Are Consumers Willing to Pay for Conservation Agriculture in Low-Income Countries? The Case of White Maize in the Democratic Republic of the Congo

Willy Mulimbi[a], and Lanier Nalley[a*]

[a]Department of Agricultural Economics and Agribusiness, University of Arkansas. 217 Agricultural Building, Fayetteville, Arkansas 72704, USA.

*****Corresponding author: llnalley@uark.edu

Working Paper

Selected paper prepared for presentation at the Southern Agricultural Economics Association (SAEA) 52th Annual Meeting, Louisville, Kentucky, February 1 - 4, 2020

Introduction

Deforestation has proved to be instrumental in exacerbating global climate change (Bala et al., 2007; Fearnside, 2000; Stocker et al., 2013). Annually an area of the size of Austria vanishes globally via deforestation (Seymour and Busch, 2016). The majority of the world has come to a consensus that saving the remaining rainforest is pivotal to help mitigate global warming. Multilateral climate funds are increasingly funding projects that mostly support both climate change adaptation and mitigation, and not specifically deforestation (Watson and Schalatek, 2019). Efforts to stop deforestation still appears to be a reactionary issue and not a proactive one. The international community mobilization to save forests tends to surface only when the public views large fires in the Amazon rainforest (2019), or the Australian outback (2020). Proactively integrating sustainable mechanisms in natural resources management should be the logical way to offset vulnerability and the effects of underdevelopment in favor of millions of people in low-income countries (LICs) who rely on the rainforest for a living and humanity as a whole who rely on the rainforests for climate stability.

In low Income countries such as the Democratic Republic of the Congo (DRC), where people rely on rainforests for their livelihoods; understanding the synergies that were put forth by the United Nations sustainable development goals (SDGs) is crucial considering the trade-offs between climate change, reducing food insecurity, and eliminating poverty, and the ultimate goal of forest conservation (Campbell et al., 2018). The issues of natural resources management, such as deforestation intersect with the global problems of poverty and climate change (Seymour and Busch, 2016). In the DRC, where farmers, who are predominately women, walk long distance away from home to cultivate in the forest (Mulimbi et al., 2019), deforestation is, unfortunately, an action taken by rural communities to overcome food insecurity. Farmers always have a strong motivation when they choose to cut trees of the natural rainforest (Cannon, 2018). The expansion of small-scale forest clearing for agriculture and fuelwood are among the direct drivers of the increasing primary forest losses encountered the last decades in the DRC (Turubanova et al., 2018; Tyukavina et al., 2018). The situation is likely to escalate in the future due to the growing population and demand for food and natural resources. In developing countries, like the DRC, as population grows and as arable land becomes scarcer, more farmers may choose to move to fragile lands such as rainforests (Sunderlin et al., 2005). Based on the United Nations projections (2019), the DRC's current population will double by 2050 due to a 3.2% yearly population growth rate. The country will be ranked 10th globally in terms of population size (Bongaarts, 2009). Unfortunately, food insecurity is still unsolved with the DRC Ministry of Agriculture (2018) reporting a 22% national deficit in food supply in 2018. Currently, there are no incentives; in fact there are disincentives, for small scale producers in the DRC to stop the practice of slash-and-burn agriculture, a major driver of deforestation. According to the Ministry of Environment (2012), the local population conducts Slash-and-burn agriculture in order to address their subsistence or financial needs and such rural activities are encouraged by a difficult economic environment and a weak institutional framework – political decisions, civil wars, bad governance, crisis, unemployment, and poverty.

The United Nations Food and Agriculture Organization (FAO) is on the frontline of transforming agricultural systems to meet the United Nations Sustainable Development Goals (SDGs) by bolstering approaches that aim to increase agricultural productivity and to enhance soil health (FAO, 2018), the two missions that define conservation agriculture. Conservation Agriculture (CA) is a farming system that promotes maintenance of a permanent soil cover, minimum soil disturbance (i.e. no tillage), and diversification of plant species (FAO, 2019). It enhances biodiversity and natural biological processes above and below the ground surface, which contribute to increased water and nutrient use efficiency, and improved and sustained crop production (FAO, 2019). CA is a climate-smart technology universally applicable to several types of lands that have both economic, agronomic, and environmental benefits (FAO, 2019). Until recently, the knowledge about CA in the DRC, especially how this climate-smart technology would benefits producers, who are mostly small-scale semi-subsistence, and its potential impacts, was unexplored. CA has the potential to contribute to improving farmers' revenue and food security (Mulimbi et al., 2019). The adoption of agricultural technologies like CA emerges as a mechanism that can help LICs to catch-up on the development ladder (Foster and Rosenzweig, 2010), especially by reducing poverty in a region such as Africa (de Janvry and Sadoulet, 2002). Yet farmers' decision to adopt depends on their individual's perception of expected profit, understanding of risk and attitude to risk (Abadi Ghadim and Pannell, 1999).

Given the nature and difficulty of obtaining data for markets and value chains in the DRC, little research has been conducted to see if consumers in the DRC are willing to pay a premium for food produced in a sustainable manner. So far, no study has explored whether DRC's consumers would be willing to act to reduce deforestation. While many consumers in LICs simply focus on price minimization when it comes to meeting dietary needs, deforestation is an issue that many Congolese understand. If consumers would be willing to pay a premium for food produced under CA guidelines it could spur the adoption of CA technologies by producers, and ultimately may curtail deforestation. To estimate if Congolese consumers are willing to pay for CA we surveyed consumers in the city of Bukavu, DRC to elicit if they were willing to pay a premium for white maize flour (a staple in that part of DRC) produced using CA. The results of this study are important as if it is found that consumers are not willing to pay for CA, then it may indicate to the international community that NGO intervention is needed to try and reduce deforestation. If it is found that Congolese consumers are willing to pay a premium for CA white maize, it may indicate that market forces could help alleviate deforestation. Regardless, this study is the first of its kind in Africa to test if consumers are willing to reduce deforestation.

Importantly, the survey provided different information sets to see their effects on the consumers WTP for CA. While there are obvious environmental impacts from deforestation, there are also social issues as well. Like most central - African countries, women do most of the agricultural work. As producers (mostly women) harvest the nutrients from a cleared forest floor, they continue the practice of slash-and-burn agriculture to harvest new rents. Problematically, they have to move further away from their village. As women work and walk to/from home to these further distances, they find themselves a target for violence and rape. Millions of women have been raped in unstable rural DRC, and some were just small-scale farmers (Mulimbi et al., 2019).

Thus, this study wanted to analyze if framing the problem of deforestation from either a social or environmental impacts could affect the consumers' willingness-to-pay (WTP) in favor of CA. Both deforestation and rape are prevalent in the DRC and while CA will not eliminate either, it has the possibility to curtail both issues. In the absence of enough CA-adoption related literature in the DRC, assessing the WTP for a commodity produced under CA would be a compelling appraisal technique of the need for this agricultural technology. Taken together, this study sets out to link consumers' behavior to producers' technology adoption decision (CA). A better understanding this relationship is critical in designing the appropriate strategies in agricultural research and development. At this point, it is relevant to recall that policymakers, development agencies, and governmental and international research institutions need evidence to guide policy and program designs. Additionally, this study aims to identify particular traits that should contribute to understanding CA adoption and scale-up. The main one being to understanding how far consumers would be supportive of sustainable agricultural practice preserving the environment and benefiting producers.

Conceptual considerations

Demonstrating the value of CA is not is not always straightforward, especially in the DRC where this agricultural technology is still new. The beneficial features of CA make its valuation peculiar and for that, the following points are important background to have in mind for this study's investigation. Exploring WTP to value CA make this work unique in its genre. Close agricultural technologies studies related to soil conservation practices like CA, and utilizing CV method's WTP using the double bounded dichotomous choice (DBDC) approach are scarce. Two studies investigating farmers' valuation of soil conservation in Ethiopia (Erango et al., 2017; Kasaye, 2015) have been encountered in the literature. On the one hand, Erango et al. (2017) found that farmers in the Highlands were willing to pay more for soil conservation practices and family size, labor availability, land size, household head education and income levels drove significantly their WTP. They suggested that farmers' WTP increased by 0.3% with each additional family member, by 4.6% when the farmer faces labor shortage, by 10% when land size goes up by 1 unit, and by 14% for each additional year of education. On the other hand, in another region of Ethiopia, Kasaye (2015) demonstrated that gender, education, livestock, problem perception, and extension service were the drivers of farmers higher WTP for soils conservation practices on communal lands. Kasaye (2015) suggested that farmers' WTP increased by 8% for male farmers than female, by 13% if the household head is literate, by 2% if the household has livestock, by 19% for farmers who perceived soil erosion to be a great problem, and by 0.11% if the farmers were visited by extension agents regularly. Both studies conclude that the recognition of negative impact of soil erosion motivated farmers' WTP.

Most WTP studies with CV method are subject to hypothetical bias, the major weakness of stated preferences approaches. Even though this bias is not always found in all studies, it has been documented and, unfortunately, there is no accepted theory around it (Loomis, 2011). Hypothetical bias arises from the hypothetical nature of stated preferences. To illustrate hypothetical bias, List and Gallet (2001) found that on average subjects overstated their preferences. Hypothetical bias can be addressed using ex-ante and ex-post approaches (Loomis, 2011). The first group includes cheap talk, a technique integrated in the design of several WTP studies recently. The technique itself refers to a process of explaining hypothetical bias to individual before asking a valuation question (Lusk, 2003). Cummings and Taylor (1999) were the first to introduce cheap talk, which was later used by Lusk (2003). Silva et al. (2011) confirmed the validity of cheap talk in state preferences studies albeit its potential neutral action on hypothetical bias in some cases.

Away from our interest in CA, some consumers' WTP studies using DBDC have successfully integrated cheap talks to handle hypothetical bias and so improve their methodologies and designs. A recent study by Sanjuan et al. (2012) investigated Spanish and French consumers WTP to pay for direct market of beef in their boarding region of Pyrenees. They found that regular consumers used to beef direct markets are willing to pay more driven by product freshness, more confidence in the production process, and perception that they directly contribute to producers' income. Their results also suggest that French consumers are willing to pay more than their Spanish counterparts are. More recently, another study by Lee et al. (2015) investigated Korean consumers WTP to pay a tax for a mandatory mad cow disease-testing programme. Their findings suggest that Korean have a strong preference for the programme with a WTP greater than the estimated implementation cost of the programme itself. They also found that high-income households and housewives with higher perception of BSE were willing to pay more for the tax.

WTP studies have also documented a large variety of determinants. However, the last two decades it appears in the literature that most of those studies mainly used income, education levels, demographics such as age, household size, and gender (Lee et al., 2015; Loureiro et al., 2006; Lusk, 2003; Sanjuán et al., 2012; Silva, et al., 2011) and additional variables depending on their topic and objectives. Thus, specific factors such as perception (Sanjuán et al., 2012), employment and/or health status (Cawley, 2008; Gustafsson-Wright et al., 2009; Loureiro et al., 2006), farm size (Banka et al., 2018; Knapp et al., 2018; Mezgebo et al., 2013) and/or farm labor (Erango et al., 2017, Kasaye, 2015), and others can be found. There is no precise rule of thumb in building the links with between WTP and its explanatory determinants. As results, researchers bring about various combinations. While investigating consumers' behavior in Kenya, Kimenju and De Groote (2008) found that participants' average WTP for genetically modified (GM) maize was 13.8% higher than the average price of non-GM maize. Furthermore, they demonstrated that trust in the government food quality control system, secondary education and high-income positively drove WTP while perception of health risk and ethical concerns had a negative influence on it. More recently, another study by Knapp et al. (2018) explored Arkansans WTP for irrigation water when groundwater is scarce. They found that local producers located in areas of low access to groundwater resources had higher WTP and would choose to take their croplands out of production due to groundwater supply reduction. In this study, awareness of state tax credit and participation to the conservation reserve program are the key factors that drove WTP in divergent directions. Finally, a WTP study on soil conservation practices

By focusing on CA, a soil conservation practice, our research in line with Kasaye (2015) and Erango et al. (2017) whose choice of WTP determinants are consistent with Asrat et al. (2004). Given all that has been mentioned so, we ended up with a typical consumers' WTP study that uses DBDC to estimate how white maize flour consumers would value CA, and integrates a cheap tall script in the survey to control any to potential hypothetical bias from the targeted urban consumers.

Research design and informational treatments

We designed an electronic survey questionnaire using *Qualtrics* survey software and uploaded it to tablets and smartphones for use by four surveyors. All the surveyors were familiar with the work and data collection tools, and they attended a one-day training session where they also pretested the survey questionnaires prior to field work. The questionnaire had three sections. The first section introduced the study to the participants detailing its purpose and the type of information required about consumers' preferences. Respondents were reminded that participation was voluntary. Furthermore, we informed participants about the implications of the study and collected their individual consent to participate. To participate, individuals were required to be at least 18 years old and to consume white maize flour at least once per week.

Respondents were randomly assigned to treatment groups that varied the type of information that respondents read about conservation agriculture following the introductory survey details. Next, respondents viewed a "cheap talk" script before answering the double bounded dichotomous choice questions (Cummings and Taylor, 1999). The third section had a series of questions collecting demographic and maize-related information. The section ended with a question about respondent knowledge about CA.

The research experimental design had a between-subject format and involved four treatments, with participants randomly assigned to either a control group or three informational treatments. Table 1 summarizes the four treatment groups. Participants exposed to the first information group, the control, had just were simply shown a picture of package of a 1 Kilogram package of white maize flour commonly purchased throughout eastern DRC. There was no brand name or identification on the package itself to mitigate consumer preference for branding. Participants in the second information group, the FAO-Definition treatment (*Def*), had the FAO's definition of CA in addition to the picture of package of 1 Kilogram of white maize flour. This definition stated that

> *According to the United Nations (2017), Conservation Agriculture (CA) is a farming system that promotes maintenance of a permanent soil cover, minimum soil disturbance (i.e. no tillage), and diversification of plant species. It enhances biodiversity and natural biological processes above and below the ground surface, which contribute to increased water and nutrient use efficiency and to improved and sustained crop production* (FAO, 2019).

Participants were told that the 1-Kilogram bag of white maize flour was produced following the FAO guidelines of CA.

Participants in the second information group, the Social-benefits-of-CA treatment (*Soc*), had the FAO's definition of CA plus a short paragraph stating how CA help to reduce women farmers burdens, vulnerability and risk in rural area based, and help farmers to save more time and energy; in addition to the picture of package of 1 Kilogram of white maize flour. The social information stated that

> *In the Maniema province of DRC, CA has been applied through farming practices involving crop rotation, no-tillage, and mulching. CA has the potential to reduce or will reduce farmers' workload burdens and vulnerability in the DRC. For female farmers, CA allows them to farm closer to their homes, which can (or has been shown to) reduce the incidence of harassment and risk of violent assaults* (Mulimbi et al., 2019). *Further, CA has the potential to save time and energy as labor requirements decrease* (CRS, 2015).

Participants in the third information group, the Environmental-benefits-of-CA - treatment (*Env*), had the FAO's definition of CA plus a short paragraph stating how CA improves soil quality and can help to reduce deforestation; in addition to the picture of package of 1 Kilogram of white maize flour. The environmental information stated that

> *In the Maniema province, CA has been applied through farming practices involving crop rotation, no-tillage (or at least minimum tillage), and mulching. CA can enhance soil quality that has the potential to reduce deforestation in the DRC* (CRS, 2015*). In 2017, the DRC lost 1.46 million ha of forest cover through deforestation* (Weisse and Goldman, 2018).

The second section of the survey questionnaire incorporated the contingent valuation method used to determine consumers' Willingness-to-Pay (WTP) for white maize flour produced under CA. Contingent valuation (CV) approach has the ability to inform producers how their future clients – consumers –, would value CA. The CV approach was chosen as it is a simple, flexible nonmarket valuation method used for cost-benefit analysis and environmental impact assessment (Venkatachalam, 2004). In this study, instead of single bounded approach, we use a double bounded dichotomous choice (DBDC) contingent valuation to improve the statistical information provided by respondents (Hanemann et al., 1991). The survey tool attempts to capture consumers' behavior when exposed to treatments that provide them with a descriptive definition of CA, environmental benefit of CA, or social benefit of CA. Several studies on WTP are similar to this in using DBDC approach but are still various in framing their informational treatments. WTP was estimated, for consumers who were exposed to a tax for a mandatory testing program (Lee et al., 2015), to a potential access to irrigation water (Knapp et al., 2018; Mezgebo, et al., 2013) or renewable energy in rural areas (Abdullah and Jeanty, 2011). More studies also estimated WTP for biofertilizers (Banka et al., 2018), a new rice-grading system (Choi et al., 2018), genetically modified food technology (Kimenju and De Groote, 2008), or childhood obesity reduction policy (Cawley, 2008), for example. This array of flexibility has led to the popularity of contingent valuations (Carson et al., 2001).

To rule out the possibility of hypothetical bias – that participants declared WTP might differ from their real WTP for white maize truly produced under CA –, a cheap talk script was integrated in the second section of the survey questionnaire, and administered straight before the DBDC CV part. Hypothetical bias is an issue in most CVM studies (List and Gallet, 2001). As such, we purposely read the following cheap talk script to each participant:

> *Recent studies show that people tend to act differently when they face hypothetical decisions. In other words, they say one thing but do something different. It is particularly common that one states a different willingness to pay (WTP) than what one actually is willing to pay for the good in the store or the local market. We believe this is due to the fact that one does not really consider how big an impact an extra cost actually has to the family budget. It is easy to be generous when one does not really need to make the choices in a store or a local market. So please, keep your household budget in mind when answering the willingness to pay questions.*

The application of this cheap talk aimed to let the participants not overstate their WTP (Loomis, 2011). While this cannot eliminate hypothetical bias, we hoped to mitigate it. Including a cheap talk was a reasonable technique to potentially reduce this bias, knowing that this study on CA in DRC maize production is the first of its kind.

In the DBDC CV part of the second section, each subject was asked if "Yes" or "No" he/she would be willing to pay a fixed given amount for white maize flour. Then, a follow-up bid was asked and here the follow-up bid was lower if the person answered, "No" to the starting bid and higher if the person answered "Yes" (Patterson, 1996). A contingent valuation that narrows WTP bounds such as DBDC are known to provide more efficient estimation (Hanemann et al., 1991). The prices for white maize flour used in the DBDC were built around the average market price for one kilogram of flour, which was 1,500 Congolese Francs (CDF) found from the *Cellule d'Analyses des Indicateurs de Développement* database (CAID, 2019). We chose to increase and decrease this average price by 200 CDF. This led to having five prices (1,100 CDF, 1,300 CDF, 1,500 CDF, 1,700 CDF and 1,900 CDF) being used and randomly picked as starting price in the DBDC. Table 2 illustrates the configuration of bounded prices based on bid responses.

Data and research site

The survey was conducted in the city of Bukavu in the Democratic Republic of the Congo. Bukavu, the capital of the South Kivu province, is a large city with a population of 1,012,053 people[1] and is located in the eastern part of the country.

Participation in the survey was voluntary and the instructions clearly stated at the beginning that there was no any compensation at all. Participants were recruited on the sidewalks around six separate local open markets in the city. The team of four surveyors recruited 638 participants in four weeks in June 2019. Several (14) observations were discarded (prior to the

[1] https://www.thelostgeographer.org/country.php?country=DEMOCRATIC%20REPUBLIC%20OF%20THE%20CONGO

analysis of the data) for issues such as abnormally long survey times (over 60 minutes) and incomplete observations. After cleaning, the dataset used included 624 participants.

We chose maize, especially maize flour, for this study, as it is the most traded and consumed cereal, and ranked second staple food following cassava in the DRC (FEWSNET, 2015). Cassava and maize flour are two main food consumed by the poor households in the Eastern DRC (FEWSNET, 2017). Middle and better off households mostly prefer to purchase maize flour and rice (FEWSNET, 2017). In urban areas like Bukavu, most of households choose to mix cassava and maize flour to make their *ugali* (FEWSNET, 2017). Maize flour is mostly utilized to make porridge and *ugali*. Based on personal experience and field observations, urban consumers prefer to use white maize flour. Our observation in locals markets indicated that approximately 90% of maize flour sold was white and 10% yellow.

WTP DBDC empirical modeling

The WTP analysis using DBDC in this study is consistent with Hanemann et al. (1991) who provided empirical evidence of increased statistical efficiency of this approach. Similarly described by Holmquist et al. (2012), McLeod and Bergland (1999) and Patterson (1996), in a study applying the DBDC model, two prices are revealed to each subject. The level of the second price option is contingent upon the response to the first price choice. When the subject's answer is "yes," meaning that they are willing to pay the amount of the initial price (B_i), they are presented with a second but higher price (B_h). As a matter of choice, if the subject's answer is "no," meaning that they are not willing to pay the amount of the initial price, then they are presented with a second but lower bid (B_l).

The subsequent questions attempting to elicit upper or lower bounds of the WTP lead to four possible outcomes: (i) both answers are "no", meaning the participant's WTP is lower than B_l; (ii) a "no" followed by a "yes", meaning the participant's WTP is lower than B_i but greater than or equal to the accepted B_l amount; (iii) a "yes" followed by a "no" meaning the participant's WTP is greater than or equal to B_i but lower than the rejected B_h amount; and (iv) both answers are "yes" meaning the participant's WTP is greater than or equal to B_h. By denoting the WTP for individual *i* as WTP_i, we describe the following discrete outcomes in the bidding procedure:

$$y_i = \begin{cases} 1 & if \;\; WTP_i < B_l \qquad (no, no) \qquad (1a) \\ 2 & if \; B_l \le WTP_i < B_i \qquad (no, yes) \qquad (1b) \\ 3 & if \; B_i \le WTP_i < B_h \qquad (yes, no) \qquad (1c) \\ 4 & if \;\; WTP_i \ge B_h \qquad (yes, yes) \qquad (1d) \end{cases}$$

In a WTP analysis of sensory characteristics, the objective is to examine the maximum an individual consumer would pay for the product in question and how the sensory properties influence this amount. The CV methodology is commonly used to estimate WTP.

Accordingly, based on Carson and Hanemann (2006), the response probabilities for the outcomes in set (1) will be given by :

$$\Pr(no, no) = \Pr(B_l \; > \; WTP_i^*) = \; G_{WTP}(B_l), \qquad (2a)$$

$$\Pr(no, yes) = \Pr(B_i \; > \; WTP_i^* \ge B_l) = \; G_{WTP}(B_i) - \; G_{WTP}(B_l), \qquad (2b)$$

$$\Pr(yes, no) = \Pr(B_l \; \ge \; WTP_i^* \ge B_l) = G_{WTP}(B_h) \; - G_{WTP}(B_i), \qquad (2c)$$

$$\Pr(yes, yes) = \Pr(B_h \; \le \; WTP_i^*) = \; 1 - \; G_{WTP}(B_h). \qquad (2d)$$

where G_{WTP} is the WTP cumulative distribution function.

The DBDC design generated interval censored data on WTP. Following several applications of DBDC (Basu, 2013; Lang, 2010; Nosratnejad et al., 2014), we use the interval regression method in this study. As the latent value of WTP could be effectively observed by analyzing respondents' stated information and there is a probability that the latent value is located within an interval, interval regression is a suitable method for assessing consumers' WTP for white maize flour (Alberini, 1995; Cameron, 1991). In fact, Basu (2013) argues that other discrete choice models such as ordered logit or ordered probit models, even though appropriate, could rank the WTP as an ordinal model and ignore the boundary point values.

The participant's WTP for white maize flour produced under CA is then determined in linear form of its function as follows:

$$WTP_i^* = \beta X + \varepsilon \qquad (3)$$

where WTP_i^* is the subject i's unobserved true WTP, X is the vector of variables associated with respondents, β is the vector of the coefficients representing the parameters to be estimated, and ε denotes the error term following a normal distribution with mean 0 and variance σ^2.

Given that initial, lower and upper bounds are used to figure different bids within the sample of respondents, the likelihood function for the interval regression model takes the form (Bettin and Lucchetti, 2012; Lu and Shon, 2012):

$$L = \sum_i \left[\Phi\left(\frac{U_i - \beta' x_i}{\sigma}\right) - \Phi\left(\frac{L_i - \beta' x_i}{\sigma}\right) \right] \quad (4)$$

where U_i and L_i are the upper bound and lower bound of the interval in which WTP_i^* falls and ϕ is the standard cumulative normal.

To explain the participants' WTP, we used a series of independent variables fitting with the particular goals of this research. These include demographics, and environmental and social related questions pertaining to deforestation, all with categorical responses. These variables are listed in Table 3. The demographic variables include age, gender, education, and if the participant is involved in farming (exposing the dual behavior of consumers who also do farming in rural areas).

Environmental variables include the following questions, “Do you think climate change will affect the livelihoods of the DRC in the future?”, “Do you think deforestation is an important issue in the DRC?”, “The earth has plenty of natural resources if we just learn how to develop them”, and “Human are seriously abusing the environment”. The first question in this group aimed to certify possible relationship that could exist between consumers’ climate change knowledge and their WTP. The second question aimed to double-check consumers’ concern about deforestation. The two last questions in this subsection – which are New Ecological Paradigm statements – aimed to explore consumers’ endorsement of a pro-ecological view of the world (Anderson, 2012). Taken together, we wanted to investigate participants’ sensitivity in WTP to these particular measures of environmental opinion.

Social questions related to life in rural areas – where deforestation and farming happens – included “Do you think women in rural areas are at higher risk of assault than women in urban areas?”, and “Who provides the majority of labor in agriculture in the DRC?” CA has social advantages for the environment and women farmers in the DRC (Mulimbi et al., 2019). We aimed to verify the extent to which reducing distance from home to farms for women in rural areas by applying CA would affect consumers’ reaction across treatments. We also thought about potential hypothetical bias that could derive from social and environmental variables. As such, we applied uncertainty adjustment technique by providing the respondents with an “I don’t know” answer option.

We used the *Survival* package (Therneau, 2015; Therneau and Grambsch, 2013) in R Studio (R version 3.5.1) to perform the interval regression modeling.

Results and Discussion

Approximately half of respondents were between 25 and 34 years old, and 40% had 35 years and above. This is consistent with the last country's Demography and Health Survey that indicated in 2013 that 32.9% of the DRC's urban population had 25 years and above (2014) as we excluded respondents under 18 years old. Our sample had 75% female respondents. This makes a lot of sense because in the DRC women conduct the majority of food shopping. However, this does not mean men respondents were not eligible because in the modern context of urban life they are likely to do food shopping as well. Among the respondents, 11% happened to be farmers living in the city. Agriculture is the activity of 70.7% women and 45.6% men in South Kivu province (MINPLAN, 2014) and this makes it possible to find urban citizens who are still farming in rural areas. Furthermore, 24% respondents had a college degree and stated at the end of the interview that it was not the first time they heard about CA. More than 80% of respondents agreed that climate change (84%), deforestation (86%), earth natural resources weak management (93%), and risk of assault on rural women (94%) were real issues. Furthermore, 72% of respondents are aware of women contribution for agricultural labor.

Several models specifications were examined to explore what determinants explain consumers' WTP for white maize flour produced under CA the best. Intuitively, the first approach was an estimation a function of only the treatments (*Def*, *Soc*, *Env*, and the control) but this did not yield on a good fitness as Model 1 had the lowest log likelihood (Table A1 in appendix). Therefore, to the treatments binaries, we added demographics and all the study variables in Table 2 to improve estimation. Table 4 reports the results of interval regressions for the specification including only demographics (model 3) and for the full specification model including all the study's variables (model 10). Furthermore, we found that while omitting study's variables weakened our model estimation their inclusion with treatment interactions significantly increased the log likelihood (Table 4).

The fitness of the estimated full model (model 10) in Table 4 is overall acceptable. This full model has the largest log likelihood and the likelihood ratio Chi square test indicates that the overall model is highly significant ($P < 0.01$). Holistically, the results in the full model (Table 4) suggests that participants' WTP for 1 kilogram of white maize flour produced under CA is 1,366 CDF which is 9% less than the average price (1,500 CDF) found on the local markets in Bukavu. This WTP value is highly statistically significant ($P < 0.01$). Additionally, the findings indicate that among the urban maize flour consumers, farmers living in the city, and consumers who were exposed to the social benefits of CA would be willing to pay respectively 103 CDF and 242 CDF less than 1,366 CDF WTP. Conversely, white maize flour consumers who think women farmers are great agricultural labor contributors, and those who think human are abusing the environment would be willing to pay respectively 74 CDF and 144 CDF more.

Our three informational treatments (*Def*, *Env*, and *Soc*) were found not to be significant ($P > 0.10$) across all treatments. This would seem to indicate that regardless how CA was presented to consumers it did not affect their WTP. CA reduces farming workloads, and allows to save time and energy (Mulimbi et al., 2019). Compared to consumers who think that both women and men contribute equally to farming labor, those who think women bring more to the farm are willing to pay 5% more for a kilogram of white maize flour produced under CA.

Looking at the demographics, the findings in Table 4 suggest that being a farmer living in the city makes a difference in estimating consumers WTP for white maize flour produced under CA. The variable *farmer* is robust across all model specifications ($P < 0.05$). Consumers who were farmer are willing to pay less and this makes sense. This reaction is not against CA but an indicator of coping strategy in urban areas by consuming their own products in addition to local purchase. These consumers would have paid 100 CDF less (Table 4) because they might have also own-produced white maize flour in storage at home. Finally, participants found in the city agree that human are abusing the environment and for that reason, they are willing to pay 11% (144 CDF) more for white maize flour produced under CA (Table 4). This illustrates that in the long-run consumers who are adequately informed would be more supportive to sustainable agricultural impact.

Policy implications

In light of indications that human societies need to rethink and improve food system, multiples evidence to date have proven that CA has the potential but also fit well in the sustainable agriculture framework (Friedrich et al., 2017; Hobbs et al., 2007; Knowler and Bradshaw, 2007; Mulimbi et al., 2019). Improving agricultural productivity remains challenging for policymakers, especially in LIC regions such as Sub-Saharan Africa (SSA), where additionally issues such a poverty, and climate change. In the DRC, agriculture appears to be a main driver of deforestation and its impact will likely increase due to population growth (Ickowitz et al., 2015). Scaling up CA could offset the threat on the Congolese rainforest while improving agricultural productivity and contributing to climate change mitigation. CA is among the practices that, according to Lal (2006), would advance food security and outweigh fossil fuel emissions by $0.5PgCy^{-1}$ through carbon sequestration. Right now, the issue for CA in SSA is its low adoption due to lack of information and funds to promote the agricultural technology. Even though, for its promotion the question of how to incentivize producer to adopt remains unanswered. This study attempted to explore the way consumers could play a role in supporting local producers but it happened that there is little clue. That said, the international community through the Intergovernmental Panel on Climate Change (IPCC) should allocate more resources to fight deforestation, and push for strong policies in favor of the scale-up of sustainable practice such as CA.

Our findings also have demonstrate that in urban areas people are not well informed about climate change, an issue that unfortunately affects their food security and increase vulnerability. From a policy standpoint, the public deserve the right information to better their daily household's decisions. For the case of food system that contribute to sustainability, policy makers should support agricultural research and development to better communication. The FAO's mission of changing the way we produce food should work only within a clear behavioral change communication framework that involve not only producers but also consumers of agricultural commodities.

Conclusion

Consumers' WTP for white maize flour produced under CA is a signal that can incentivize more the diffusion of CA in the DRC. CA has already proven globally to be a way of sustainably taking care of the soils and the environment but also contributing to improve the social component of farming households in LICs. Assessing consumers' WTP in this study aimed to bring about more strategical ways of encouraging smallholders' farmers to adopt CA through the maize value chain while. Building on research that supports the role of information in shaping consumer behaviors, considering agricultural technology that would benefit the society in various ways, this study investigated the level of support CA adopters and potential adopters should expect.

This study used a DBDC CV survey to derive how consumers in a LIC city would value white maize flour knowing that the agricultural technology used to produce it will help to reduce deforestation and help smallholders' farmers, especially women farmers in rural areas. Respondents received information sets that highlighted respectively environmental and social impacts of CA, or just described CA. We expected a broad reaction from consumers of white maize flour knowing that, according to the FAO (2019), CA brings sustainability, enhanced biodiversity, carbon dioxide sequestration, labour savings, healthier soils, increased yields, and reduced costs.

In general, our findings suggest that consumers of white maize flour could not make the link between their produce and CA. Several contextual aspects such as low skill level to process given information, respondents' inclination to the interview, or socioeconomics factors may have contributed to those results. Whilst the study did not confirm any treatment effect, the findings indicated that the way human treat the environment and rural women labor contribution in the farming make a difference by increasing consumers' WTP. Results further show that a consumer who identify himself as a farmer living in the city tends to pay less for white maize flour, and white maize flour consumers seem to present an equivocal reaction to social benefits of CA. The later may be some local cultural effects that open the door for more research to figure out cultural responsiveness to CA.

Finally, our results also show that consumers are either not aware of climate change in agriculture and how that may affect their plates and pockets, or just insensitive to the climate issue. The same reaction can be argued for deforestation even though it seemed to be well known by respondents. Study findings also demonstrate policy makers should adjust their plan for agricultural transformation by investing more in research for development, communication, and adapted policies as consumers of white maize flour are still hesitant to encourage producers. Future research can explore whether the effects of our information sets persist in rural areas where CA is still unknown, or include food security and markets determinants to see how they could affect WTP.

References

Abadi Ghadim, A.K., Pannell, D.J., 1999. A conceptual framework of adoption of an agricultural innovation. *Agricultural Economics*, 21(2), 145-154.

Abdullah, S., Jeanty, P.W., 2011. Willingness to pay for renewable energy: Evidence from a contingent valuation survey in Kenya. *Renewable & Sustainable Energy Reviews*, 15(6), 2974-2983.

Alberini, A., 1995. Optimal Designs for Discrete Choice Contingent Valuation Surveys: Single-Bound, Double-Bound, and Bivariate Models. *Journal of Environmental Economics and Management*, 28(3), 287-306.

Anderson, M., 2012. New Ecological Paradigm (NEP) Scale. Berkshire Encyclopedia of Sustainability, 6, 260-262.

Asrat, P., Belay, K., Hamito, D., 2004. Determinants of farmers' willingness to pay for soil conservation practices in the southeastern highlands of Ethiopia. *Land Degradation & Development*, 15(4), 423-438.

Bala, G., Caldeira, K., Wickett, M., Phillips, T.J., Lobell, D.B., Delire, C., Mirin, A., 2007. Combined climate and carbon-cycle effects of large-scale deforestation. Proceedings of the National Academy of Sciences, 104(16), 6550.

Banka, M., Aidoo, R., Abaidoo, R.C., Fialor, S.C., Masso, C., 2018. Willingness to pay for biofertilizers among grain legume farmers in northern Ghana.

Basu, R., 2013. Willingness-to-pay to prevent Alzheimer's disease: a contingent valuation approach. *International Journal of Health Care Finance and Economics*, 13(3/4), 233-245.

Bettin, G., Lucchetti, R., 2012. Interval regression models with endogenous explanatory variables. *Empirical Economics*, 43(2), 475-498.

Bongaarts, J., 2009. Human population growth and the demographic transition. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 364(1532), 2985-2990.

Cameron, T.A., 1991. Interval Estimates of Non-Market Resource Values from Referendum Contingent Valuation Surveys. *Land Economics*, 67(4), 413-421.

Campbell, B.M., Hansen, J., Rioux, J., Stirling, C.M., Twomlow, S., Wollenberg, E., 2018. Urgent action to combat climate change and its impacts (SDG 13): transforming agriculture and food systems. Current Opinion in *Environmental Sustainability*, 34, 13-20.

Cannon, J.C., 2018. DR Congo–Maps tease apart complex relationship between agriculture and deforestation in DRC. *Mongabay Series: Global Forest Reporting Network (Global Forests).*

Carson, R., Hanemann, M., 2006, Contingent Valuation. In: K.G. Mäler, J.R. Vincent (Eds.). *Handbook of Environmental Economics*. Elsevier, pp. 821-936.

Cawley, J., 2008. Contingent valuation analysis of willingness to pay to reduce childhood obesity. *Economics & Human Biology*, 6(2), 281-292.

Cellule d'Analyses des Indicateurs de Développement [CAID], 2019, Surveillance des Prix des Produits Alimentaires de Base - mKengela. In: CAID (Ed.).

Choi, Y.W., Lee, J.Y., Han, D.B., Nayga, R.M., 2018. Consumers' Valuation of Rice-Grade Labeling. *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie*, 66(3), 511-531.

CRS, 2015, No-tillage agriculture in Kailo, Kasongo and Kabambare territories of Maniema - Ex post evaluation report. Catholic Relief Services (CRS), Kinshasa, DRC.

Cummings, R.G., Taylor, L.O., 1999. Unbiased Value Estimates for Environmental Goods: A Cheap Talk Design for the Contingent Valuation Method. *The American Economic Review*, 89(3), 649-665.

de Janvry, A., Sadoulet, E., 2002. World Poverty and the Role of Agricultural Technology: Direct and Indirect Effects. *Journal of Development Studies*, 38(4), 1-26.

Erango, E., Bersisa, M., Shewangizaw, M., Etensa, T., Tolera, T., 2017. Economic Valuation of Soil Conservation in Highlands of Hadiya Zone of Ethiopia: The Case of Soro Woreda Ajacho Watershed. *Journal of Resources Development and Management*, 37, 16 - 23.

Famine Early Warning Systems Network [FEWSNET], 2015. Democratic Republic of the Congo: Staple Food Market Fundamentals.

Famine Early Warning Systems Network [FEWSNET], 2017. Democratic Republic of the Congo: Livelihoods Baseline Profiles - Eastern DRC Household Economy Analysis (HEA) Livelihood Profiles.

Fearnside, P.M., 2000. Global Warming and Tropical Land-Use Change: Greenhouse Gas Emissions from Biomass Burning, Decomposition and Soils in Forest Conversion, Shifting Cultivation and Secondary Vegetation. *Climatic Change*, 46(1), 115-158.

Foster, A.D., Rosenzweig, M.R., 2010, Microeconomics of Technology Adoption. *Annual Reviews, Palo Alto*, pp. 395-424.

Friedrich, T., Derpsch, R., Kassam, A., 2017, Overview of the global spread of conservation agriculture. Sustainable Development of Organic Agriculture. Apple Academic Press, pp. 75-90.

Gustafsson-Wright, E., Asfaw, A., van der Gaag, J., 2009. Willingness to pay for health insurance: An analysis of the potential market for new low-cost health insurance products in Namibia. *Social science & medicine*, 69(9), 1351-1359.

Hanemann, M., Loomis, J., Kanninen, B., 1991. Statistical efficiency of double-bounded dichotomous choice contingent valuation. *American journal of agricultural economics*, 73(4), 1255-1263.

Hobbs, P.R., Sayre, K., Gupta, R., 2007. The role of conservation agriculture in sustainable agriculture. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 363(1491), 543-555.

Holmquist, C., McCluskey, J., Ross, C., 2012. Consumer Preferences and Willingness to Pay for Oak Attributes in Washington Chardonnays. *American Journal of Agricultural Economics*, 94(2), 556-561.

Ickowitz, A., Slayback, D., Asanzi, P., Nasi, R., 2015, Agriculture and deforestation in the Democratic Republic of the Congo: A synthesis of the current state of knowledge, vol. 119. CIFOR.

Kasaye, B., 2015. Farmers‟ Willingness to Pay for Improved Soil Conservation Practices on Communal Lands in Ethiopia (Case Study in Kuyu Woreda), Addis Ababa University.

Kimenju, S.C., De Groote, H., 2008. Consumer willingness to pay for genetically modified food in Kenya. *Agricultural Economics*, 38(1), 35-46.

Knapp, T., Kovacs, K., Huang, Q., Henry, C., Nayga, R., Popp, J., Dixon, B., 2018. Willingness to pay for irrigation water when groundwater is scarce. *Agricultural Water Management*, 195, 133-141.

Knowler, D., Bradshaw, B., 2007. Farmers' adoption of conservation agriculture: A review and synthesis of recent research. *Food Policy*, 32(1), 25-48.

Lal, R., 2006. Enhancing crop yields in the developing countries through restoration of the soil organic carbon pool in agricultural lands. *Land Degradation & Development*, 17(2), 197-209.

Lang, H.-C.P., 2010. Willingness to Pay for Lung Cancer Treatment. *Value in Health*, 13(6), 743-749.

Lee, S.H., Lee, J.Y., Han, D.B., Nayga, R.M., 2015. Are Korean consumers willing to pay a tax for a mandatory BSE testing programme? *Applied Economics*, 47(13), 1286-1297.

List, J.A., Gallet, C.A., 2001. What Experimental Protocol Influence Disparities Between Actual and Hypothetical Stated Values? *Environmental and Resource Economics*, 20(3), 241-254.

Loomis, J., 2011. What's to Know About Hypothetical Bias in Stated Preference Valuation Studies? *Journal of Economic Surveys*, 25(2), 363-370.

Loureiro, M.L., Gracia, A., Nayga Jr, R.M., 2006. Do consumers value nutritional labels? *European Review of Agricultural Economics*, 33(2), 249-268.

Lu, J.-L., Shon, Z.Y., 2012. Exploring airline passengers' willingness to pay for carbon offsets. *Transportation Research Part D: Transport and Environment*, 17(2), 124-128.

Lusk, J.L., 2003. Effects of Cheap Talk on Consumer Willingness-to-Pay for Golden Rice. *American Journal of Agricultural Economics*, 85(4), 840-856.

McLeod, D.M., Bergland, O., 1999. Willingness-to-Pay Estimates Using the Double-Bounded Dichotomous-Choice Contingent Valuation Format: A Test for Validity and Precision in a Bayesian Framework. *Land Economics*, 75(1), 115-125.

Mezgebo, A., Tessema, W., Asfaw, Z., 2013. Economic values of irrigation water in Wondo Genet District, Ethiopia: An application of contingent valuation method. *Journal of Economics and Sustainable Development*, 4(2), 23-36.

Ministere de l'Environement, Conservation de la Nature et Tourisme [MECNT], 2012. Synthèse des études sur les causes de la déforestation et de la dégradation des forêts en République Démocratique du Congo, MECNT-UNREDD Programme.

Ministere de l'Agriculture [MINAGRI], 2018. Sécurité alimentaire, niveau de production agricole et Animale, Évaluation de la Campagne Agricole 2017- 2018 et Bilan Alimentaire du Pays (Rapport 2018), MINAGRI.

Ministere du Plan et Suivi de la Mise en Oeuvre de la Revolution de la Modernite, M.d.l.S.P., MEASURE DHS, ICF International, 2014, République Démocratique du Congo Enquête Démographique et de Santé (EDS-RDC) 2013–2014. MPSMRM, MSP, and ICF International Rockville, MD.

Mulimbi, W., Nalley, L., Dixon, B., Snell, H., Huang, Q., 2019. Factors Influencing Adoption of Conservation Agriculture in the Democratic Republic of the Congo. *Journal of Agricultural and Applied Economics*, 51(4), 622-645.

Nosratnejad, S., Rashidian, A., Mehrara, M., Akbari Sari, A., Mahdavi, G., Moeini, M., 2014. Willingness to pay for the social health insurance in Iran. *Global journal of health science*, 6(5), 154-163.

Patterson, D., 1996, An extended model for double-bounded dichotomous choice data. Western North American Region of The International Biometric Society [WNAR] Meeting, June 1993, Laramie, WY.

Sanjuán, A.I., Resano, H., Zeballos, G., Sans, P., Panella-Riera, N., Campo, M.M., Khliji, S., Guerrero, A., Oliver, M.A., Sañudo, C., 2012. Consumers' willingness to pay for beef direct sales. A regional comparison across the Pyrenees. *Appetite*, 58(3), 1118-1127.

Seymour, F., Busch, J., 2016, Why forests? Why now? The science, economics, and politics of tropical forests and climate change. Brookings Institution Press.

Silva, A., Nayga, R.M., Campbell, B.L., Park, J.L., 2011. Revisiting Cheap Talk with New Evidence from a Field Experiment. *Journal of Agricultural and Resource Economics,* 36(2), 280-291.

Stocker, T.F., Qin, D., Plattner, G.-K., Alexander, L.V., Allen, S.K., Bindoff, N.L., Bréon, F.-M., Church, J.A., Cubasch, U., Emori, S., Forster, P., Friedlingstein, P., Gillett, N., Gregory, J.M., Hartmann, D.L., Jansen, E., Kirtman, B., Knutti, R., Krishna Kumar, K., Lemke, P., Marotzke, J., Masson-Delmotte, V., Meehl, G.A., Mokhov, I.I., Piao, S., Ramaswamy, V., Randall, D., Rhein, M., Rojas, M., Sabine, C., Shindell, D., Talley, L.D., Vaughan, D.G., Xie, S.-P., Stocker, T.F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S.K., Doschung, J., Nauels, A., Xia, Y., Bex, V., Midgley, P.M., 2013, Technical summary. Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK, pp. 33 -115.

Sunderlin, W.D., Angelsen, A., Belcher, B., Burgers, P., Nasi, R., Santoso, L., Wunder, S., 2005. Livelihoods, forests, and conservation in developing countries: an overview. *World development*, 33(9), 1383-1402.

Therneau, T.M., 2015, A Package for Survival Analysis in S.

Therneau, T.M., Grambsch, P.M., 2013, Modeling survival data: extending the Cox model. Springer Science & Business Media.

Turubanova, S., Potapov, P.V., Tyukavina, A., Hansen, M.C., 2018. Ongoing primary forest loss in Brazil, Democratic Republic of the Congo, and Indonesia. *Environmental Research Letters*, 13(7), 074028.

Tyukavina, A., Hansen, M.C., Potapov, P., Parker, D., Okpa, C., Stehman, S.V., Kommareddy, I., Turubanova, S., 2018. Congo Basin forest loss dominated by increasing smallholder clearing. *Science advances,* 4 (11), eaat2993.

United Nations Food and Agriculture Organization [FAO], 2018. Transforming Food and Agriculture to Achieve the SDGs: 20 interconnected actions to guide decision-makers., Rome, Italy.

United Nations Food and Agriculture Organization [FAO], 2019, Conservation Agriculture. In: FAO (Ed.).

United Nations, Population Division, 2019, *World Population Prospects 2019*, Online Edition.

Venkatachalam, L., 2004. The contingent valuation method: a review. *Environmental Impact Assessment Review*, 24(1), 89-124.

Watson, C., Schalatek, L., 2019, Climate Finance Thematic Briefing: REDD+ Finance. Climate Finance Fundamentals. Climate Funds Update. Heinrich Boll Stiftung, 2019.

Weisse, M., Goldman, L., 2018, 2017 Was the Second-Worst Year on Record for Tropical Tree Cover Loss. Global Forest Watch.

Table 1. Study's treatment groups

Treatment group	Information	N
Control	Picture	149
Def (FAO-Definition treatment)	Picture + Definition	170
Soc (Social-benefits-of-CA treatment)	Picture + Definition + Social	156
Env (Environmental-benefits-of-CA – treatment)	Picture + Definition + Environmental	149

Table 2. Bounded prices for a kilogram of white maize flour

Prices		Responses			
Starting (B_i)	Bounded	Yes – Yes	Yes – No	No – Yes	No – No
1,500	Lower (B_l)	1,700	1,500	1,300	-
	Higher (B_h)	-	1,700	1,500	1,300
1,700	Lower (B_l)	1,900	1,700	1,500	-
	Higher (B_h)	-	1,900	1,700	1,500
1,900	Lower (B_l)	2,100	1,900	1,700	-
	Higher (B_h)	-	2,100	1,900	1,700
1,300	Lower (B_l)	1,500	1,300	1,100	-
	Higher (B_h)	-	1,500	1300	1,100
1,100	Lower (B_l)	1,300	1,100	900	-
	Higher (B_h)	-	1,300	1,300	900

Table 3. Summary statistics

Variable	Categories	Control	*Def*	*Soc*	*Env*	Full sample
Household size	Average	6.9	6.7	6.6	6.9	6.8
Age	Between 25 – 34	48.3%	50.0%	47.4%	48.3%	49%
	35 and over	36.9%	41.8%	40.4%	41.6%	40%
	Less than 25	14.8%	8.2%	12.2%	10.1%	11%
Farmer	No	92.6%	88.8%	85.3%	89.9%	89%
	Yes	7.4%	11.2%	14.7%	10.1%	11%
Woman	No	22.1%	25.9%	29.5%	21.5%	25%
	Yes	77.9%	74.1%	70.5%	78.5%	75%
College	No	77%	75%	78%	73%	76%
	Yes	23%	25%	22%	27%	24%
Heard about CA	No	75.2%	78.2%	74.4%	75.2%	76%
	Yes	24.8%	21.8%	25.6%	24.8%	24%
Climate	I don't know	14.8%	17.1%	10.3%	15.4%	14%
	No	0.7%	1.8%	1.9%	3.4%	2%
	Yes	84.6%	81.2%	87.8%	81.2%	84%
Deforestation	I don't know	8.7%	8.2%	6.4%	12.1%	9%
	No	7.4%	2.4%	6.4%	4.0%	5%
	Yes	83.9%	89.4%	87.2%	83.9%	86%
Earth plenty	I don't know	8.1%	5.3%	8.3%	3.4%	6%
	No	4.0%	3.5%	3.2%	1.3%	3%
	Yes	87.9%	91.2%	88.5%	95.3%	91%
Human abuse	I don't know	4.7%	5.3%	6.4%	3.4%	5%
	No	2.7%	1.2%	2.6%	2.7%	2%
	Yes	92.6%	93.5%	91.0%	94.0%	93%
Women risk	I don't know	5.4%	4.1%	5.1%	2.7%	4%
	No	0.7%	1.8%	1.3%	2.7%	2%
	Yes	94.0%	94.1%	93.6%	94.6%	94%
Major labor	I don't know	1.3%	0.0%	0.6%	0.7%	1%
	Men	2.0%	2.4%	1.9%	2.7%	2%
	Women	71.1%	74.1%	75.0%	68.5%	72%
	Both	25.5%	23.5%	22.4%	28.2%	25%
Observations		149	170	156	149	624

Table 4. Interval regression results

	Dependent variable: *WTP**	
	(only demographics)	(full model)
Def	39.788	27.422
	(41.999)	(41.841)
Env	48.471	41.204
	(43.699)	(43.464)
Soc	66.236	61.861
	(43.176)	(42.745)
College	-38.344	-17.823
	(34.232)	(34.582)
Woman	-39.522	-55.899*
	(31.756)	(31.680)
Farmer	-110.495***	-103.402**
	(42.859)	(42.459)
Household size	4.777	7.190
	(4.717)	(4.707)
Age > 35	33.282	17.322
	(27.979)	(27.785)
Age < 25	-3.203	4.876
	(42.910)	(42.836)
Climate change - No	-	115.045
		(98.643)
Climate change - Yes	-	-32.382
		(41.276)
Deforestation - No	-	-68.403
		(74.864)
Deforestation - Yes	-	-60.072
		(49.559)
Earth plenty - No	-	166.187*
		(93.746)
Earth plenty - Yes	-	-10.425
		(60.110)
Human abuse - No	-	-65.631
		(103.978)
Human abuse - Yes	-	143.610**
		(65.749)
Majority labor - I don't know	-	-162.864
		(168.737)

Majority labor - Men	-	-36.554
		(89.789)
Majority labor - Women	-	73.598**
		(30.088)
Women risk - No	-	46.537
		(125.355)
Women risk - Yes	-	68.386
		(65.551)
Heard CA - Yes	111.398*	86.007
	(63.755)	(64.119)
Interactions		
Heard CA x Env	-158.178*	-142.686
	(87.330)	(86.880)
Heard CA x Soc	-254.685***	-241.600***
	(85.652)	(85.130)
Heard CA x Def	-115.640	-104.889
	(85.745)	(85.488)
Constant	1,522.553***	1,365.953***
	(54.782)	(105.985)
Log Likelihood	-692.986	-678.993
Chi^2	23.699** (df = 13)	51.685*** (df = 26)
Note:		*p<0.1; **p<0.05; ***p<0.01

Appendix

Table A1. All Interval Regression model specifications

	Dependent variable: *WTP**									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Def	7.576	-	39.788	11.190	8.376	37.815	4.809	2.644	34.525	27.422
	(37.378)		(41.999)	(36.843)	(36.971)	(41.835)	(36.817)	(36.885)	(41.825)	(41.841)
Env	6.653	-	48.471	11.209	5.979	45.695	9.277	4.361	52.693	41.204
	(38.885)		(43.699)	(38.171)	(38.319)	(43.535)	(38.095)	(38.215)	(43.410)	(43.464)
Soc	-2.215	-	66.236	9.056	6.691	72.015*	-2.709	-4.642	59.755	61.861
	(38.195)		(43.176)	(37.528)	(37.535)	(42.848)	(37.654)	(37.676)	(42.991)	(42.745)
College	-	-48.630	-38.344	-37.221	-37.080	-33.502	-26.051	-25.793	-23.620	-17.823
		(32.370)	(34.232)	(33.978)	(34.049)	(34.020)	(34.692)	(34.788)	(34.677)	(34.582)
Woman	-	-39.356	-39.522	-48.762	-51.437	-47.801	-45.542	-50.086	-44.173	-55.899*
		(31.971)	(31.756)	(32.063)	(32.124)	(31.743)	(31.924)	(32.097)	(31.566)	(31.680)
Farmer	-	-121.224***	-110.495***	-117.830***	-119.003***	-111.683***	-107.274**	-107.651**	-102.705**	-103.402**
		(42.514)	(42.859)	(42.940)	(42.943)	(42.485)	(43.192)	(43.217)	(42.714)	(42.459)
Human abuse - No	-	-	-	-34.796	-59.134	-34.178	-	-	-	-65.631
				(104.033)	(105.430)	(102.791)				(103.978)
Human abuse - Yes	-	-	-	155.866**	155.857**	160.874**	-	-	-	143.610**
				(66.457)	(66.556)	(65.829)				(65.749)
Household size	-	5.305	4.777	6.885	6.611	6.248	6.779	6.472	6.159	7.190
		(4.748)	(4.717)	(4.738)	(4.742)	(4.688)	(4.774)	(4.774)	(4.721)	(4.707)
Climate change - No	-	-	-	-	129.281	-	-	105.208	-	115.045

					(100.523)			(98.335)		(98.643)
Climate change - Yes	-	-	-	-	-23.546	-	-	-29.054	-	-32.382
					(41.894)			(38.725)		(41.276)
Deforestation - No	-	-	-	-20.093	-25.133	-35.103	-	-	-	-68.403
				(74.618)	(75.202)	(73.864)				(74.864)
Deforestation -Yes	-	-	-	-58.905	-45.690	-59.160	-	-	-	-60.072
				(48.588)	(50.042)	(48.216)				(49.559)
Earth plenty - No	-	-	-	195.912**	197.522**	175.795*	-	-	-	166.187*
				(94.160)	(94.696)	(93.551)				(93.746)
Earth plenty - Yes	-	-	-	19.293	16.949	14.302	-	-	-	-10.425
				(57.747)	(58.330)	(57.321)				(60.110)
Majority labor - I don't know	-	-	-	-	-	-	-106.341	-106.103	-103.625	-162.864
							(167.033)	(166.386)	(167.484)	(168.737)
Majority labor - Men	-	-	-	-	-	-	-76.840	-72.625	-59.228	-36.554
							(91.210)	(91.235)	(90.217)	(89.789)
Majority labor - Women	-	-	-	-	-	-	75.770**	77.497**	74.929**	73.598**
							(30.082)	(30.113)	(29.750)	(30.088)
Women risk - No	-	-	-	-	-	-	76.175	46.851	72.350	46.537
							(122.671)	(124.329)	(121.988)	(125.355)
Women risk - Yes	-	-	-	-	-	-	73.567	75.420	79.030	68.386
							(62.535)	(62.822)	(62.183)	(65.551)
Age > 35	-	35.076	33.282	21.616	21.861	21.425	27.594	27.465	26.709	17.322
		(28.256)	(27.979)	(28.195)	(28.178)	(27.929)	(28.136)	(28.126)	(27.869)	(27.785)
Age < 24	-	-6.501	-3.203	-5.388	-2.728	0.022	-3.594	-1.773	-0.623	4.876

		(43.148)	(42.910)	(43.283)	(43.315)	(42.951)	(43.130)	(43.179)	(42.745)	(42.836)
Heard CA - Yes	-	-	111.398*	-36.551	-32.632	88.197	-29.533	-23.749	104.537	86.007
			(63.755)	(33.390)	(33.488)	(64.018)	(33.157)	(33.397)	(63.629)	(64.119)
Heard CA x Env	-	-	-158.178*	-	-	-138.583	-	-	-171.433**	-142.686
			(87.330)			(87.359)			(86.803)	(86.880)
Heard CA x Soc	-	-	-254.685***	-	-	-250.436***	-	-	-245.541***	-241.600***
			(85.652)			(85.393)			(85.169)	(85.130)
Heard CA x Def	-	-	-115.640	-	-	-106.846	-	-	-114.325	-104.889
			(85.745)			(85.493)			(85.616)	(85.488)
Constant	1,547.561***	1,556.183***	1,522.553***	1,439.915***	1,453.825***	1,411.565***	1,429.293***	1,454.935***	1,392.164***	1,365.953***
	(27.613)	(46.607)	(54.782)	(92.646)	(94.707)	(92.819)	(84.183)	(89.186)	(84.831)	(105.985)
Log Likelihood	-704.785	-697.755	-692.986	-689.656	-688.304	-685.310	-691.904	-690.664	-687.525	-678.993
Chi^2	0.101 (df = 3)	14.160** (df = 6)	23.699** (df = 13)	30.358** (df = 16)	33.062** (df = 18)	39.051*** (df = 19)	25.863** (df = 15)	28.343** (df = 17)	34.621** (df = 18)	51.685*** (df = 26)
Note:										*p<0.1; **p<0.05; ***p<0.01