Estimating the Supply of Forest Carbon Offsets: A Comparison of Best-Worst and Discrete Choice Valuation Methods

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Abstract

The use of carbon markets to regulate greenhouse gasses has been promoted as a cost-effective tool to deal with global warming. These markets often encourage forest landowners to capture carbon in exchange for compensation, by using different platforms that vary in terms of contract length, penalties for withdrawal, etc. These differences in available carbon programs send signals to both consumers, and potential producers of carbon credits, which often cause confusion, price variations, and potential barriers to participation. This study uses one of the most comprehensive lists of Florida non-industrial private forest landowners to implement two different conjoint choice tasks (best worst choice and discrete choice experimentation), which offer multiple options to estimate attitudes of landowners towards different carbon programs, as well as various avenues to estimate willingness to accept. Results indicate that landowners would need between $20 to $30 acre-per-year to be positively affected by revenue, while the inclusion of penalty for early withdrawal increases cost of participation by approximately $4.45 to $10.41 acre-per-year. In addition, this study compares the performance of best worst choice with the traditional discrete choice experimentation method, and finds similar estimates of willingness to accept from both models, but disagreement with overall attribute impact estimates.

Keywords: Carbon Offsets; Best-Worst Choice; Best-Worst Scaling; Discrete-Choice Experimentation; Willingness-to-Accept

1. Introduction

When policy makers set out to develop mechanisms to reduce greenhouse gas emissions via prohibitions, pollution permits, taxes, etc., it is important to understand regional and cultural barriers, in order to design the most cost-effective program. The use of carbon markets that pay landowners to capture these gases, for example by planting trees, preventing forest degradation, or improving forest management techniques, are currently being considered by 22 U.S. states, two Canadian provinces, and six Mexican observant regions[1]. Understanding institutional barriers to these potential environmental markets (e.g., contract length, institutional trust, compensation, etc.) can lead to increased pollution reductions at optimal abatement

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[1] See Regional Greenhouse Gas Initiative, Western Climate Initiative, and Midwestern Accord

costs. Lack of available knowledge on these issues has been cited in the literature as barriers to participate in similar programs (e.g., Butterfield et al., 2005).

Cap-and-trade programs typically create such markets by allowing polluters to emit more than they are allowed, while paying others to either stop polluting or capture these gasses (for an extensive definition of cap-and-trade, please see Raymond and Shievely, 2008). In spite of past setbacks to creating a national carbon-trading program in the U.S., a recent national survey revealed that 75% of U.S. voters favor regulating carbon dioxide as a greenhouse-gas pollutant[1]. In 2010, "North America provided the second-largest sources of both supply and demand in the (global) market, with companies taking on 5.6 MtCO2e (Metric-ton carbon dioxide equivalent), just over the 4.9 MtCO2e supplied from projects in the region" (Diaz et al., 2011).

In recent years, Florida universities, cities, counties, and land managers have expressed interest in engaging carbon markets, both as producers and consumers. Since 2008, the University of Florida has purchased nearly 8,000 tons of carbon offsets from Earth Givers Inc. (a local non-profit), to spearhead the first carbon-neutral football season in NCAA history, and to have its first carbon-neutral commencement ceremony (Jacob Cravey, Executive Director of Earth Givers, personal communication, March 8th, 2011). In 2007, the City of Miami entered into a contract with the Chicago Climate Exchange to further their goal of reducing 6% of emissions by 2010, while allocating $500,000 of their 2007-08 budget to the Office of Sustainability (Acosta, 2009). Last year, the state legislature passed the "Florida is Keeping Pace: House Bill 7179," which allows for local governments to levy non-ad valorem (no value added for taxation purposes) assessments to fund qualifying improvements in energy conservation, renewable energy, and wind resistance, as well as allowing them to adopt ordinances or resolutions that provide upfront funds to cover the financial costs of these environmental improvements (Friedman and Glinn, 2010).

Florida has yet to take part in any regional cap-and-trade agreement, but there is certainly a framework in place in multiple national programs (where it is currently participating with seven land field methane capturing projects under Climate Action Reserve) to take advantage of its more than 16 million acres of forest, which according to Mulkey et al. (2008), can potentially yield $139.6 million to producers[2].

In this study, in partnership with the Florida Forest Stewardship Program, we characterize the guiding structure of carbon production in Florida, by identifying barriers to participate in a hypothetical carbon-offset program, and estimating willingness-to-accept (WTA).

In addition, this research makes a marginal contribution to the measurement of best-worst scaling (BWS), by applying and comparing an innovation introduced by Coast et al. (2006), best-worst choice (BWC), with the conventional discrete choice experiment (DCE) method (see Louviere et al. 2000). The limitation of BWS with regard to the estimation of willingness-to-pay (see Louviere and Islam, 2008) has been somewhat circumvented in the field of applied economics by implementing both BWS and DCE tasks in a single survey (e.g., Lusk and Parker, 2009). This approach is very likely to increase both choice task complexity and survey length. BWC may solve this problem, by asking respondents to perform two tasks: 1) select a best and a worst attribute from a profile, and 2) to accept or reject the scenario as a whole (see Figure 2).

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[1] Zabanko, Deborah (2012) U.S. voters favor regulating carbon dioxide: survey. Chicago Tribune, April 26, 2012.

[2] These estimates were done using $20 per tonne CO2 equivalent and do not reflect costs of creation and maintenance of mitigation projects.

Preliminary results indicate that non-industrial private forest landowners in our study are more influenced by carbon-offset revenue, than penalty for early withdrawal, and contract duration. Carbon-market programs that offer compensations $20 or $30 acre-per-year have a positive impact on participation, while $5-$10 are less favored. The least desirable component of our study seems to be a contract commitment of 100 years. A program with this duration would elicit an increase in cost of participation of $29.81 to $37.78 acre-per-year. As expected, BWC was able to approximate most of the WTA values of DCE, but with a slight over estimation.

2. Background

Florida landholders have three major national options to engage carbon markets: Climate Action Reserve (CAR), American Carbon Registry (ACR), and Voluntary Carbon Standard (VCS). These are non-profit carbon offset certification programs that slightly differ in protocol requirements, but encompass similar types of forest-offset activities. The programs have commitment periods that range from 40 to 100 years (ACR 40, VCS 20-100, CAR 100), and compensations range from $2.50 to $30 per ton of carbon-dioxide equivalent (see Charnley et al., 2010). Risk from intentional or unintentional (i.e. natural disaster) reversals is managed by instituting a series of accountability measures, such as, allowing participants to propose insurance products (ACR), carbon buffer pools (ACR, VCS, CAR), and in some cases a buy-out option (ACR).

Buffer tools are used by programs to “pool” or spread the risk of reversals among all registered producers, similar to insurance. They work by allowing project managers to deposit a percentage of offsets (similar to insurance premiums) into an account controlled and managed by the program. The pool of offsets is used to cover carbon losses from unexpected events (e.g., wildfires).

A number of recent empirical studies have explored some of the institutional aspects of carbon markets in North America (see Table 1). In a 2000 survey of 2,000 randomly selected farmers of northeastern British Colombia, Alberta, Saskatchewan, and Manitoba, Shaikh et al. (2007), used a discrete-choice random utility model to elicit WTA bids of a hypothetical Western Canadian carbon program to afforest marginal agricultural land. The bids offered participants a tree-planting program with a 10-year duration, no monitoring, establishment, or management costs, annual compensations that ranged from $1-60 acre per year (bid levels were selected from a pilot study), and the option for ownership of all trees after the end of the program. Participants were asked to provide a “yes”/”no” response, which resulted in 45% accepting the bid, with 13% of surveys fully completed (260 observations). Price (bid) was the only varying factor in their surveys, which were randomly sent to different participants. The study illustrated various demographic, cultural, and social factors (soil, education, visual landscape appeal, etc.) influencing participation, and estimated WTA bids, but only within confounds of the particular institutional structure mentioned above (to see the exact wording of this hypothetical question, please see the Appendix section of Shaikh et al. (2007)). The average WTA estimates to get farmers to plant blocks of trees was $33.59/acre.

Fletcher et al. (2009) did a similar study in 2007, using a pilot survey of 17 private landowners (randomly selected from a list of landowners who owned 3 or more parcels, each participant was compensated with $50) from Massachusetts, to also elicit the likelihood of producing carbon offsets. Participants were surveyed on socioeconomic questions, management activities, reason's for owning land, but also asked to rate (1-10, 10 being the better option) six alternative carbon credit programs with four varying institutional attributes:

eligibility (formal management plan or no plan), time commitment (5 or 10 years), expected payment ($5, $15, or $30) acre-per-year, and penalty for withdrawal (none or $10 per acre). All options required project verification by a professional forester. Their results using a Tobit model indicate that ratings increase with expected payment and commitment length, but decrease with penalty for withdrawal. Logit estimates of WTA were about 5% with $15, 13% at $30, and 33% at $50. While this study was limited by its pilot study nature, it innovated carbon market research by exploring WTA in the context of different institutional arrangements.

The Texas Forest Service conducted a similar survey in 2009 (Li, 2010), of non-industrial Texas landowners, exploring WTA at different levels of contractual duration. Participants of this study (20% survey response rate, which resulted in 1,032 observations) were presented with the following question, "would you ever consider selling environmental credits generated from your forestlands?" and if answered yes, a hypothetical carbon program was presented, otherwise, they skipped this part, and were taken to a section where they rated factors that would prevent them from selling environmental credits. The hypothetical program consisted of a contract with three different time commitment levels, each with a different annual per acre compensation (annual at $8, 5-years at $9, and conservation easement status for $10), to sell environmental credits, with an option for timber harvesting, as long as it generated additional credits (see Appendix A of Li (2009) for exact survey form). Factors affecting participation were analyzed using a Logit model, which seem to suggest that awareness of carbon credits, size of forest landownership, current cost-share participation, and importance of managing forestland for producing income and WTA was estimated using the Contingent Valuation (CV) method.

Methodologically, Shaikh et al. (2007) and Li (2010) are the closest related to this study, by postulating a hypothetical carbon-market scenario, and asking respondents to either accept or reject it (see Figure 2). The ratings method used by Fletcher et al. (2009) is similar to our use of BWC, in the sense that both are ordinal in nature, but differ in terms of choice task (see Figure 2). In addition to using BWC, we used a discrete-choice experimentation (DCE) model to assess the performance of BWC, and to use as external validity of WTA estimates (see Louviere and Islam, 2008).

The majority of attributes in Table 1 were explored in this paper (see Table 3), but using levels that closely resemble the requirements of current available carbon certification programs in the U.S. (CAR, VCS, ACR). Namely, "Time" was chosen to range 5 to 100 years, and participants were offered to choose between different "Risk Tools" (see Table 3).

Table 1
Empirical studies on willingness to participate in hypothetical carbon offset markets in North America

Reference	Method	Data	Attribute	Levels
Shaikh et al., 2007	Discrete-choice, random utility model (accept/reject)	Western Canadian carbon program (n=260)	Revenue Time	Bids ranging from $1-60 acre-per-year 10 years
Fletcher et al., 2009	Ratings (1 to 10)	Massachusetts Pilot study of randomly selected private landowners (n=17)	Eligibility Revenue Penalty for withdrawal	Formal Plan, No Plan $5, $15, or $30 acre-per year No Penalty, $10 per-acre
Li, 2010	Discrete- choice, contingent valuation (accept/reject)	Texas non-industrial private landowners (n=1,032)	Time Revenue	1 year, 5 years, and conservation easement status $8, $9, or $10 acre-per-year

3. Models for attitudes and willingness-to-accept

To choose the most appropriate discrete choice experiment model to estimate the traditional marginal WTA values, Louviere at al. (2000) advise researchers to consider the following design objectives: identification, precision, cognitive complexity, and market realism. Our research simulates market realism, by using BWC (e.g. Coast et al., 2006), and a DCE (see Figure1) with multiple profile options (e.g. Lusk and Parker, 2009). BWC produces binary-choice data, that we interpret as discrete choice experimentation to estimate WTA (please see the second task of Figure 2).

As noted in Ohler et al. (2000), "conjoint experiments rarely use binary response tasks, (but) many consumer decisions are binary (e.g., category or brand consideration, buy now or wait, etc), and binary tasks are fairly easy, (and) consistent with economic demand theory ("no's" reject options)." But, in regards to market realism, the current reality of carbon markets in the U.S. have multiple certification options (e.g. American Carbon Registry Climate Action Reserve, Verified Carbon Standard) that vary in terms of duration, risk options, etc. These real options might be better simulated by a DCE. For example, in the case of time commitments (up to 100 years), a landowner in Florida seeking carbon offset certification via one of the currently available options, would likely research or hire a consultant that will offer a cross comparison analysis of ACR, CAR, VCS and/or other program protocols, delineating the differences in attributes. Landowners would either choose one or none (maintain the status quo). DCE closely mimics this task by offering two or more options to participants, who are instructed to select one or none; whereas Binary presents conjoint options that are either accepted or rejected. It may be argued that a national carbon market program would homogenize all options by offering a single protocol, but even in that scenario, our analysis might still hold market realism, given that there may be other options to certify with international (e.g. Clean Development Mechanism), state (e.g. California AB-32), or private programs (e.g. Chicago Climate Exchange).

Figure 1
Example of Discrete-Choice Experimentation Question Presented to Survey Respondents

Of the Non-Government Carbon-Credit Programs below, which would you choose to participate in?
(Please check only <u>one</u> of the four options below)

Risk Pool	Insurance	Risk Pool	None of these
No Penalty for Withdrawal	Penalty for Withdrawal	Penalty for Withdrawal	
$5 acre-per-year	$10 acre-per-year	$20 acre-per-year	
40 year contract	100 year contract	5 year contract	
☐	☐	☐	☐

Figure 2
Example of Best-Worst Choice Question, used to estimate Best-Worst Scaling and Binary Models

Non-Government Carbon-Credit Program
(Check one option as the most important and one option as the least important)

Most Important		Least Important
☐	Risk Pool	☐
☐	No Penalty for Withdrawal	☐
☐	$5 acre-per-year	☐
☐	40 year contract	☐

Would you enroll in this program? Yes ☐ No ☐

3.1 Best-Worst Choice

For the past two decades, economists working on environmental issues have been using methods known as stated preferences, conjoint analysis, and attribute based methods. These techniques used for non-market valuations, typically require participants to rank, choose, or rate a particular scenarios of attributes on a given scale (e.g. Foster and Mourato, 2002; Elrod et al., 1992; Fletcher et al., 2009). A relatively new innovation in scaling methods (best-worst) introduced by Finn and Louviere (1992), is currently gaining popularity in the fields of marketing-business, health, and applied economics (e.g. Marley et al., 2008; Flynn et al., 2008; Lusk and Briggeman, 2009). The approach consists of creating profiles of different attribute levels, and asking participants to choose a "most important" and a "least important" option (see Flynn et al., 2006). This tool measures the maximum-difference between attribute-levels, while offering an alternative over some of the shortcomings of the previously mentioned methods.

Best-Worst Choice was first implemented by Coast et al. (2006), and is one of the most recent innovations in the field of BWS. This model can be interpreted as a single profile choice model, and it works by constraining all attributes to have a represented level in each profile, and to include a second instruction, asking participants to choose to "accept" or "not accept" a particular profile (e.g. Coast et al., 2006).

The characterization of properties for this model were derived by Marley et al. (2008), where they also propose an empirical design that may allows for the separation of "importance" and "utility."

$$\mathrm{BWz(Zi,Zj)} = \frac{\tilde{b}(z_i)^{\beta_i} / \tilde{b}(z_j)^{\beta j}}{\sum_{k,\ell \notin M, k \neq \ell} [\, \tilde{b}(z_k)^{\beta_k} / \tilde{b}(z_\ell)^{\beta \ell}]} \quad i \neq j \qquad (1)$$

Equation 1 from Marley et al. (2008) is the estimation of a BWS paired of "importance," where Zi and Zj are a chosen best-worst pair, and Zk and Z_ℓ are other pairs within **M**. The influence of the judgment can show up in the utility value $\tilde{b}(z_i)$, the weight β_i, or both. BWS (without the Binary task) measurements come from Equation 2, which observes $b(z_i) = \tilde{b}(z_i)^{\beta_i} / \tilde{b}(z_j)^{\beta j}$.

$$\text{BWz(Zi,Zj)} = \frac{b(z_i) \ / b(z_j)}{\sum_{k,\ell \notin M, k \neq \ell} [\ b(z_k) \ / b(z_\ell)\ ]} \quad i \neq j \qquad (2)$$

As seen in Figure 2, BWC attempts to capture BWS behavior as well as binary-choice data of an entire profile of attributes; we can observe utility values from the latter, and BWS weights from the former. The utility component of this model is of particular importance to applied economists, given that it allows for the conventional estimation of one the most widely used measurements, willingness-to-pay or WTA.

This method is estimated with two models, namely, the first task (BWS from now on) of choosing a "most important" and "least important attribute level is estimated using the tools of BWS, and the second task (Binary from now on) of "enrolling" or "not enrolling" in the carbon-credit program can be estimated using a binary logit, or random effects logit (e.g. Coast et al., 2006). There are multiple ways to estimate BWS, but these generally fall into two categories: "paired" estimation, which uses best-worst pairs, and "marginal" models that use attribute level observations (see Flynn et al., 2006). The latter is an approximation of the former, and it may lead to larger standard errors. This paper uses Paired estimation for BWS and random effects logit for Binary. An orthogonal main effects plan (OMEP) taken from "Table 9" of Street et al. (2005) was used to construct this survey, which resulted in 16 BWC scenarios (see Flynn et al., 2006).

3.2 Discrete-Choice Experimentation

Discrete-Choice Experimentation was first introduced by McFadden (1974), and it is amongst the most widely used methods of stated preference elicitation (e.g., Lusk and Parker, 2009; Lancsar et al., 2007). Multiple fields, and a significant amount of studies have vetted this model, and when compared with real choices, the model has been found to estimate results with a high degree of preference regularity and accuracy (see Louviere et al. (2000) for a literature review of comparative studies). A number of comparative studies of conjoint models have used it for external validation (e.g., Louviere and Islam 2008; Elrod et al., 1992).

As seen in Figure 1, DCE models consist of several choice sets, each containing two or more options, where participants are asked to choose one (see Louviere et al., 2000). We constructed choice sets of size three, with a "status quo" option, following the guidelines of Strategy 6 in Street et al. (2005). This strategy uses an OMEP to create the first choice of each set, followed by systematic changes to the levels of attributes to create the remaining choices. Given that Street et al. (2005) had created an optimal design with the attributes and levels of our desired model, we simple took their example in "Table 9" of this paper to create our choice sets. This resulted in 16 questions, each with four choices (see Figure 1).

3.3 Best-Worst Choice vs. Discrete-Choice Experimentation

This study uses DCE for external validity, and performs a cross-validation/comparison of BWC. There are certain aspects of the latter model that may provide more accurate estimates. Both models elicit tradeoffs between attributes/features, which reflect real market decisions, but BWS is easier to implement (Louviere and Islam, 2008), and the same may be true of BWC.

To the best of our knowledge, this study is the first comparative study of BWC and DCE. Louviere and Islam (2008) did a similar comparative study of BWS importance weights, and DCE willingness-to-pay (WTP) estimates. They used "most important" and "least importance" frequencies to estimate BWS importance, and a binary response DCE model for external validity. Their results indicated low correlations between BWS estimates and marginal WTP. Our study uses a different DCE model for external validity, which includes more choices, and is more common in the field of applied economics. The BWS estimation of BWC is also performed differently, using a paired model conditional logit, which allows for inferences about the effects of respondent-level covariates (see Flynn et al., 2008). This paper also compares the marginal WTA estimates of BWC-Binary and DCE. The separation of "importance" and "utility" mentioned in section 3.4 is not address in this paper, but is the subject of upcoming research.

4. Data

4.1 Data sources

The electronic surveys were administered to members of the Florida Stewardship Program[1] (FSP). One of the most comprehensive non-industrial private landowner lists in the state (see Pancholy et al., 2009). This subpopulation (over 900 members) of Florida landowners is an ideal representation of private managers, for they are highly motivated, versed in forest management techniques and barriers, organized into a reliable extension network, and likely be to the group who would seriously consider taking advantage of a forest carbon offset market. We are currently in the process of collecting data from 700 members of the Tree Farm System in Florida.

Following the guidelines of Dillman et al. (2009), some key questions from the National Woodland Owners Survey[2] (NWOS) were adopted, in order to compare the characteristics of our subpopulation of forest landowners, to those of the most representative statewide forest landowners survey. The NWOS is carried out as part of the USDA, with the goal of characterizing the private forest landowners of the U.S. They follow Dillman (2001), and randomly select a portion (10-20%) of the full sample of private owners in each state. Surveying private landowners including forest industry companies, partnerships, tribes, families, and individuals. (Butler and Leatherberry, 2004) Florida is currently being surveyed by NWOS. See Table 2 for a comparison our survey respondent demographics with those of 2002-2006 NWOS survey.

4.2 Choices and variables in the model

The general guidelines in Ch.9 of Louviere et al. (2000) for stated preference choice modeling were used to develop our choice tasks. The attributes and levels for this study were selected from a qualitative research on features in currently available carbon-offset programs (e.g., Climate Action Reserve, American Carbon Registry, etc.), similar studies (e.g., Fletcher et al., 2009), and nine phone interviews with FSP members. A similar approach was taken to

1 http://www.sfrc.ufl.edu/Extension/florida_forestry_information/additional_pages/forest_stewardship_program.html
2 http://www.fia.fs.fed.us/nwos/quest/

select demographic and personal questions. These efforts were followed by the implementation of a pilot data collection instrument that was tested for performance and accuracy. The final survey was electronically implemented following the aesthetic and procedural recommendations of Dillman et al. (2009).

Table 2
Characteristics of Survey Respondents

Category	NWOS[b] (n=4900)	BWC (n=88)	DCE (n=83)
Under 35 years	1.65%[a]	0.00%	1.11%
35 to 44 years	7.10%	3.37%	6.67%
45 to 54 years	18.04%	31.46%	21.11%
55 to 64 years	28.69%	31.46%	40.00%
65 to 74 years	21.14%	20.22%	24.44%
75+ years	19.29%	8.99%	5.56%
Less than 12th grade	7.76%	0.00%	2.22%
High school graduated or GED	16.08%	2.25%	6.67%
Some College	16.61%	10.11%	6.67%
Associate or technical degree	9.76%	12.36%	13.33%
Bachelor's degree	19.96%	35.96%	40.00%
Graduate degree	23.18%	35.96%	30.00%
Female	14.47%	17.98%	15.91%
Annual HH income less than $25,000	10.90%	2.25%	2.22%
Annual HH income $25,000 to $49,999	17.84%	11.24%	10.00%
Annual HH income $50,000 to $99,999	22.84%	31.46%	31.11%
Annual HH income $100,000 to $199,999	14.45%	20.22%	24.44%
Annual HH income $200,000 or more	18.71%	7.87%	7.78%
1-9 acres	18.49%	3.82%	3.85%
10-49 acres	22.71%	18.32%	18.46%
50-99 acres	6.71%	17.56%	18.46%
100-499 acres	33.53%	31.30%	29.23%
500-999 acres	10.80%	8.40%	10.77%
1000-4999 acres	3.94%	8.40%	3.08%
5000+ acres	3.80%	12.21%	16.15%
Home <1 mile from their forestland	47.14%	37.50%	42.53%

[a] Percent of respondents falling in the respective category
[b] National Woodland Owners Survey results for Florida

Table 3
Attributes and attribute levels in Discrete-Choice Experimentation and Best-Worst Choice

Attribute	Definition	Levels
Risk Tool	Options for risk reduction in forest project	Insurance Risk Pool
Penalty	Fines for leaving the program early	No Penalty Penalty
Time	Commitment period	5-years 10-years 40-years 100-years
Revenue	Carbon-credit payments of acre-per-year, after costs	$5 $10 $20 $30

5. Results

5.1 Estimation results

A total of 191 surveys were completed, which implies a 24% response rate. After accounting for filter questions, and participants who did not provide full answers to all demographic questions, our sample size was reduced to 171 (88 with a BWC task, and 83 with DCE). Issues of sampling bias and other considerations are currently being analyzed, along with further data collection. All WTA estimates for DCE and Binary are marginal estimates, namely, the ratio of the attribute's marginal effects coefficient to the price coefficient, with units of dollars per choice.

Table 4 presents the results of three estimations of DCE. Model 1 uses effects coding for all variables, Model 2 quantitatively codes "Revenue," and Model 3 quantitatively codes "Revenue" and "Time." Effects coding works by coding all, except one (base level), with a 0 if absent, 1 present, and -1 if the base level is present. The base level then corresponds to the negative sum of the estimates of all other levels of the given attribute. These models were estimated using a multinomial logit model (Louviere et al., 2000), and adjusted to represent the population of landowners in Florida (e.g., Lusk and Parker, 2009). Namely, population weights were created using all the demographic variables in Table 2, by implementing iterative proportional fitting techniques. This practice is common in survey research and it works by forcing the sample proportions to match those of the population (NWOS in our case). The last two columns display marginal WTA estimates for models 2 and 3.

The results in Table 4 are very robust in terms of significance and expected signs. The coefficient of "Insurance" is negative, but loses significance in models 1 and 2. This reflects a preference for the use of "Risk Pool" to manage project uncertainty. As anticipated, "Penalty" is negative and significant at a 1% level for all models, and elicits the second highest increase in WTA for Model 2 and the highest for Model 3. This indicates that the inclusion of "penalty for withdrawal" would require an increase of $7.24 acre-per-year in compensation for Model 2 and $4.45 in Model 3. Model 1 shows a negative and significant relationship of the lower two levels of compensation ($5 and $10), and positive and significant for the $20 and $30. The highest association with "Revenue" came from "$30 acre-per-year." Models 1 and 2 reveal a significant association of all "contract duration" levels, with positive coefficients for the lowest three levels (5, 10, and 40 years), and negative for a "100 years contract." The WTA estimates of Model 2, show the same relationship in terms of sign, and estimate an increase in compensation cost of $37.78 acre-per-year to include a commitment period of 100 years. The inclusion of all other time commitments would elicit a decrease in WTA of $12.51, $11.13, and $14.14, for 5, 10, and 40 years, respectively.

Table 5 shows landowner WTA compensation to switch between attribute levels, as well as "order of impact" for DCE Model 2. Order of impact was used by Lancsar et al. (2007) to compare attribute impacts of various methods of estimating a discrete choice experimentation model. The order is determined by the absolute value of column 2, which means that the higher the order of impact, the higher the absolute WTA difference between attribute levels. This table shows that it would require a $51.92 acre-per-year compensation to have a landowner switch from a program that has a "40 year contact" to one with 100 years. Participants of a "10 year contact" would give up $3.01 acre-per-year in compensation to move to a "40 year contract." Moving to a carbon program with "no penalty" for withdrawal would elicit a decrease in compensation cost of $14.49 acre-per-year.

Table 4
Results from Discrete-Choice Experimentation: Multinomial Logit Model Estimations

Attribute	Model 1: All effects coded	Model 2: Revenue quantitative	Model 3: Revenue & Time quantitative	WTA: Model 2	WTA: Model 3
Insurance	-0.07***[a] (0.04)[b]	-0.07** (0.03)	-0.13* (0.04)	$1.93	$1.91
Risk Pool	0.07[e]	0.07[e]	0.13[e]	-$1.93	-$1.91
No Penalty	0.28* (0.04)	0.27* (0.03)	0.30* (0.04)	-$7.24	-$4.45
Penalty	-0.28[e]	-0.27[e]	-0.30[e]	$7.24	$4.45
Revenue Quantitative		0.037* (0.00)	0.07* (0.00)		
Time Quantitative			-0.03* (0.00)		$0.45
$5 acre-per-year	-1.33[e]				
$10 acre- per-year	-0.42* (0.08)				
$20 acre- per-year	0.45* (0.06)				
$30 acre- per-year	1.30* (0.06)				
5 year contract	0.60[e]	0.47[e]		-$12.51	
10 year contract	0.51* (0.07)	0.41* (0.06)		-$11.13	
40 year contract	0.58* (0.07)	0.53* (0.06)		-$14.14	
100 year contract	-1.70* (0.11)	-1.41* (0.09)		$37.78	
Number of Respondents	83	83	83		
Number of Choices	5312	5312	5312		
Log Likelihood	-1281.77	-1500.08	-1382		
Chi-Square Statistic[c]	1118.46	681.84	916.06		

[a] One (*), two (**), and (***) asterisk represent 0.01, 0.5, 0.10 level of statistical significance, respectively.
[b] Number in parentheses are standard errors.
[c] Chi-square statistic associated with a test of the hypothesis that all model parameters are zero.
[e] Effects coding: negative sum of the above level scale values corresponding to this attribute.

Table 5
Differences in Marginal Willingness–to-Accept ($/choice) for DCE (Model 2) estimates

Attribute	Difference in WTA	Absolute value	Order of impact
WTA to go from Insurance to Risk Pool	$3.87	3.87	3
WTA to go from No Penalty - Penalty	$14.49	14.49	4
WTA to go from a 5 to 10 year contract	$1.39	1.39	1
WTA to go from a 10 to 40 year contract	-$3.01	3.01	2
WTA to go from a 40 to 100 year contract	$51.92	51.92	5

BWC was estimated with two models, BWS and Binary. Table 6 presents the results of the binary component of BWC, which asks respondents to “accept” or “reject” a hypothetical carbon offset program (see Figure 2). The three models in this table were estimated using random effects logit to adjust for clustering of individuals’ responses (e.g. Coast et al., 2006). An effort was made to adjust the model to represent the population of landowners in Florida, using the same approach described in the previous model, but the estimations were drastically changing in sign and significance. We suspect that this underperformance was due to a low number of observations, or an insufficient representative sample. DCE has more choices per profile, and hence, more number of choice observations (four times the number of choices). As seen in Table 2, the BWC has does not have respondents under “35 yrs old,” or the “under 12th grade education” categories, which may also be affecting the use of these weights. Given that we are in the process of increasing our sample size by at least 300 new participants, this adjustment was suspended, and will be revisited in the near future.

Table 6 presents the preliminary results of three Binary models with the same coding used for DCE (Table 4). These estimates are similar in terms of sign and significance to the results of DCE from Table 4, safe for the attribute "risk tool," which is insignificant. The magnitudes of most coefficients in this table are higher than those of their DCE counterparts. "Penalty" carries the same interpretation given for Table 4, but the WTA was estimated higher for models 2 and 3, at $3.17 acre-per-year, and $5.95 acre-per-year respectively. The coefficient "40 year contract" switches sign in this model and the magnitude of WTA for Model 2 also is higher. The attribute with the highest WTA estimate is also "100 year contract" for Model 2, but slightly lower at $29.81acre-per-year. The most preferred, or lowest WTA estimate in Model 2 is "5 year contract," whereas DCE estimated this attribute level to be the second lowest in terms of WTA. As seen in Figure 3, WTA estimates for both Binary and DCE seem to correlate, but the most drastic difference in WTA came from "40 year contract," which has a relatively similar magnitude, but with opposite sign.

Table 6
Results from Binary Choice Model: Random Effects Model Estimations

Attribute	Model 1: All effects coded	Model 2: Revenue quantitative	Model 3: Revenue & Time quantitative	WTA: Model 2	WTA: Model 3
Insurance	0.02 (0.09)	0.02 (0.08)	-0.02 (0.08)	-$0.31	$0.49
Risk Pool	-0.02[e]	-0.02[e]	0.025[e]	$0.31	-$0.49
No Penalty	0.71*[a] (0.10)[b]	0.59* (0.09)	0.54* (0.08)	-$10.41	-$10.40
Penalty	-0.71[e]	-0.59[e]	-0.54[e]	$10.41	$10.40
Revenue Quantitative		0.057* (0.01)	0.05* (0.01)		
Time Quantitative			-0.03* (0.00)		$0.63
$5 acre-per-year	-0.31[e]				
$10 acre- per-year	-1.28* (0.18)				
$20 acre- per-year	1.11* (0.15)				
$30 acre- per-year	0.48* (0.16)				
5 year contract	2.05[e]	1.88[e]		-$33.00	
10 year contract	0.90* (0.15)	0.75* (0.14)		-$13.19	
40 year contract	-1.03* (0.16)	-0.93* (0.15)		$16.38	
100 year contract	-1.92* (0.19)	-1.70* (0.17)		$29.81	
Constant	-0.08 (0.42)	-1.00** (0.40)	1.22* (0.37)		
Number of Respondents	88	88	88		
Number of Choices	1408	1408	1408		
Log Likelihood	-540.26	-567.87	-595.05		
Chi-Square Statistic[c]	202.20	204.53	179.22		

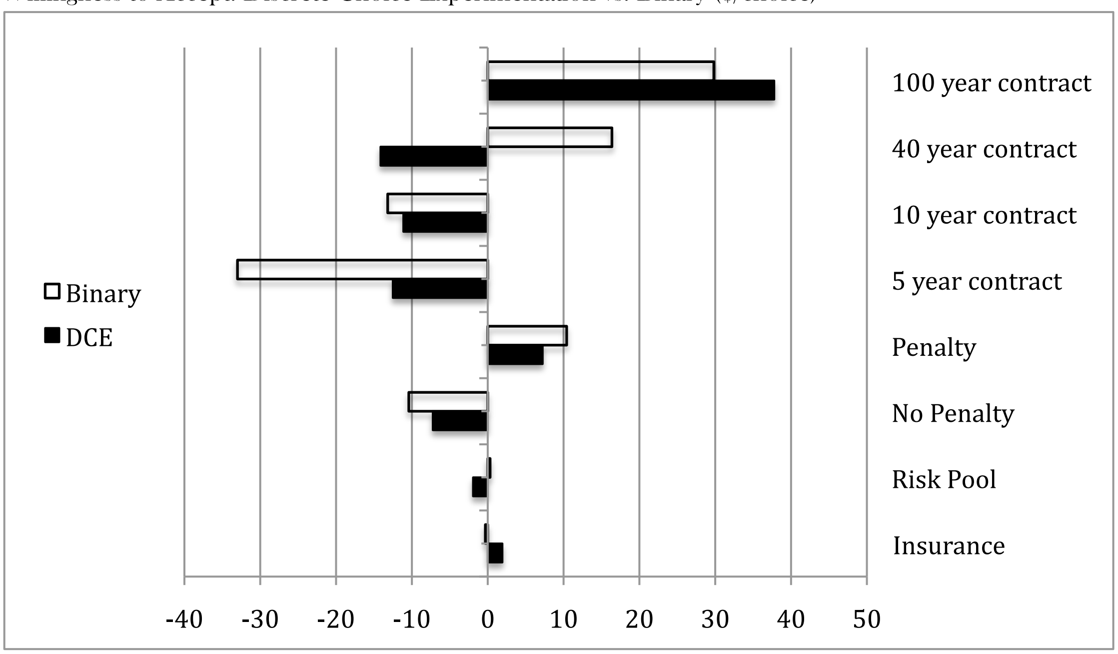
[a] One (*), two (**), and (***) asterisk represent 0.01, 0.5, 0.10 level of statistical significance, respectively.
[b] Number in parentheses are standard errors.
[c] Chi-square statistic associated with a test of the hypothesis that all model parameters are zero.
[e] Effects coding: negative sum of the above level scale values corresponding to this attribute

Table 7 makes the same analysis of WTA estimates and "order of impact" for Binary Model 2, seen in Table 5. These estimates are significantly different than those of DCE. The magnitudes are higher, and the order of impact is different. For these estimates, it would require a $13.43 acre-per-year compensation to have a landowner switch from a program that has a "40 year contact" to "100 years contract," whereas DCE estimates this to be $51.92 acre-per-year. The most drastic change came from the WTA required to have participants switch from a "40 year contract" to a "10 year contact," which went from $3.01 acre-per-year in DCE, to $29.57 acre-per-year. This model indicates that moving to a carbon program with "no penalty" for withdrawal would elicit a decrease in compensation cost of $20.82 acre-per-year.

Table 7
Differences in Marginal Willingness–to-Accept ($/choice) for Binary (Model 2) estimates

Attribute	Difference in WTA	Absolute value	Order of impact
WTA to go from Insurance to Risk Pool	-$0.63	0.63	1
WTA to go from No Penalty – Penalty	$20.82	20.82	4
WTA to go from a 5 to 10 year contract	$19.81	19.81	3
WTA to go from a 10 to 40 year contract	$29.57	29.57	5
WTA to go from a 40 to 100 year contract	$13.43	13.43	2

Figure 3
Willingness to Accept: Discrete-Choice Experimentation vs. Binary ($/choice)



The "most preferred" and "least preferred" choice task of BWC (see Figure 2) was estimated using paired estimation, which fits the data to a clogt model, and allows to adjust for covariates (see Flynn et al., 2006). Given that our OMEP was unbalanced, namely, not all best-worst pairs were equally available for selection (see Table 9 of Street et al., 2005), we adjusted for this bias using the guidelines provided by Flynn et al. (2006). The adjustment is performed by a two step process: 1) dividing each of the best-worst pairs, by the number of times it was available to be in across all scenarios and individuals (availability total); 2) multiplying this string of numbers by one of the availability totals. All attributes were effects coded, according to Flynn et al. (2006).

Table 8
Results from Best-Worst Scaling: clogit estimates adjusting for covariates

Attribute impacts	Coefficient	Rank
Time	0 (reference)	1
Risk Tool	0.63*[a] (0.05)[b]	3
Penalty	0.42* (0.05)	2
Revenue	3.34* (0.05)	4
Age * Risk Tool	0.13* (0.00)	
Age * Penalty	0.04* (0.01)	
Age * Revenue	0.07* (0.01)	
Education * Risk Tool	-0.34* (0.01)	
Education * Penalty	-0.12* (0.01)	
Education * Revenue	-0.33* (0.01)	
Male * Risk Tool	-0.22* (0.01)	
Male * Penalty	-0.23* (0.01)	
Male * Revenue	-0.14* (0.01)	
Income * Risk Tool	0.05* (0.00)	
Income * Penalty	-0.03* (0.00)	
Income * Revenue	0.05* (0.00)	
Acres * Risk Tool	-0.00* (0.00)	
Acres * Penalty	-0.00* (0.00)	
Acres * Revenue	-0.00* (0.00)	
NGO * Risk Tool	-0.01*** (0.00)	
NGO * Penalty	-0.01 (0.01)	
NGO * Revenue	-0.23* (0.01)	
Level Scale Values	**Coefficient**	
Insurance	-0.25* (0.04)	
Risk Pool	0.25[e]	
No Penalty	1.28* (0.04)	
Penalty	-1.28[e]	
$5 acre-per-year	-0.11[e]	
$10 acre- per-year	-0.69* (0.08)	
$20 acre- per-year	0.63* (0.08)	
$30 acre- per-year	0.16*** (0.09)	
5 year contract	0.61[e]	
10 year contract	0.85* (0.07)	
40 year contract	-0.80* (0.07)	
100 year contract	-0.67* (0.07)	
Age * Insurance	-0.08* (0.01)	
No Penalty	-0.07* (0.00)	
Age * $10 acre- per-year	0.02*** (0.01)	
Age * $20 acre- per-year	-0.08* (0.01)	
Age * $30 acre- per-year	-0.01 (0.01)	
Age * 10 year contract	0.08* (0.01)	
Age * 40 year contract	-0.06* (0.01)	
Age * 100 year contract	-0.07* (0.01)	
Education * Insurance	0.08* (0.01)	
Education * No Penalty	-0.04* (0.01)	
Education * $10 acre- per-year	0.01 (0.01)	
Education * $20 acre- per-year	0.03** (0.01)	
Education * $30 acre- per-year	0.07* (0.01)	
Education * 10 year contract	-0.15* (0.01)	
Education * 40 year contract	0.07* (0.01)	
Education * 100 year contract	0.15* (0.01)	
Male * Insurance	0.08* (0.01)	
Male * No Penalty	-0.07* (0.01)	
Male * $10 acre- per-year	0.05** (0.02)	
Male * $20 acre- per-year	0.06* (0.02)	
Male * $30 acre- per-year	0.04*** (0.02)	
Male * 10 year contract	-0.12* (0.02)	
Male * 40 year contract	0.08* (0.02)	
Male * 100 year contract	0.34* (0.02)	
Income * Insurance	0.01** (0.00)	
Income * No Penalty	-0.03* (0.00)	
Income * $10 acre- per-year	0.00 (0.01)	
Income * $20 acre- per-year	0.02* (0.01)	
Income * $30 acre- per-year	-0.03* (0.01)	
Income * 10 year contract	-0.09* (0.01)	
Income * 40 year contract	0.01 (0.01)	
Income * 100 year contract	0.05* (0.01)	
Acres * Insurance	0.00* (0.00)	
Acres * No Penalty	-0.00** (0.00)	
Acres * $10 acre- per-year	-0.00** (0.00)	
Acres * $20 acre- per-year	0.00* (0.00)	
Acres * $30 acre- per-year	0.00 (0.00)	
Acres * 10 year contract	-0.00* (0.00)	
Acres * 40 year contract	0.00* (0.00)	
Acres * 100 year contract	0.00* (0.00)	
NGO * Insurance	0.02* (0.00)	
NGO * No Penalty	-0.07* (0.00)	
NGO * $10 acre- per-year	0.04* (0.01)	
NGO * $20 acre- per-year	-0.02** (0.01)	
NGO * $30 acre- per-year	-0.06* (0.01)	
NGO * 10 year contract	-0.00 (0.01)	
NGO * 40 year contract	0.17* (0.01)	
NGO * 100 year contract	-0.01 (0.01)	
Number of Respondents	88	
Number of Choices	16896	
Log Likelihood	-144107.84	
Chi-Square Statistic[c]	103087.88	

[a] One (*), two (**), and (***) asterisk represent 0.01, 0.5, 0.10 level of statistical significance, respectively.
[b] Number in parentheses are standard errors.
[c] Chi-square statistic associated with a test of the hypothesis that all model parameters are zero.
[e] Effects coding: negative sum of the above level scale values corresponding to this attribute.

Table 8 provides two categories of estimates, “impact” values and “scale values.” Impact values are the average utility for the given attribute across all its levels, and scale values are the estimations of attribute levels. In accordance with common practice, a full model was estimated to identify the attribute with the lowest impact (Time), in order to omit it from the final model, and use it as the reference case. These results were estimated on the same latent scale, where “Time” is the reference point. We have assigned “Time” to equal 0, in order to allow for a more intuitive understanding of the estimates. A negative sign on a coefficient does not imply a negative relationship with the dependent variable, but that it lays to the negative side of the reference case, under a common underlying scale. For example, the impact attribute “Revenue” has a value of 3.34, which means that the average utility across all levels of this attribute is higher than the average utility across all levels of “Time.”

Given that respondent level data does not vary for potential best-worst pairs, these covariates were interacted with choice outcomes, in order to provide variation to individual characteristics (e.g. Flynn et al., 2008). The use of covariates still allows for impact and scale values to be interpreted as averages across the entire sample. The interactions represent the additional utility that the particular demographic experiences for the given attribute or level. The preliminary model in Table 8 was evaluated using other covariates, such as “home <1 mile from their forest land,” but they were found insignificant in most interactions with choice outcomes, and thus excluded from the final model. The “NGO” covariate found in this table, represents an institutional trust proxy created from a demographic question that asked respondents “how important is it to have a non-governmental carbon-credit program rather than a governmental carbon-credit program.” It has five levels (1-5), and it takes a value of 1 if the answer was “very unimportant,” and 5 if “very important.”

All of the choice outcomes in Table 8 where significant to a 1% level, safe for “$30 acre-per-year,” which was significant at the10% level. Only five of the covariate interactions were insignificant to a 10% level. “Revenue” is the most highly valued attribute, followed by “Risk Tool,” which is slightly more valued than “Penalty.” “Time” was the least valued. The average effects of attribute levels indicate similar preferences found in the previous models. That is, “Risk Pool” has a higher importance than “Insurance,” which is consistent with DCE. “Penalty” has a lower importance than “No Penalty,” which was the case in previous two models. In terms of the levels of “Revenue,” “$20 acre-per-year” has the most importance, and “10 acre-per-year” the least. The three models agree that the lower two levels are less preferred to those with the two higher levels of compensation. “10 year contract” had the highest importance of the “Time” levels, and “40 year contract” the lowest, followed very closely by “100 year contract.”

Table 9
Differences between Best-Worst Scaling Level Scale Attributes (1 having the lowest distance)

Level Scale Attribute	Difference between levels	Order of difference between levels
Difference between Insurance to Risk Pool	0.50	4
Difference between No Penalty - Penalty	2.57	8
Difference between $5 to $10 acre-per-year	0.58	5
Difference between $10 to $20 acre-per-year	1.32	6
Difference between $20 to $30 acre-per-year	0.47	3
Difference between 5 to 10 year contract	0.24	2
Difference between 10 to 40 year contract	1.65	7
Difference between 40 to 100 year contract	0.13	1

Table 9 presents the differences between BWS level scale values, and orders them according to their magnitude. Notice how the biggest difference between levels came from the attribute “Penalty,” which is not the most important attribute. This fact BWS allows for the separate estimation of impact values and scale levels, “illustrates a key advantage of best-worst-scaling over traditional discrete choice experiments: in the latter, only these differences between the levels are estimable.” (Flynn et al., 2008)

5.4 Model Comparisons

Table 10 presents a comparative display of relative “impacts” of attribute/scale level ranges across methods. The values of the second and third columns correspond to the ordering of WTA ranges of DCE Model 1, and Binary Model 1, respectively; the fourth column reflects the hierarchy of level scale value range in BWS. These values range from 1 to 5, where 5 match the attribute with biggest range. As explained by Louviere and Islam (2008), attribute level ranges of DCE and Binary parameter estimates are confounded with weight and utility scale, and therefore potentially misleading in terms of assessing the importance of the attribute. By transforming these estimates to WTA, the values take on a common metric scale ($/choice), which allows for the estimates of WTA ranges to provide a more accurate measure importance. BWS has the advantage of providing estimates on a common underlying scale. As noted above, level scale ranges do not necessarily correspond to the measure of impact; BWS has the advantage of providing separate measurements for these values. DCE and Binary agree 100% with the ordering of impact, namely, “Time” has the highest impact, and “Risk Tool” the lowest (given that these are WTA estimates, the impact of “Revenue” was not computed). The measurements of BWS agree that the ordering of “Risk Tool,” but places “Penalty” with lowest impact.

Table 10
Ordering of relative impact of attribute/scale level ranges across methods (1 having the least impact)

Variable	DCE-Model 2: Ordered by absolute WTA range	Binary-Model 2: Ordered by absolute WTA range	BWS: Ordered by magnitude of attribute scale range
Time	3	3	3
Risk Tool	1	1	1
Penalty	2	2	4
Revenue			2

Table 11
Ordering of relative impact of attribute/scale level ranges across methods (1 having the least impact)

Variable	DCE-Model 2: Ordered by absolute WTA range	Binary-Model 2: Ordered by absolute WTA range	BWS: Attribute impact rank
Time	3	3	1
Risk Tool	1	1	3
Penalty	2	2	2
Revenue			4

In Table 11 replaces the fourth column of Table 10 with the appropriate attribute impact ranks BWS (see Table 8). Here we notice a strong disagreement of impact measurements coming from discrete choice experimentation models (DCE/Binary) and BWS. The attribute with the least impact (Risk Tool) in DCE and Binary, places second in BWS. “Time,” which has the lowest impact rank in BWS, corresponds to the highest impact in the other two models. Notice that the inaccurate measurement of "Time" BWS from Table 10, agrees with the DCE and Binary assessments. As previously noted, the ability to separately measure attribute impact from level scale values is the strength of best-worst scaling over traditional discrete choice experiments.

5.5 Discussion of alternative model specifications

The precise measurement of the separate values of utility and importance is another interesting element to explore both and compare with these models. BWC allows for this type of separation, which produces a more precise assessment of the influence of attributes. As we increase our sample size with new surveys from Tree Farm certified participants, our data will be more representative of landowners in Florida. The cross-validation/comparison with BWC and DCE will continue with new demographic/population weights for Binary and DCE, testing the hypothesis that both models estimate marginal WTA accurately.

We graphed the parameter estimates of DCE Model 1 (as well as DCE Model 1) against their attribute levels, and a non-linear relationship was visually detected for the attribute "contract duration" (see Appendix A). This model will be revisited using a linear and a non-linear attribute variable of this variable.

6. Summary and conclusion

In this study we have used three different models to estimate the attitudes and willingness-to-accept of a subpopulation of Florida landowners towards different aspects of contemporary carbon markets in North America. The use of preliminary data indicates that landowners in our sample would prefer a carbon-market program that uses risk-pooling, where they deposit carbon credits to address project uncertainty, instead of an insurance type that is typically used in crops. An inclusion of penalty for early withdrawal in this type of program seems to increase the cost of participation by approximately \$4.45 to \$10.41 acre-per-year. The effect of a program that offers compensations of \$5 or \$10 acre-per-year seems to have a negative or less desirable effect than \$20 or \$30. Landowners seem to prefer contract durations of 5 to 40 years, while strongly disfavoring a 100 year commitment. A program with a 100 year contract would elicit an increase in cost of participation of \$29.81 to \$37.78 acre-per-year, while a 10 year commitment would lower the cost by \$11.13 or \$13.19. Overall, project revenue appears to be the most highly valued aspect of the components of this study, followed by the type of risk tool used to manage uncertainty, which is slightly more valued than having a penalty for early withdrawal. Contract length was the least valued aspect.

In addition to exploring the attitudes of landowners, this paper compared a relatively new innovation in best-worst scaling that includes an additional task per question. It asks respondents to evaluate the options presented in each question as a single profile, and to reject or accept it. There is no publication to our knowledge in the field of applied economics using this model, and the potential of this method to accurately estimate wiliness-to-accept (or pay), as well as measuring attribute impact, makes it appealing to applied researchers interested in binary discrete-choice experimentation. Our preliminary results seem to indicate that the estimates of WTA from this model are higher in magnitude than those of the traditional discrete-choice experimentation, but they generally correlate in sign and relative magnitude. We are currently in the process of collecting more data, and these preliminary results will be revisited with the inclusion of another significant subpopulation of Florida landowners.

Appendix

Appendix A. Frequencies of Best and Worst

Figure 4
DCE estimates of Mode 1 vs. attribute levels

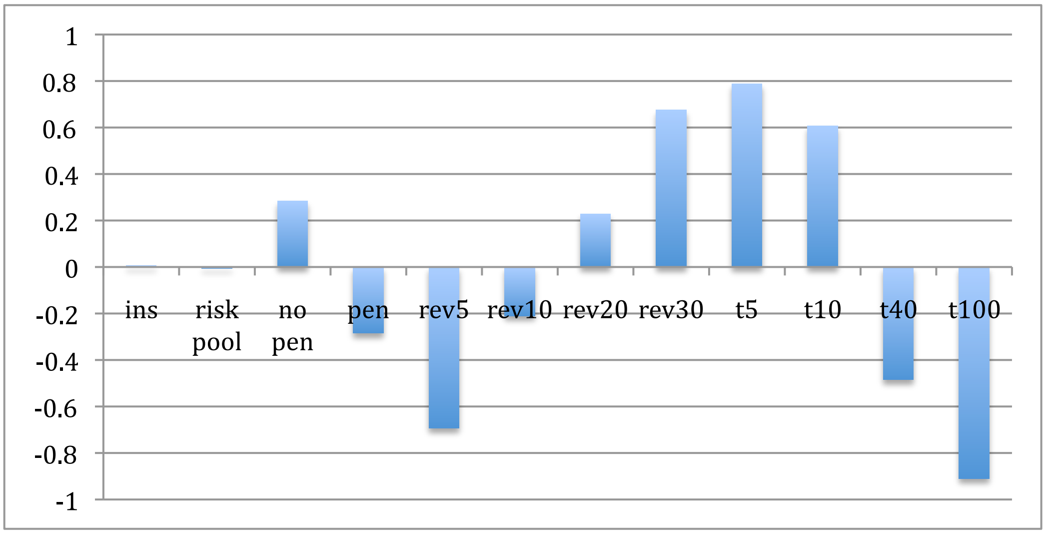
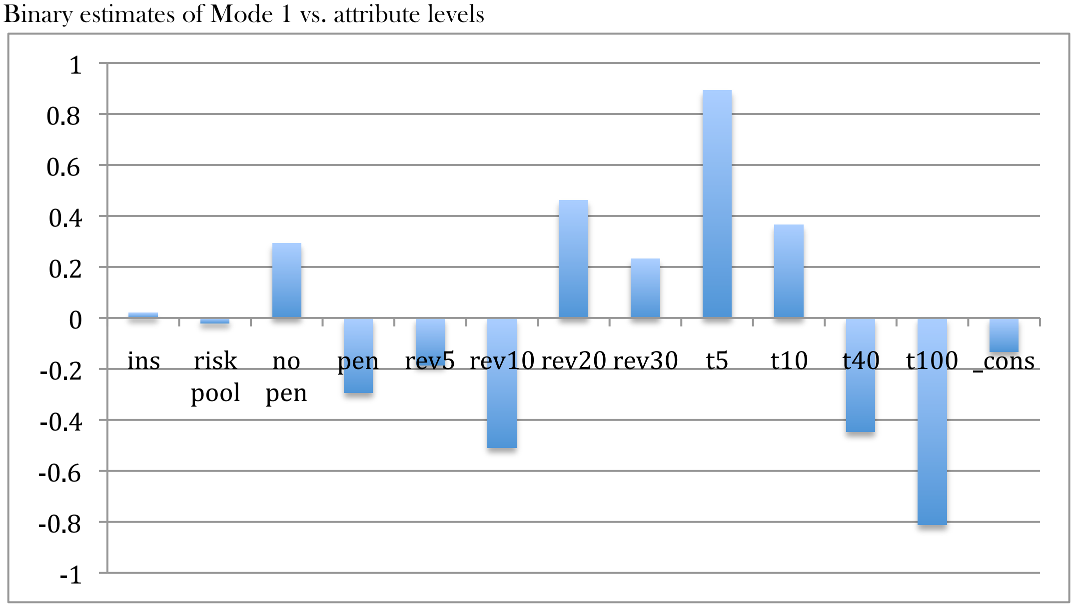
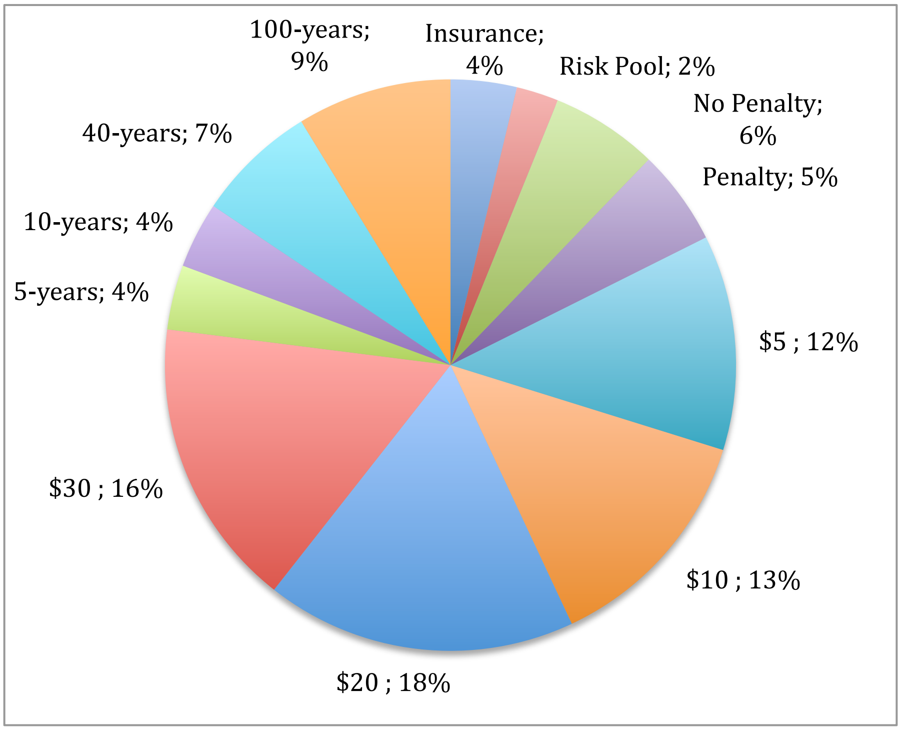


Figure 5
Binary estimates of Mode 1 vs. attribute levels



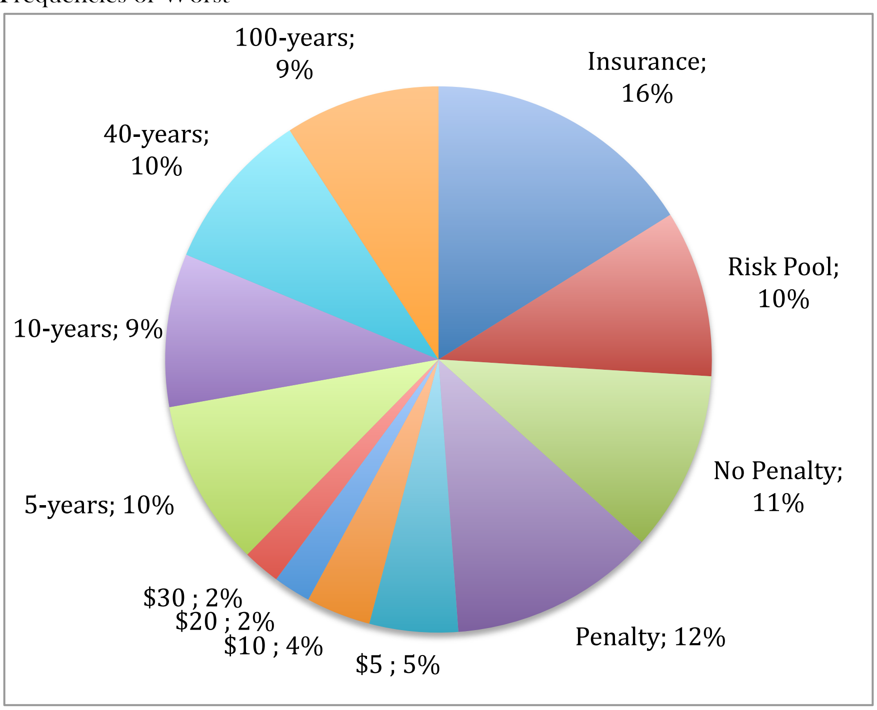
Appendix B. Frequencies of Best and Worst

Figure 6
Frequencies of Best[N]



[N] Frequencies of "Best" and "Worst" attribute choices divided by the number of times they were available.

Figure 7
Frequencies of Worst[N]



[N] Frequencies of "Best" and "Worst" attribute choices divided by the number of times they were available.

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