenure security to avert uncertainty.

Declaration of interest

None

Funding

The authors would like to acknowledge and appreciate funding for this research from the Rockefeller Foundation (Grant number: 2016 YWS 328).

References

Alabi, O. O., A. F. Lawal, A. A. Coker, and Y. A. Awoyinka. (2014). Probit model Analysis of Smallholder farmers' decision to use agrochemical inputs in Gwagwalada and Kuje Area Councils of Federal Capital Territory, Abuja, Nigeria. *International Journal of Food and Agricultural Economics*, 2 (1): 85-93.

Andrea, C. (2012). Understanding the marketing chain of mango and grapes in the Sao Francisco valley. Sao Francisco: Universidade.

Atreya, K. (2007). Farmers' willingness to pay for community integrated pest management training in Nepal. *Agriculture and Human Values*, 24, 399–409. https://doi.org/10.1007/s10460-007-9063-3

Arrow, K., R. Solow, P. R. Portney, E. E. Leamer, R. Radner, and H. Schuman. (1993). Report of the NOAA Panel on Contingent Valuation. *Federal Register*, 58 (10): 4601–4614.

ABD. (2011). The Mango Sub-Sector in Kenya. The Results of the Mango Tree Census and Baseline Survey for Eastern Province. Agricultural Business Development Final Report. Nairobi: IDMS.

Bateman, I. J., R. T. Carson, B. Day, M. Hanemann, N. Hanley, T. Hett, and D. W. Pearce. (2002). *Economic Valuation with Stated Preference Techniques: A Manual*. Edward Elgar Publishing Ltd, Cheltenham, UK.

Bokusheva, R., R. Finger, M. Fischler, R. Berlin, Y. Marín, F. Pérez, and F. Paiz. (2012). Factors determining the adoption and impact of a postharvest storage technology. *Food Security*, 4, 279–293. https://doi.org/10.1007/s12571-012-0184-1

Box, G. E. P., and D. R. Cox. (1964). An analysis of transformations. *Journal of the Royal Statistical Society*, 26: 211–252. https://doi.org/10.1111/j.2517-6161.1964.tb00553.x

Boyle, K., P. W. Michael, and R. Bishop. (1988). Validation of empirical measures of welfare change. *Land Economics*, 64 (1): 94-98.

Carroll, J., S. McCarthy, and C. Newman. (2006). An econometric analysis of charitable donation. *The Economic and Social Review*. 36 (3): 229-249.

Channa, H., A. Z. Chen, P. Pina, J. R. Pina, and D. Stein. (2019). What drives smallholder farmers' WTP for a new farm technology? Evidence from an experimental auction in Kenya. *Food Policy*, 85, 64-71. https://doi.org/10.1016/j.foodpol.2019.03.005

Cochran, W. G. (1963). Sampling Techniques (2nd ed.). John Wiley & Sons Inc, New York.

Cummings, R. G., W. D. Schulze, S. D. Gerking, and D. S. Brookshire. (1986). Measuring the elasticity of substitution of wages for municipal infrastructure: A comparison of the survey and wage hedonic approaches. *Journal of Environment and Economic Management*, 13 (3): 269-276. https://doi.org/10.1016/0095-0696(86)90027-6

Deaton, A. S., and M. Irish. (1984). Statistical models for zero expenditures in household budgets. *Journal of Public Economics*, 23: 59-80. https://doi.org/10.1016/0047-2727(84)90067-7

Elemasho, M. K., S. D. Y. Alfred, C. C. Aneke, A. J. C. Chugali, and O. Ajiboye. **(**2017). Factors affecting adoption of post-harvest technologies of selected food crops in Rivers State, Nigeria. *International Journal of Agricultural Economics and Extension*, 5 (5): 295-301.

FAO. (2020). The state of food security and nutrition in the world 2020. Transforming food systems for affordable healthy diets. FAO, Rome. Retrieved 20 June 2020, from http://www.fao.org/3/ca9692en/ca9692en.pdf

FAO. (2017). The state of food security and nutrition in the world. Building resilience for peace and food security. FAO, Rome. Retrieved 15 August 2020, from http://www.fao.org/3/i7695en/i7695en.pdf

FAO. (2015). Global initiative on food loss and waste reduction. FAO, Rome. Retrieved 20 January 2020, from http://www.fao.org/3/a-i4068e.pdf

FAO. (2014). Kenya Food Loss Assessments: Causes and Solutions. Case Studies in Small-scale Agriculture and Fisheries Subsectors. http://www.fao.org/fileadmin/user_upload/savefood/PDF/Kenya_Food_Loss_Studies.pdf

Fernandez, C., C. J. Leon, M. F. J. Steel, and F. J. V. Polo. (2004). Bayesian analysis of interval data contingent valuation models and pricing policies. *Journal of Business and Economic Statistics*, 22 (4): 431-442. https://doi.org/10.1198/073500104000000415

Griesbach, J. (2003). Mango growing in Kenya. ICRAF, Nairobi.

GIZ. (2013). Reducing postharvest losses conserves natural resources and saves money. Report of GFFA expert panel discussion held on 18 January 2013 in Berlin.

Haab, T. C., and K. E. McConnell. (2002). *Valuing Environmental Natural Resources*: *The Econometrics of Non-Market Valuation*. Edward Elgar Publishing, Northampton, MA.

Herriges, J. A, L. Catherine, and J. P. Daniel. (2004). What's the Use? Welfare Estimates from Revealed Preference Models When Weak Complementarity Does Not Hold. *Journal of Environmental Economics and Management*, 47 (1): 55–70. https://doi.org/10.1016/S0095-0696(03)00058-5

Hodges, R. J., J. C. Buzby, and B. Bennett. (2011). Postharvest losses and waste in developed and less developed countries: opportunities to improve resource use. *The Journal of Agricultural Science*, 149 (S1):37-45. https://doi.org/10.1017/S0021859610000936

HCD (Horticultural Crops Directorate). (2017). *Horticulture Validated Report,* Ministry of Agriculture, Kenya. Retrieved 3 July, 2020 from http://kilimodata.developlocal.org/dataset/3534b0b9-e49e-4c72-a90a-e423844a83a2/resource/c7758a80-9102-481e-a6c2-fa983081221d/download/horticulture-validated-data-2016-2017.pdf

Heckman, J. (1979). Sample selection bias as specification error. *Econometrica*, 47 (1): 153-162. https://doi.org/10.2307/1912352

Hudson, D., and D. Hite. (2003). Producer willingness to pay for precision application technology: implications for government and the technology industry. *Canadian Journal of Agricultural Economics*, 51: 39-53. https://doi.org/10.1111/j.1744-7976.2003.tb00163.x

Kader, A. A. (2009). Handling of horticultural perishables in developing vs. developed countries. *VI International Postharvest Symposium,* 877: 121-126. https://doi.org/10.17660/ActaHortic.2010.877.8

Kitinoja, L. (2013). Innovative small-scale postharvest technologies for reducing losses in horticultural crops. *Ethiopian Journal of Applied Science and Technology*, 1: 9-15.

Kwak, S.-Y, S.-H. Yoo, and C.-S. Kim. (2013). Measuring the willingness to pay for tap water quality improvement. Results of a contingent valuation survey in Pusan. *Water*, 5:1638-1652. https://doi.org/10.3390/w5041638

Lera-Lopez, F., J. Faulin, M. Sanchez, and A. Serrano. (2014). Evaluating factors of the willingness to pay to mitigate the environmental effects of freight transportation crossing the Pyrenees. *Transportation Research Procedia*, 3: 423-432. https://doi.org/10.1016/j.trpro.2014.10.023

Liebe, U., P. Preisendörfer, and J. Meyerhoff. (2010). To Pay or Not to Pay: Competing Theories to Explain Individuals' Willingness to Pay for Public Environmental Goods. *Environment and Behavior*, 43(1): 106-130

Maalouf, A., and A. Chalak. (2019). Farmers' willingness to pay for operating a collective postharvest refrigeration unit in an eastern Mediterranean rural community. *Journal of Agriculture, Food Systems, and Community Development*, 9(1): 89–99. https://doi.org/10.5304/jafscd.2019.091.012

McFadden, D. (1974). Conditional Logit Analysis of Qualitative Choice Behaviour. P. E. Zarembka, ed., Frontiers of Econometrics. New York: Academic Press.

Migwi, B. G. (2016). Assessment of farmers' perceptions of and willingness to pay for Aflasafe KE01, a biological control for aflatoxins in Kenya. MSc. thesis, University of Nairobi, Kenya.

Mujuka, E., J. Mburu, A. Ogutu, and J. Ambuko. (2019). Returns to investment in postharvest loss reduction technologies among mango farmers in Embu County, Kenya. *Food and Energy Security*, 9 (1). https://doi.org/10.1002/fes3.195

Mukarumbwa, P., A. Mushunje, A. Taruvinga, B. Akinyemi, and S. Ngarava. (2017). Factors influencing number of postharvest practices adopted by smallholder vegetable farmers in Mashonaland East Province of Zimbabwe. *International Journal of Sustainable Development*, 6 (11): 1774-1790.

Musyoka, J. K., H. N. Isaboke, and S. N. Ndirangu. (2020). Farm-level value addition among small-scale mango farmers in Machakos County, Kenya. *Journal of Agricultural Extension*, 24 (3). https://dx.doi.org/10.4314/jae.v24i3.8

Mwaura, F., F. R. Muwanika, and G. Okoboi. 2010. Willingness to pay for extension services in Uganda among farmers involved in crop and animal husbandry. *A Paper presented at the Joint 3rd African Association of Agricultural Economists (AAAE) and 48th Agricultural Economists Association of South Africa (AEASA) Conference, Cape Town, South Africa, September 19-23, 2010.*

O'Brien, B., and J. L. Viramontes. (1994). Willingness to pay: A valid and reliable measure of health state preference? *Medical Decision Making*, 14: 289-297. https://doi.org/10.1177/0272989X9401400311

Owach, C., G. Bahiigwa, and G. Elepu. (2017). Factors influencing the use of food storage structures by agrarian communities in northern Uganda. *Journal of Agriculture, Food Systems, and Community Development, 7* (2): 127–144. https://doi.org/10.5304/jafscd.2017.072.003

Perman, R., Y. Ma, J. McGilvray, and M. Common. (2003). *Natural Resources and Environmental Economics*. Third Edition. Pearson Education Limited, the Great Britain.

Ready, R. C., J. C. Buzby, D.Y. Hu. (1996). Differences between continuous and discrete contingent value estimates. *Land Economics*, 72 (3): 397-411.

Shitanda, D., O. K. Oluoch, and A. M. Pascal. (2011). Performance evaluation of a medium size charcoal cooler installed in the field for temporary storage of horticultural produce. *Agricultural Engineering International: CIGR Journal*. 13 (1): 1596.

Steve, N. (2010). Market Opportunities for Mango Growers. Kenya Horticultural Development Program 2004-2010. USAID, Kenya.

Ternent, L., and A. Tsuchiya. (2013). A note on the expected biases in conventional iterative health state valuation protocols. *Medical Decision Making*, 33: 544–546.

Umberger, W. J., D. Thilmany, M. C. Fadden, and R. S. Amanda. (2009). Does Altruism Play a Role in Determining US Consumer Preferences and Willingness to Pay for Natural and Regionally Produced Beef? *Agribusiness*, 25 (2): 268–85. https://doi.org/10.1002/agr.20194

Venkatachalam, L. (2004). The contingent valuation method: a review. *Environmental Impact Assessment Review*, 24 (1): 89-124. https://doi.org/10.1016/S0195-9255(03)00138-0

Vilane, B. R. T. (2012). Adoption of postharvest technologies used by small-holder farmers in Swaziland. *African journal of agricultural research*, 7 (35): 4983-4995. https://doi.org/10.5897/AJAR11.106

Wattage, P. (2002). Effective management for biodiversity conservation in Sri Lankan Coastal Wetlands: An estimation of economic value for conservation of wetlands. Darwin Initiative; University of Portsmouth CEMARE.

Whitehead, J. C. (2002). Incentive incompatibility and starting-point bias in iterative valuation questions. *Land Economics*, 78 (2): 285-97.

Whittington, D., J. Briscoe, M. Xinming, and B. William. (1990). Estimating the Willingness to Pay for Water Services in Developing Countries: A Case Study of the Use of Contingent Valuation Surveys in Southern Haiti. *Economic Development and Cultural Change,* 38 (2): 293–311. https://doi.org/10.1086/451794

Willis, K. G. (2002). Iterative bid design in contingent valuation and the estimation of the revenue maximizing price for a cultural good. *Journal of Cultural Economics*, 26: 307-324.

Wooldridge, J. M. 2010. *Econometric analysis of cross section and panel data*. Cambridge, MA: MIT Press.