ESTIMATING THE SUPPLY OF FOREST CARBON OFFSETS: A COMPARISON OF BEST-WORST AND DISCRETE CHOICE VALUATION METHODS

By

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The use of forests to offset greenhouse gas (GHG) emissions has been promoted as a cost-effective policy to deal with global warming. Carbon markets often encourage forest landowners to sequester carbon in exchange for compensation. This dissertation uses one of the most comprehensive lists of Florida non-industrial private forest landowners to examine the role of forests within a carbon market framework. First, it discusses the opportunities of Florida landowners to participate in existing carbon markets, and provides a description of the State's forests and their carbon sequestration potential. Next, it describes the implementation of two different conjoint choice tasks (best-worst choice and discrete choice experimentation), which offer multiple options to assess attitudes of landowners towards different carbon offset programs, as well as various avenues to estimate willingness-to-accept compensation to participate in these programs. This is followed by a comparison of these two methods of choice elicitation, and a description of the implications to the field of limited dependent variables. Lastly, it predicts the potential for enrollment in various carbon-

offset programs, and estimates the supply of carbon from sample plots located in the Northeast, Northwest, and Central areas of Florida.

Carbon markets often use 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 causes confusion, price variations, and potential barriers to participation. This study examines these barriers and attitudes, and identifies the carbon market institutional components that are best suited to engage Florida's forest landowners.

Florida's forests cover almost 50 percent of the State's land area. Thus, these lands can play a key role in reducing GHGs by sequestering approximately 9.5 million metric tons of carbon per year[1]. Despite the fact that the majority (65%) of forests are owned by non-industrial private forest (NIPF) landowners[2], no previous research has been done to assess their institutional preferences regarding carbon-offset markets. This dissertation therefore investigates barriers to participate in forest carbon markets in Florida, and estimates the supply of offsets for the most promising institutional arrangements.

The results of this study indicate that landowners would need between $20 to $30 acre-per-year to be positively affected by revenue, while the inclusion of a penalty for early withdrawal from a program increases the cost of participation by approximately $4.45 to $10.41 acre-per-year.

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[1] See Mulkey S., J. Alavalapati, A. Hodges, A.C. Wilkie and S. Grunwald (2008), Opportunities for greenhouse gas reduction by agriculture and forestry in Florida. University of Florida, School of Natural Resources and Environment - Department of Environmental Defense, Washington D.C.

[2] Florida 2010 Forest Inventory & Analysis Factsheet http://www.srs.fs.usda.gov/pubs/su/su_srs043.pdf

CHAPTER 1
INTRODUCTION

Climate change is likely to impact the environmental and economic stability of the World. Global warming has been associated with the anomalous heat waves and droughts in Texas, Oklahoma, and Mexico in 2011 (Hansen et al., 2012), which cost the State of Texas an estimated $5 billion.[1] Florida, as a peninsula, is particularly vulnerable to this threat. Sixty year projections of current climate trends have placed major port cities like Miami at risk of coastal flooding from storm surges and high winds, with massive population exposure (4.8 million people) and close to $3.5 trillion assets at risk (Nicholls et al., 2008).

When policy makers seek to develop instruments to ameliorate the threat of global climate change by reducing greenhouse gas emissions, they have several policy options to consider, namely, prohibitions, pollution permits, taxes, etc. It is often important to understand regional differences (Kaetzel et al., 2012) and cultural barriers (see Fisher and Charnley, 2010), in order to design the most cost-effective program, with optimal enrollment. Forest carbon markets currently exist, but continue to emerge in the US (Charnley et al., 2010). 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 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).

[1] Time Magazine article retrieved on Aug. 31, 2011: http://www.time.com/time/nation/article/0,8599,2091192,00. html

Greenhouse gasses have been identified as drivers affecting the warming and cooling of global climate. They include carbon dioxide (CO^2), methane, and nitrous oxide, which have significantly increased as a result of human activities since 1750 (IPCC, 2007). Carbon dioxide is the second most abundant of all GHGs, but has a high capacity to influence incoming and outgoing energy in the Earth-atmospheric system, via its radiative force (IPCC, 2007). Regardless of the emission's origin, the long-run atmospheric accumulation of these gases is global, which allows for their removal from any location to impact long-term climate trends. It is widely recognized that forests have the capacity to sequester and store CO^2 from the atmosphere (e.g., U.S. EPA, 2005). Several regional and national studies have found that using forests for this purpose merits consideration from both policy makers and landowners (e.g., Lubowski et al., 2005; Stainback and Alavalapati, 2002).

Anthropomorphic GHGs emissions resulting from economic activities, which have harmful economic consequences that are borne (at least in part) by the "non-emitting" party, are what economists call negative "externalities" (Jaffe et al., 2005). The problem with an output of production such as GHG emissions, which is not "internalized" by emitters, is that emitters have no economic incentive to minimize the "external" costs of pollution (Jaffe et al., 2005). Coase (1960) resolved that these types of problems stem from ambiguous specification of property rights, namely, whether GHG emitters have the right to release GHGs, or non-emitters have the right to "clean air." If property rights are clearly specified (and market transaction costs are sufficiently low), then there will be an incentive to have an arrangement that will either compensate for the costs of pollution, or compensate for the economic loss of pollution abatement (Coase, 1960).

Another potential solution would be to incentivize forest landowners to sequester GHGs (Raymond and Shievely, 2008).

Emissions trading or cap-and-trade (CAT) programs create carbon markets, by allowing polluters to emit more GHGs than they are allowed, while paying others to stop polluting or capture/offset them elsewhere (for an extensive definition of CAT, please see Raymond and Shievely, 2008). These frameworks typically include CO^2 "offsets" generated by forest projects (see Charnley et al., 2010). In 2010, "North America provided the second-largest sources of both supply and demand in the (global voluntary carbon) market, with companies taking on 5.6 $MtCO^2e$ (metric-ton carbon dioxide equivalent), just over the 4.9 $MtCO^2e$ supplied from projects in the region" (Diaz et al., 2011). The US does not have a national CAT program, but a recent national survey revealed that 75% of U.S. voters favor regulating CO^2 as a greenhouse-gas pollutant[2].

The State of Florida has yet to create a carbon-offset market or take part in any regional cap-and-trade agreement (e.g., Regional Green House Gas Initiative), but there is certainly a framework in place in multiple voluntary national programs (e.g., Climate Action Reserve, Voluntary Carbon Standard) to potentially take advantage of its vast public and private forestlands (over 17 million acres) to not only protect the state from climate change, but to create wealth by carbon-offsets. Mulkey et al. (2008) estimate that the afforestation of 5% of Florida range and pasture lands, along with increased management intensity on pine plantations, can potentially yield $139.6 million

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

to producers[3]. Yet, despite the economic benefits of engaging these markets, no empirical study has been done to assess the attitudes of Florida private forest landowners towards these programs, in such a way that informs policymakers and resource managers.

The overall purpose of this research is to examine barriers to participate in forest carbon-offset markets in Florida. The specific goals are 1) to identify optimal institutional structures of carbon market programs that increase participation at efficient costs; 2) to estimate the supply of carbon in Florida; and 3) to make a contribution to the measurement of best-worst scaling by assessing the potential of best-worst choice to produce measurements of "traditional" discrete-choice experimentation, and best-worst scaling.

Existing Carbon Markets

Chapter 2 discusses current and emerging forest carbon market opportunities for Florida landowners. The use of forest carbon markets that pay landowners to capture GHG emissions for example by planting trees, preventing forest degradation, or improving forest management practices, are currently being considered by 22 U.S. states, two Canadian provinces, and six Mexican observant regions[4]. "However, a number of environmental, economic, and social constraints currently limit carbon market participation by forest owners. Key issues include: the low price of carbon and high cost of market entry; whether small landowners can gain market access; how to meet

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

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

requirements such as management plans and certification; and whether managing for carbon is consistent with other forest management goals. ” (Charnley et al., 2010)

Landowners in the Southeast are currently able to participate in three major carbon offset certification programs: American Carbon Registry (ACR), Climate Action Reserve (CAR), and Voluntary Carbon Standard (VSC). Georgia, Alabama, Mississippi, South Carolina, and Louisiana are currently participating in these programs with more than 25 forest projects with thousands of acres, but Florida only makes use of these opportunities with six landfill projects and one energy program[5,6,7].

This chapter qualitatively analyzes the major requirements of ACR, VCS, and CAR, and reviews existing literature related to Florida non-industrial private forest landowners to identify potential barriers to participate. Three major categories were identified as potential barriers to participation: compensation, contractual commitment (length and penalties for early withdrawal), and risk.

Attitudes and Willingness to Accept

Chapter 3 characterizes the guiding structure of carbon production in Florida, by identifying barriers to participate in a hypothetical carbon-offset program, and estimating willingness-to-participate of non-industrial private forest landowners. To explore opportunities in new markets, it is not only appropriate to elicit willingness to accept (WTA) compensation for landowners to produce offsets (e.g., Shaikh et al., 2007), but also to research institutional factors that may influence the likelihood of land managers

[5] See project listings for CAR: http://www.climateactionreserve.org/how/projects/

[6] See project listings for ACR: http://americancarbonregistry.org/carbon-registry/projects/project-list-by-type/acr_atct_topic_view?b_start:int=0&-C=

[7] See project listings for VCS: http://www.vcsprojectdatabase.org/

to participate in such programs (e.g., Fletcher et al., 2009). To address this, a conjoint choice survey was developed and electronically administered in December 2011 to 920 Florida Forest Stewardship Program participants, with a response rate of 34%, of which 189 completed the entire survey.

Four program attributes were included: contract length (5 to 100 years), annual compensation ($5 to $30 per-acre), penalty for early withdrawal (penalty, or no penalty), and the type of risk tool (insurance or risk pool), along with demographic and institutional trust questions. Two methods of choice elicitation were used (discrete choice experimentation and best-worst choice), which only varied on the type of conjoint method. Respondents were randomly presented with only one survey type, which resulted in equal response rates. One that required respondents to choose among three variant programs with a “none of these” option (DCE), and the other (BWC) presented a single profile of attributes and consisted of two separate instructions: 1) to select a most preferred and least preferred attribute level, and 2) to consider the profile as a single carbon program and choose whether to enroll or not.

The three different sets of instructions for these two conjoint tasks resulted in three valuation models: Best-Worst Scaling (BWS), Binary Logit (Binary), and Discrete Choice Experimentation (DCE), and their elicitation formats in the context of hypothetical carbon sequestration markets in Florida. These models were used to test the hypotheses that several factors do not affect willingness-to-accept payments for carbon sequestration: (1) carbon contract revenue, (2) institutional factors (risk tool, contract length), and (3) respondent characteristics.

The results from this chapter indicate that non-industrial private forest landowners in this 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 and $10 acre-per-year are less desirable. The least preferred component of this study seems to be a contract commitment of 100 years. A program with this duration would elicit an increase in cost of participation of $28.53 to $37.78 acre-per-year, while a 10 year commitment would lower cost by $12.48 or $15.07 acre-per-year.

Best-Worst Choice vs. Discrete Choice Experimentation

Chapter 4 makes a contribution to the measurement of BWS, by applying and comparing best-worst choice (BWC), an innovation proposed by Flynn et al. (2007) and applied by Coast et al. (2006), 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. But, 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. Thus, the latter instruction resembles the Binary model, which allows for the estimation of WTA.

This chapter builds on the work done by Louviere and Islam (2008) that compares BWS with Binary estimates, and Potoglou et al. (2011), which analyzes differences between BWS and DCE measurements. By comparing BWC with DCE, we provide the first assessment of measurements of BWC, compared to the sufficiently

well-documented DCE. The results of this study will provide applied economists evidence of the performance of a conjoint tool that takes advantage of BWS, while estimating “traditional” values of WTA, without having to resort to two choice tasks in a single survey, thereby reducing choice-task-complexity.

The Supply of Carbon Offsets

Finally, Chapter 5 combines carbon sequestration data from the Forest Inventory Analysis of the USDA Forest Service[8] to simulate an improved forest management practice carbon program, and trace a supply curve of forest carbon-offsets of Florida Stewardship Program participants. Using the findings of previous chapters, a Linear logit model (see Louviere et al., 2000) is used to predicted the probability of participating in various carbon offset programs scenarios of low, medium, and high preference (e.g. Markowski-Lindsay et al., 2011; Kline et al., 2000).

Estimates of carbon additionality were estimated using the findings of Mulkey et al. (2008) that estimate average per-acre forest carbon sequestration rates in Florida via simulation tools. This chapter finds a higher probability of participation in programs that offer more than $30 per-acre-per-year, and commitment periods of 30 years or less, along with significant supply shifts stemming from the inclusion of characteristics such as penalty for early withdrawal from a carbon offset contract. The respondents in this survey are well represented in areas of the Northeast, Northwest, and Central portions of Florida.

[8] http://www.fia.fs.fed.us/

Summary

This study uses Best-Worst Choice modeling and Discrete Choice Experiment to estimate WTA compensation for producing carbon-offsets in Florida, and identifying potential barriers to participation. The data from these models was enriched with carbon sequestration data from the Forest Inventory Analysis, in order to estimate the supply of carbon offsets of representative plots in the Central and Northern portions of Florida. The surveys had a response rate of 34%, and the results show a preference for hypothetical programs with high revenues and no penalty for withdrawal; and a positive and high correlation in the importance weights of BWC and the 'conventional' estimates of WTA from DCE. Florida has great potential for producing carbon-offsets, and the results of this study will generate interest the forest landowner community, private sector consumers of carbon-offsets, and policy makers. In addition, this dissertation will also be a contribution to the applied economics community, by exploring the potential of Best-Worst Choice modeling to estimate 'conventional' measurements of Willingness to Accept.

CHAPTER 2
CARBON OFFSET OPPORTUNITIES FOR FLORIDA LANDHOLDERS

In recent years, several institutions and entrepreneurs in Florida have expressed interest in engaging carbon markets or projects that aim to reduce greenhouse gas emissions. 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 (Cravey [personal communication], 2011). Also, in 2007, the City of Miami entered into a contract with the Chicago Climate Exchange to further their goal of reducing 6% of GHG emissions by 2010, while allocating $500,000 of their 2007-08 budget to the Office of Sustainability (Acosta, 2009). Two years ago, 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, and renewable energy, 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). As of this writing, Florida has yet to register any current forest carbon offset projects using the major available certification platforms (see ACR, CAR, and VCS project listings[1,2,3]).

The long-term negative effects associated with climate change (see IPCC, 2007) highlight an additional role for forestlands to assist the economic and human wellbeing

[1] See project listings for CAR: http://www.climateactionreserve.org/how/projects/

[2] See project listings for ACR: http://americancarbonregistry.org/carbon-registry/projects/project-list-by-type/acr_atct_topic_view?b_start:int=0&-C=

[3] See project listings for VCS: http://www.vcsprojectdatabase.org/

of the State of Florida. In spite of having almost 50% of its land area covered by forests, the state's net emissions for the year 2005 were 309 million metric tons (MMt) of CO^2 equivalent (CO^2e) units (Center for Climate Strategies, 2008). Converting 1.85 million acres of forestland from lower to higher forest management intensity, and 2.9 million from medium to high intensity, along with 5% afforestation of range and pasture lands could result in 2.7 MMt of additional carbon sequestration per year (Mulkey et al., 2008). Using a $20 per metric ton CO^2e, this change can potential yield $23 million for afforestation and $116.8 million for changes in management intensity. The proposed additional sequestration will not make Florida carbon neutral, but it will certainly contribute to efforts that mitigate the negative effects of climate change.

This second chapter provides an overview of the current opportunities available for Florida forest landowners to seek compensation for sequestering carbon. The chapter first provides a brief historical overview of GHG markets in the US, then elaborates on existing national frameworks to certify carbon offsets, followed by an analysis of potential barriers to participate.

A Brief History of US GHG Markets

Over the past 20 years, there have been several major efforts to institute federal policies that regulate GHG emissions in the US. In 1992, the US ratified the United Nations Framework Convention on Climate Change, which became the negotiating framework of GHG reductions under the Kyoto Protocol (Charnley et al., 2010). This protocol required countries to reduce GHG emissions to an average of 5% below 1990 levels by 2012 (the requirements differed by schedule), with developed countries facing more obligations than their less developed counterparts. The widely recognized success (by business and environmental groups) of the 1990s Acid Rain Program paved the way

for the European Union to initiate a cap-and-trade program in 2005, in order to meet their Kyoto Protocol obligations (Raymond and Shively, 2008). Yet all the excitement of the 1990s was not enough to overcome bipartisan disagreement on exempting developing countries from emissions reduction requirements under the Kyoto Protocol, and the US failed to ratify the 1997 protocol (see Senate Resolution 98, 105th Congress, 1st Session).

However, the idea of a national CAT program weathered through and resurfaced in the late 2000s, with a Supreme Court ruling (Massachusetts v. EPA) requiring the Environmental Protection Agency to regulate GHGs as air pollution, Vice President Al Gore's "An Inconvenient Truth," highly influenced public opinion, as did presidential candidates showing support for a national CAT (Adams, 2009). This momentum culminated with the passing of US House of Representatives Bill 2454 (the American Clean Energy Security Act of 2009), which included the possibility of utilizing forest carbon offsets to mitigate GHG emissions. The bill lost viability with the recent economic down turn, and it did not make out of the US Senate (Broder and Krauss, 2010). In 2011, the CCX (the nation's first CAT system) lost its CAT component (Gronewold, 2011), leaving potential carbon producers less than satisfied (Sager [personal communication], 2011).

The resiliency of CAT continues to merit consideration by 22 states under three major regional blocks: Western Climate Initiative (WCI), Regional Greenhouse Gas Initiative (RGGI), and the Midwestern Greenhouse Gas Accord (MGGA). As of this writing, RGGI is the only active CAT regional program in the US, and is currently facing

the withdrawal of one of its 10 regional members (New Jersey),[4] and MGGA negotiations appear to be idle[5]. The majority of WCI member states are not planning to implement a CAT program, except for New Mexico (although the current governor apparently intends to keep the state's CAT in a sort of stasis), California, and three Canadian Provinces (Alter [personal communication], 2011).

The demand for RGGI CO^2 allowances has fallen dramatically and the prices have reached their virtual price floor of $1.86 per ton[6]. This CAT program in the Northeast regulates power plants, and only allows for 3.3% of their allowances to come from CO^2 offsets. Forest projects are included in this system, but only within the 10 participating member states (Connecticut, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Rhode Island, Vermont, and New Jersey).

January 2013 marks the start date of California's Global Warming Solutions Act of 2006 (AB32). The goals are to reduce GHG emissions to 1990 levels by the year 2020[7]. This initiative aims to create a very ambitious statewide CAT program on all aggregate GHG emitters, and it plans to allow forest carbon offsets. The California Department of Forestry and Fire Protection estimates that 5 million metric tons of CO^2 equivalents will be sequestered in California's forests by 2020[8]. "Bloomberg New Energy Finance predicts the allowance market to be worth $7.7 billion" (Peteres-Stanley

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[4] WJS Article, May 26th, 2011: http://online.wsj.com/article/SB10001424052702304520804576347560078618994.html

[5] Point Carbon, Fed 25th, 2011: http://www.pointcarbon.com/pages/shop/1.1510367

[6] Robert Stavins' Huffington Post Blog, April 28th, 2012: http://www.huffingtonpost.com/robert-stavins/low-prices-a-problem-maki_b_1461501.html

[7] CA EPA website: http://www.arb.ca.gov/cc/ab32/ab32.htm

[8] The Legislative Analyst's Office, February 16th, 2012: http://www.lao.ca.gov/analysis/2012/resources/cap-and-trade-auction-revenues-021612.aspx

and Hamilton, 2012), and is likely to be linked to other networks under the Western Climate Initiative[9].

Supplying and Certifying Offsets

Florida is not currently participating in RGGI or WCI, but landholders have three major certification options to engage carbon offset markets: CAR, ACR, and VCS. These are voluntary non-profit carbon offset certification programs that slightly differ in protocol requirements, but encompass similar types of forest offset activities: afforestation/reforestation (AR), improved forest management (IFM), and reducing emissions from deforestation and degradation (REDD). They play the role of independent third-party standards for carbon credits that are sold in domestic and foreign markets. In 2011, these certifiers guided the development of 76% of all (independent third-party standards) transacted credits in voluntary markets (Peter-Stanly and Hamilton, 2012).

As of this writing, no Florida forest projects have been registered under these three programs, but there are six landfills certified to receive CO^2 equivalent credits for capturing methane under ACR, one “transport fleet efficient” truck stop that powers idle trucks with electricity to avoid using diesel under ACR, one VCS project in Lee County receiving credits for incinerating municipal waste to generate electricity,[10,11,12] and 39

[9] Robert Stavins’ Huffington Post Blog, Oct. 4th, 2010: http://www.huffingtonpost.com/robert-stavins/ab-32-rggi-and-climate-ch_b_749791.html

[10] See project listings for CAR: http://www.climateactionreserve.org/how/projects/

[11] See project listings for ACR: http://americancarbonregistry.org/carbon-registry/projects/project-list-by-type/acr_atct_topic_view?b_start:int=0&-C=

[12] See project listings for VCS: http://www.vcsprojectdatabase.org/

“domestic energy efficiency” small scale projects under Gold Standard (another certification program)[13].

The southeastern states of Georgia, Alabama, Louisiana, Mississippi, and South Carolina are however currently participating in these programs with: 25 forest projects, 34 landfill sites, 4 “transport fleet efficient” truck stops, and 3 energy conversion projects. (Figure 2-1 & Figure 2-2)

One of the most ambitious forest projects in ACR (GreenTrees Forest Carbon Project) is privately managed, and aims to “reforest one million acres in the Lower Mississippi Alluvial Valley, the nation’s largest watershed, covering approximately 25 million acres in Louisiana, Mississippi, Arkansas, Kentucky, Tennessee, Missouri and Illinois[14].” (Figure 2-3)

Figure 2-1. Map of Voluntary Carbon Standard project sites. [Figure adapted from VCS project listings website: http://www.vcsprojectdatabase.org]

[13] The Gold Standard project website: https://gs2.apx.com/mymodule/mypage.asp

[14] Project website: http://americancarbonregistry.org/carbon-registry/projects/greentrees-forest-carbon-project

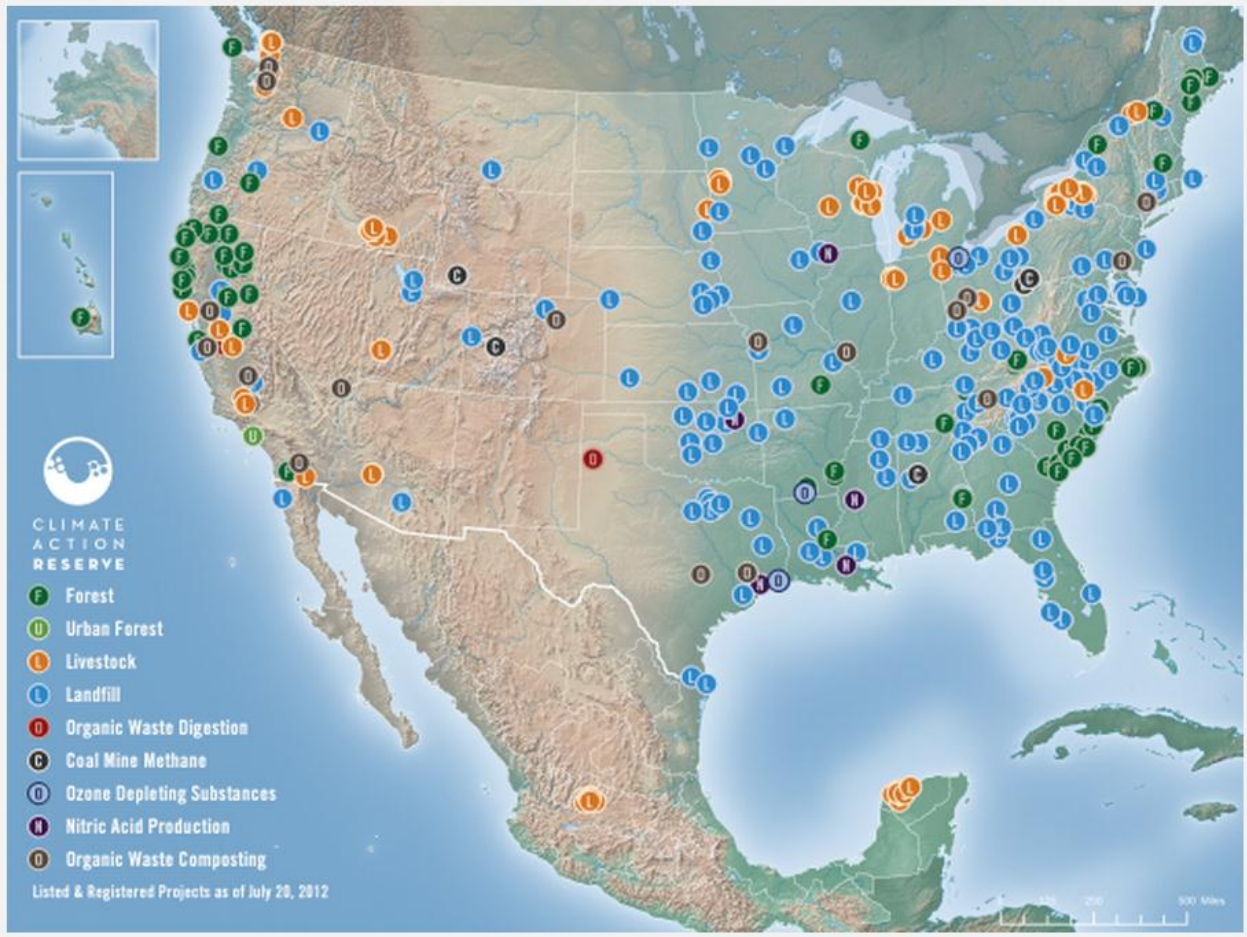


Figure 2-2. 2012 map of Climate Action Reserve projects sites. [Figure adapted from CAR project listings website: http://www.climateactionreserve.org/how/projects/]

A

B

C

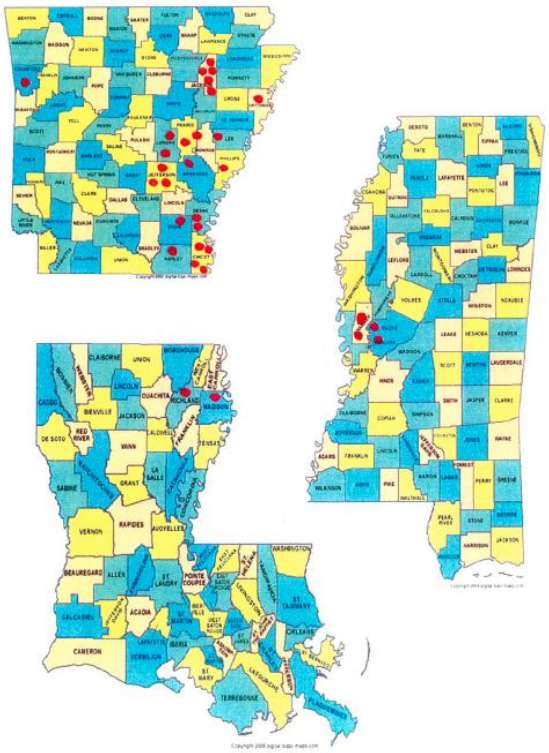


Figure 2-3. Map of GreenTrees Forest Carbon Project identifying GHG sources. The dots in this figure represent sources and sinks of carbon. A) Arkansas. B) Louisiana. C) Mississippi. [Figure adapted from American Carbon Registry project listings website: http://americancarbonregistry.org/carbon-registry/projects/project-list-by-type/acr_atct_topic_view?b_start:int=0&-C=]

Contract Length and General Description

These three programs have commitment periods that range from 40 to 100 years (ACR 40, VCS 20-100, CAR 100). Recent (e.g., Markowski-Lindsay et al., 2011) studies have identified contract duration as a potential barrier to participation in similar programs. Landownership can be both private and public, and they typically retain their ownership status during their production period, except for CAR, which requires participants of REDD to reclassify their property as conservation easements or to transfer them to public ownership.

Most programs allow for the use of the clean development mechanism methodologies defined by the Kyoto Protocol, and for the implementation of multiple

activities, that is, a mix of AR, REDD, and IFM. The registration processes and procedures vary within each project type, but all involve a project manager who submits a proposal to an offset certification program (ACR, VCS, CAR) that screens applications, and determines who is eligible to then be inspected by an independent third-party verifier who confirms the validity of the project. If approved, the project is registered and carbon credits are issued in accordance with project type and production capacity.

Afforestation/Reforestation

AR involves the restoration of forest-covered lands that are not at “optimal stocking levels.” Programs certification is considered for areas that were not converted to non-forests within the last 10 years prior to the beginning of a project, or for areas that suffered a significant natural disturbance, such as hurricane or fire (ACR, VCS, CAR). Some programs have special requirements, such as ACR, that normally considers projects with start dates after 1997, or CAR, which does not allow lands that have been previously registered as Forest Projects (unless the project was terminated due to unavoidable reversal).

The starting date for this project type is at the beginning of the planting season (ACR, VCS), or at the removal of obstacles to growth (CAR). After the project is approved, it receives a crediting period of 40 to 100 years (40 ACR, 20-100 VCS, 100 CAR), where they acquire carbon credits depending on the project’s production characteristics.

Carbon offsets are measured by comparing a “baseline estimation” of all GHG sinks with the subsequent sequestration rates implemented by project. The three programs offer slightly different ways to calculate baselines, but in essence, all of them

take an inventory of current GHG stocks and leaks, which are then compared with the project's absorption improvements.

Improved Forest Management

The IFM activities include: making managerial adjustments of conventional logging, no logging, extending rotation periods, going from low to high productive forests, thinning diseased or suppressed trees, managing competing brush and short-lived species, and increasing tree density. This project is considered to have started after the application of the new management regime. Their crediting period ranges from 20-100 years (20 ACR, 20-100 VCS, 100 CAR). The VCS considers lands that have not been converted to non-forests for at least 10 years prior to the beginning of the project, and CAR requires lands that have not been previously registered as Forest Projects (unless project was terminated due to unavoidable reversal), and to have less than 10% tree canopy cover.

The baseline estimation used to compare improvements of carbon stock requires land managers to identify a credible alternative forest management scenario (ACR), or to provide 5-10 years of management records in order to show "normal historical practices" (VCS). CAR requires a qualitative characterization of likely vegetative conditions and activities that would have occurred without the project (including laws, statutes, regulations or other legal mandates), along with 20 samples plots to perform a computer simulation for 100 years.

REDD and Avoided Conversion

REDD is an approach to avoid planned, unplanned, and/or illegal deforestation of lands that are threatened by urban development, industrial tree production, and/or changes in legislation. The starting dates for ACR and VCS are at the implementation of

the project's actions, and CAR initiates after the recording of a conservation easement, or transfer to public ownership.

REDD projects are credited for 10-100 years (10 ACR, 20-100 VCS, 100 CAR), and CAR does not allow projects to take place on previously registered Forest Projects, unless the project was terminated due to unavoidable reversal.

The additional sequestration of this protocol is measured by comparing existing carbon stocks, with the expected stocks of the threatening contingency (i.e., roads, buildings, timber harvest), namely, the carbon stocks of the treating contingency become the baseline of the project. Also, VCS demands a reassessment every 10 years, while CAR requires the same type of qualitative and forecasting methods of IFM.

Permanence

The project's boundaries (standard sources, sinks, and reservoirs) are defined within the property, but managers are responsible for "leaks" that may occur outside its bounds, due to the project's own activities. Hence, if a project displaces cattle grazing, urban development, transportation, or tree farming, then those activities would be considered leaks. This caveat specially applies to REDD, which requires regular monitoring of the owner who was originally planning to degrade or deforest a land.

Leaks from intentional or unintentional (i.e. natural disaster) reversals are managed by instituting a series of risk management tools, such as: allowing participants to propose insurance products (ACR), carbon banking pools, a.k.a. 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 projects. 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 reversals (e.g., wildfires, hurricanes, etc.). The amount deposited and refunded varies with each program, for example, ACR refunds 10% of offsets to producers every 5 years of non-reversals, whereas VCS and CAR ask for a certain percentage of offset deposits, depending on the project's risk level, which is considered lower in cases of easements or deed commitments. Each buffer or insurance is required for entire duration of the commitment period.

Market Demand

The only existing CAT market in the US is RGGI, but as previously mentioned, Florida lands are not authorized to participate in this market. In 2013, California's Assembly Bill 32 will create a CAT market in the State of California, but the participation of out of state forest projects has yet to be determined. In 2011, the California Air Resources Board approved CAR protocols for early-action compliance of CAR credits (Peter-Stanly and Hamilton, 2012). ACR, CAR, and VCS can only be traded in voluntary carbon markets (VCM). In 2010, the only available VCMs in the US were over-the-counter (OTC) transactions and CCX (Charnley et al., 2010), but the latter no longer exists. (Figure 2-3)

Florida landowners attempting to sell their certified credits would have to make use of OTC markets. These involve the use of private contracts between offset provider and buyer (Charnley et al., 2010). The transaction occurs via a private exchange (e.g., Climax) or directly thought a broker or online retail (Peter-Stanly and Hamilton, 2012). Most transactions occur directly. (Figure 2-4)

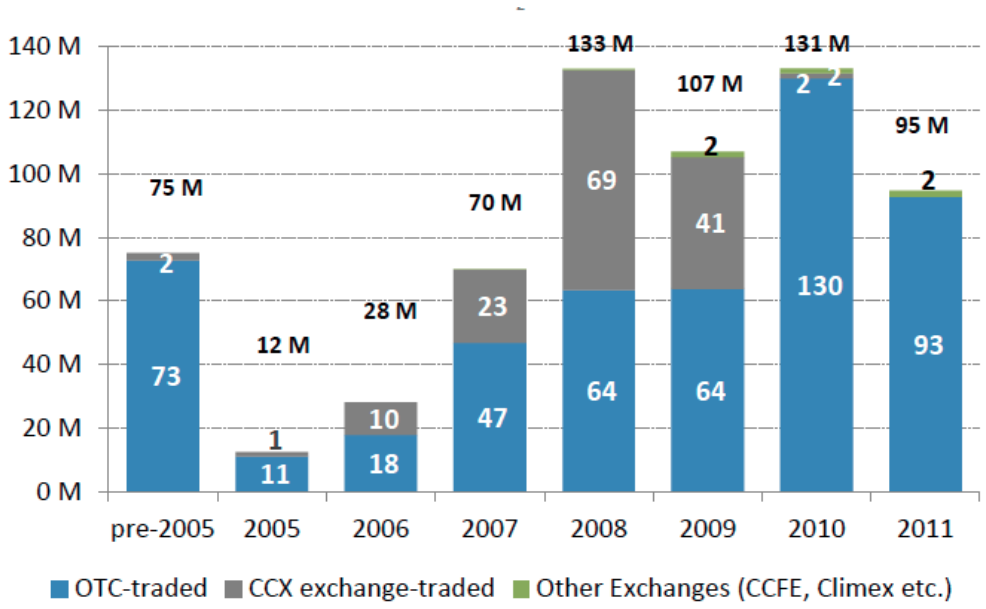


Figure 2-4. Historic Voluntary Carbon Market transaction volume. [Figure adapted from Peters-Stanley M, Hamilton K (2012), State of the Voluntary Carbon Markets 2012: Developing Dimension (Page 9, Figure 7), Ecosystem Marketplace and Bloomberg New Energy Finance, Washington, DC.]

The rest of this section summarizes the findings of the State of the Voluntary Carbon Market 2012 by Peter-Stanly and Hamilton (2012). Since the vast majority of OTC transactions occur via private brokers and individuals, prices and transacted volumes are not centralized in a market type dataset. Peter-Stanly and Hamilton report the findings of a survey collected from 312 offset suppliers, seven exchanges, and all major registries (including ACR, VCS, and CAR).

In 2010-2011, the market share of over-the-counter (OTC) transactions grew by 20%, while forest projects decreased by 38%. Respondents of the survey attributed this decrease to the recent financial crisis. The OTC volume in 2011 constituted 1% (95 $MtCO^2e$, valued at $572 million) of the global carbon market. AR and IFM projects transacted 7.6 $MtCO^2e$ and REDD 7.3 $MtCO^2e$.

North America bought 41% of the world's OTCs (Europe 47%). The US purchased 28 $MtCO^2e$ at a cost of $151 million. North America supplied 30$MtCO^2e$ (23% forest) worth $178 million. Of this volume, 92% were sold domestically, and the rest in Europe.

In 2011, the US purchased a total of $159 million worth of OTC offsets, at an average price of $6 per $MtCO^2e$. ACR, VCS, and CAR had a price range of $0.10 to $30 per $MtCO^2e$. The average prices for VCS, ACR, and CAR during 2011 were $3.70, $5.8, $7.30 per $MtCO^2e$, respectively. CAR appeared to be fetching higher prices, given the pre-compliance approval of their protocols under the California CAT. ACR had the highest forest OTC transactions in North America with 2.56 $MtCO^2e$, followed by 1.63 of VSC, and 1.17 with CAR. Most transactions for these programs occurred in North America, with the exception of 25% of VCS. (Table 2-1)

Table 2-1. Market share and prices of over-the-counter transactions for 2011.

	Market Share	World Volume ($MtCO^2e$)	North American Volume ($MtCO^2e$)	Forest Share	Price range ($/$MtCO^2e$)	Avg. prices ($/$MtCO^2e$)
VCS	58%	41	≈ 10.2	16%	≈ 0.12-30.00	3.70
ACR	6%	4	≈ 4	64%	≈ 0.10-10.00	5.80
CAR	12%	9	≈ 9	13%	≈ 0.35-15.35	7.30
US	41%	30	30	23%	-	6

[Data adapted from Peters-Stanley M, Hamilton K (2012), State of the Voluntary Carbon Markets 2012: Developing Dimension, Ecosystem Marketplace and Bloomberg New Energy Finance, Washington, DC.]

Potential Barriers to Entry

Specific barriers to participate in forest carbon-offset markets have yet to be examined in the State of Florida, but similar programs have been explored in Massachusetts, Texas, and Western Canada (e.g., Markowski-Lindsay et al., 2011; Lee

2010; Shaikh et al. 2007). Fischer and Charnley (2010) have also explored the literature of non-industrial private forest landowners to identify the cultural elements that may influence participation in sequestration programs. Other land-use studies of NIPF landowners in Florida have explored willingness-to-accept compensation to convert forestland to biofuel crops area, which offer interesting information on reservation prices and forest attitudes (Pancholy et al., 2011).

A Massachusetts study of NIPFs from 2010 by Markowski-Lindsay et al. (2011), presented participants with different carbon sequestration programs and elicited their ratings. The programs included the following attributes: management plan (required/not required), contract length (15 or 30 years), percent of land required to enroll (50 or 100%), revenue ($10, $100, $1000), additionality, penalty for early withdrawal (no penalty or repay earnings plus 20% fee), and institutional trust (implemented by public or private sector). With a response rate of 43%, the study found significant preferences for programs with higher net revenue, no withdrawal penalty, shorter contract lengths, and no additional requirements, such as “no requirement that forests must be managed to sequester more carbon than if nothing was done.”

The following subsections discuss some of the key barriers identified by Markowski-Lindsay (2011) and Fischer and Charnley (2010), which may be applicable to Florida NIPF landowners in ACR, CAR, and VCS.

Improve Forest Management, Afforestation and Reforestation, and Reduce Emissions from Deforestation and Degradation

Fischer and Charnley (2010) identify REDD as being compatible with the “owners’ amenity, ecological, and family legacy values and their reluctance to harvest timber and convert forestland.” IFM is also found to conform to the aesthetic, and

ecological values of family landowners. They cite literature evidencing a potential reluctance to engage in AR, on the grounds that planting new trees commits them to long-term financial investments, but the fact that the economics of afforestation values are highly regional, and the high stumpage values of the South might make it more appealing.

Contract Duration and Penalty for Early Withdrawal

Fischer and Charnley (2010) find evidence that family forest owners are concerned about losing property rights, as well as reluctant to make large financial investments for long-term benefits. Markowski-Lindsay et al. (2011) also identified preferences for shorter durations and no penalty for withdrawal. Having commitment periods that range from 40 to 100 years (ACR 40, VCS 20-100, CAR 100) might create rigidity in the property rights of landholders who might be considering developing their Florida lands in the not so distant future.

Additionality

Markowski-Lindsay et al. (2011) found evidence that NIPFs prefer programs that do not require additionality, that is, “to manage land so that trees sequester more carbon than if nothing was done.” This attribute is present in most carbon certification programs, and it represents the method by which they justify compensation for implementing actions that increase (or protect) carbon sequestration. It is very unlikely that this component will disappear from ACR, CAR, or VCS.

Formal Management Plan

The above Massachusetts study found that eligibility requiring management plans had a no significant influence in willingness-to-participate. Fischer and Charnley (2010) also explain that NIPFs already use management practices that promote carbon

sequestration, but landowners “reluctance to participate in formal planning and management programs may be attributable to their values for privacy and autonomy and skepticism about expert knowledge.”

Risk and Institutional Trust

In spite of risk pools and insurance services, the fact that most programs see no difference between intentional and unintentional reversals might be a cause for concerns among landholders. “The lack of overriding financial motivations for forest ownership compounded by concerns about the risks and burdens of entering into agreements with government agencies and other entities will likely limit owners’ participation.” (Fischer and Charnley, 2010) The attribute “implementer” from Markowski-Lindsay et al. (2011) was found to be insignificant to a .1 level.

Perceptions and Misinformation

In a personal interview in 2011, former third party verifier Scott Sager of Environmental Services, Inc., mentioned that one of the biggest obstacles to participation was bad information. Sager gave an example of aggregators who told potential Florida clients that “CCX was going to provide ample demand, but then CCX’s prices plummeted.” (Sager [personal communication], 2011)

The Massachusetts study found that some knowledge about the role of forest in climate change (answering yes to the question: “Forests can help to reduce the impact of climate change”) had a positive and significant association with program participation to a .01 level of significance. The survey also asked the question: “Human activity is causing climate change at unprecedented rates,” but the estimates were not significant. Fischer and Charnley (2010) found that landowners would be more willing to take action if they view themselves more vulnerable to climate change.

Several efforts of key states are helping to reduce information insecurities. The State of Oklahoma provides a state run carbon program with authority to verify carbon offsets. Their efforts reduce risk by offering a list of "state approved aggregators," developing verification protocols, and supporting research[15].

Returns to scale

The Fischer and Charnley (2010) study found that lack of overriding financial motivations and contract risks will likely limit participation. Given the costs of verification and maintenance (these costs depend on project type and land characteristics), these programs may not seem profitable for small-scale landholders. Sager [personal interview] (2011) estimates that "if the project land is less than 1000 acres, given current prices, the project will not be profitable."

Special Requirements

Some programs have specific forest management requirements depending on the methodology and project type, as is the case of VCS, but CAR has a diversity of native species requirement that demands a 95% or higher level of native species within the first 50 years of their commitment period. Fischer and Charnley (2010) find evidence of family forest values that include: enjoying beauty and scenery, protecting nature and biodiversity; both of which correlate with some of these program requirements, but there might be some hidden costs associated with invasive species or planting native species.

Discussion

As seen, ACR, CAR, and VCS offer several differences in program requirements that may attract or dissuade the participation of landowners in carbon offsets. For

[15] Oklahoma Carbon Program website: open http://www.ok.gov/conservation/Agency_Divisions/Water_Quality_Division/WQ_Carbon_Sequestration/About_the_Program/

example, landowners interested in shorter time commitments might consider a REDD or IFM protocol, which does not require engaging in a long-term financial commitment. This group might also prefer to avoid the 100 year obligations of CAR, by using the more flexible commitment periods of VCS (20 -100 years) and ACR (40 years).

But landowners concerned with property rights may not be willing to participate in CAR, which requires land to be transferred to an easement or to public property for the duration of some protocols (REDD). Owners with lands invaded by non-native species would also experience additional costs associated with the diversity of native species requirement of CAR, and available in VCS.

Potential participants concerned with revenue and market stability, might prefer to participate with CAR. This certification currently fetches higher prices, and in lieu of the California Air Resources Board approval of CAR protocols for early-action compliance, this is likely to continue. CAR credits might be grandfathered into the new California CAT program, which might be a way to access this market from a non-WCI member state, like Florida.

For the most part, VCS is the more flexible platform in terms of time commitment, but it also attracts the lowest prices. An advantage of this certification is that it can be traded in more countries and exchanges than ACR or CAR (Peter-Stanly and Hamilton, 2012).

Landowners not interested in ACR, CAR, or VCS might also want to consider other options in the OTC market. If they can find a willing buyer, they would be able to craft their own protocol tailored to their own preferences. This opportunity might not be

so viable, given the existence of reputable platforms such as the ones described in this chapter.

Summary

Carbon markets offer Florida landowners the opportunity to take advantage of their vast forest resources to create wealth, decrease long-term vulnerability from climate change, and strive to maintain the natural, florid character of the state. This chapter examined existing options to participate in carbon markets, and identified differences in available certification programs. In addition, a comparison of these programs was presented, highlighting potential barriers to entry. Any national, regional, or state CAT program in the US is likely to accept forest carbon offsets to make up for pollution using protocols similar to the ones explained in this chapter. Therefore, policy makers in Florida interested in mitigating GHG or increasing options for forest landowners, are going to find useful information in this chapter regarding existing carbon offset certification options. Creating a statewide offset market or joining a regional cap-and-trade program is going to require the cooperation of all sectors of society, but a first good step would be to inform landowners about existing opportunities to engage in forest carbon offsets.

CHAPTER 3
ATTITUDES AND WILLINGNESS TO ACCEPT COMPENSATION FOR CARBON OFFSET PRODUCTION IN FLORIDA: APPLICATION OF BEST-WORST CHOICE MODELING AND DISCRETE CHOICE EXPERIMENTATION

The study of institutional, cultural, or regional preferences for forest-offset markets can shed light on potential barriers to participate in valuable efforts to mitigate the threat of climate change. This chapter characterizes the guiding structure of carbon production in Florida by identifying barriers to participate in a hypothetical carbon-offset program, and by estimating landowner willingness-to-accept (WTA) compensation for enrolment. In December 2011, 310 Florida Forest Stewardship Program (FSP) affiliates (FSP participants and Tree Farm members) responded to an electronically administered conjoint choice survey of hypothetical carbon-offset programs. This study finds evidence that landowners in this sample are willing to engage in carbon-offset markets. The survey also exhibits important preferences for various institutional components. These results can be useful to policy makers interested in regional landowner preferences of carbon-offset markets in the Southeast.

Background

Florida landholders have three major national options to engage forest carbon markets: Climate Action Reserve (CAR), American Carbon Registry (ACR), and Voluntary Carbon Standard (VCS) (Chapter 2). 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 20 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, such as wildfires, or hurricanes (American Carbon Registry, 2010).

A number of recent empirical studies have explored some of the institutional aspects of carbon markets in North America (Table 3-1). In the absence of a national (or regionally present) carbon-offset market that provides analysts with observations of indirect market transactions, the studies seen in Table 3-1 have used hedonic analysis to look for evidence of landowner WTA compensation to produce forest carbon-offsets. The State of the Voluntary Market report (Peters-Stanley and Hamilton, 2012) is the closest publication of voluntary carbon offset market data in North America. The report consists of a survey to carbon-offset brokers, and certification programs to assess market demand and prices. This annual report provides valuable aggregate secondary price data, but it lacks the specific (and regional) focus needed for regional carbon market studies.

Table 3-1. Empirical studies on willingness-to-participate in hypothetical carbon offset markets in North America

Reference	Data	Attribute	Levels
Markowski-Lindsay et al., 2011 (Ratings: 1-5)	Massachusetts family forest owners (n=930)	Revenue Management Plan Enrolled acreage Time Additionality Implementer Withdrawal Penalty	$10, $100, $1000 Require/ not required 50 or 100% 15 or 30 years Required/not required Private/Public sector No penalty or earnings plus 20% fee
Li, 2010 (Random Utility Model)	Texas non-industrial private forest landowners (n=1,032)	Time Revenue	1, 5years, or conservation easement status $2 to $42 acre/year
Fletcher et al., 2009 (Ratings: 1-10)	Massachusetts non-industrial private forest landowners (n=17)	Eligibility Revenue Withdrawal Penalty	Formal Plan, No Plan $5, $15, or $30 acre/year No Penalty, $10 per-acre
Shaikh et al., 2007 (RUM)	Canadian landowners (n=260)	Revenue Time	Bids ($1-60 acre-per-year) 10 years
van Kooten et al., 2002 (Ratings: 1-3)	Canadian farmers (n=182)	Revenue	“Adequately compensated”

In a 2000 survey of 2,000 randomly selected farmers of northeastern British Colombia, Alberta, Saskatchewan, and Manitoba, Shaikh et al. (2007), used a 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 to $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 confines 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.

Van Kooten et al. (2002) also sampled Canadian farmers in 2000 to elicit ratings (1-3) with a question asking if respondents have ever considered large-scale tree planning for “adequate compensation.” The independent variables were respondent level observations such as age, experience with contracts that restrict land use, etc. The only significant variable was “farm located in black soil zone.”

Fletcher et al. (2009) did a similar study in 2007, using a pilot survey of 17 private landowners from Massachusetts (randomly selected from a list of landowners who owned 3 or more parcels, each participant was compensated with $50), to also elicit the likelihood of producing carbon offsets. Participants were surveyed on socioeconomic questions, management activities, reasons 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.

This work by Fletcher et al. (2009) was followed by Markowski-Lindsay et al. (2011) with a 2010 Massachusetts family forest owners survey administered to 930 participants. The results yielded 402 observations of attribute level ratings (1-5) of carbon sequestration programs. The program attributes included were: management plan (required/not required), contract length (15 or 30 years), percent of land required to enroll (50 or 100%), revenue ($10, $100, $1000), additionality, penalty for early withdrawal (no penalty or repay earnings plus 20% fee), and institutional trust (implemented by public or private sector). The results from a random effects order probit found significant preferences for programs with higher net revenue, no withdrawal penalty, shorter contract lengths, and no additional requirements, such as “no requirement that forests must be managed to sequester more carbon than if nothing was done.” The researchers also calculated participation probabilities of three types of carbon program with low, medium, and high “probabilities of participation.” (Chapter 4 for a similar analysis)

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 (Appendix A of Li (2009) for exact survey form). Factors affecting participation were analyzed using a Logit model. Additional questions in this study included awareness of carbon credits, size of forest landownership, current cost-share participation, and importance of managing forestland for producing income. 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 (Figure 2-2). The ratings method used by Fletcher et al. (2009) is similar to the use of BWC in this study, in the sense that both are ordinal in nature, but differ in terms of choice task (Figure 2-2). In addition to using BWC, I used a discrete-choice experimentation (DCE) conjoint task to estimate "traditional values" of WTA used in applied economics, and to increase robustness by assessing attitudinal measurements with multiple statistical models.

The majority of attributes in Table 3-1 were explored in this paper (Table 3-2), but using levels that closely resemble the requirements of current available carbon certification programs for Florida landowners (i.e. CAR, VCS, ACR). "Management

Plan" was not selected as an attribute for this study because the majority of participants are landowners who already have something akin to this requirement via the participation in Florida Stewardship or Tree-Farm Programs. Other contractual requirements such as "100% of enrolled acreage" or specific levels of "additionality," were not included in this study to emulate existing certification programs (CAR, VCS, ACR do not require 100% enrolled acres), or to avoid survey complexity, respectively. The attribute "Implementer" (governmental or non-governmental carbon offset program) was explores in this study, but not included in the conjoint choice questions.

This study contributes to the literature (Table 3-1) by examining a new attribute, "Risk Tool," since ACR, VCS, and CAR currently have options to manage risk using various options, such as "risk pools," "insurance," etc (Chapter 2). Thus, participants were asked to choose programs with "risk pool" or insurance. We also extend the range of commitment periods explored in Table 1-1, by using a 5 to 100 years, which also simulates market realism.

Statistical Models

To choose the most appropriate discrete choice experiment model to estimate the traditional marginal WTA values, Louviere et al. (2000) advise researchers to consider the following design objectives: identification, precision, cognitive complexity, and market realism. Accordingly, this study simulates market realism by using BWC (Figure 2-2), which uses a combination of BWS and discrete-choice experimentation (e.g. Coast et al., 2006), and a DCE (Figure 2-1) with multiple profile options (e.g. Lusk and Parker, 2009). Also BWC produces binary-choice data (Binary hereafter) that I interpret as discrete choice experimentation type to estimate WTA.

The BWS was recently applied to examine preferences in forest management programs in Spain, which concluded that this tool was “a very suitable tool for stakeholder studies” (Loureiro and Arcos, 2012). 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).”

Yet, in regards to market realism, the current situation of carbon markets in the US have multiple certification options (Chapter 2) that vary in terms of duration, risk options, etc. So, existing options might be better simulated by a DCE, which offers multiple options for direct tradeoffs of entire attribute profiles. 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 platforms, would likely research or hire a consultant that will offer a cross comparison analysis of ACR, CAR, VCS and/or other program protocols, offering its customer multiple options with varying contractual length. 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 then instructed to select one or none; whereas Binary presents conjoint options, which elicits an acceptance or rejection option. It may be argued that a national carbon market program would homogenize all options by offering a single protocol, but even in that scenario, this 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). In any case, the application

of both choice elicitation methods, BWC and DCE, will add robustness to this study by exploring attribute tradeoffs in the context of multiple realistic market scenarios.

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

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

Figure 3-1. Example of discrete-choice experimentation question presented to survey respondents

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 ☐

Figure 3-2. Example of best-worst choice question, used to estimate best-worst scaling and binary models

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 non-market valuations techniques 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 (maxdiff) between attribute-levels under a common utility scale, 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 BWC were derived by Marley et al. (2008), where they also propose an empirical design that may allow for the separation of “importance” and “utility.”

Equation 3-1 is from Marley et al. (2008), and represents a paired estimation of BWS “importance” weights, where Z_i and Z_j are the chosen best-worst pair, and Z_k and Z_l can by any other pair within a set of pairs M. The influence of the judgment can show up in the utility value $\tilde{b}(z_i)$ (this is the typical measurement estimated in DCE and Binary models), the weight β_i or both.

$$\mathrm{BW}_z(\mathrm{Z_i},\mathrm{Z_j}) = \frac{\tilde{b}(z_i)^{\beta_i} / \tilde{b}(z_j)^{\beta_j}}{\sum_{k,l \notin M, k \neq l} [\ \tilde{b}(z_k)^{\beta_k} / \tilde{b}(z_l)^{\beta_l}\ ]} \quad i \neq j \tag{3-1}$$

Marley et al. (2008) propose the use of alternating BWC instructions, which alter BWC answers and allow for the Binary and BWS components of BWC to estimate various combinations of $\tilde{b}(z_i)$ and β_i that are used to effectively separates utility and importance. For example, if a survey is eliciting responses for trips to Mexico, in question 1, the participant may be asked to answer BWC instructions (Figure 3-2) assuming that the trip is for business, and in question 2, to answer assuming the trip is for personal pleasure. This allows for BWC answers to depend on instructions, and have two sets of BWS and Binary measurements that are used to solve for $b(z_i) = \tilde{b}(z_i)^{\beta_i} / \tilde{b}(z_j)^{\beta_j}$, which is the overall estimate of a typical BWS (Equation 3-2).

$$\mathrm{BW}_z(\mathrm{Z_i},\mathrm{Z_j}) = \frac{b(z_i)\ / b(z_j)}{\sum_{k,l \notin M, k \neq l} [\ b(z_k)\ / b(z_l)\ ]} \quad i \neq j \tag{3-2}$$

This study presents a BWC with consistent instructions, but the separation of these measurements is the subject of a follow-up study using the estimates from this research, along with a subsequent survey to a randomly selected subpopulation of this study.

Aside: the follow up study separating “importance” and “utility” will administer a version of the BWC conjoint choice task seen Figure 3-2, but with alternating instructions for each of the conjoint choice questions. Namely, question one will read,

“consider the following ‘non-governmental’ carbon credit program;” question two will read, “consider the following ‘governmental’ carbon credit program;” and the subsequent questions will alternate between these two instructions. Each question will continue to elicit a selection of a “most preferred” and “least preferred” attribute level, followed by a question of enrolling or not enrolling in the carbon credit program (Figure 3-2). This process will assume that their responses will depend on program provider (non-governmental vs. governmental), which allows for the separation of measurements (see Marley et al., 2008).

The BWS estimations of this study are based on Equation 3-2, which confounds weights of importance and utility measurements in $b(z_i) = \tilde{b}(z_i)^{\beta_i} / \tilde{b}(z_j)^{\beta_j}$, which is used to estimate the parameters in the equation below:

$$U^i_{diff} = \beta^i_{Att1} D^i_{Att1} + \ldots + \beta_{Att16} D^i_{Att16} + \ldots + \beta^i_{Att1levl1} D^i_{Att1level1} + \beta^i_{Att1level2} D^i_{Att1level2} + \ldots \quad (3\text{-}3)$$

$$+ \beta^i_{Att16level1} D^i_{Att16level2} + \ldots + \varepsilon^i$$

The equation above illustrates the relationship between the difference in “utility” (U^i_{diff} lays on latent utility scale) of a best and worst pair in choice question i (i=1,2,..,12), and the 16 (4 attribute impact variable and 12 level scale values) independent variables (Table 3-2). Each attribute has one impact variable and one level scale value for each level. BWS allows for a separate parameter estimation of the over all average impact of an attribute (β^i_{Att1}) and the attribute level ($\beta^i_{Att1level1}$) scale value (see Flynn et al., 2007). Hence, for choice i, the attribute chosen as best had its impact variable ($D^i_{attribute}$) taking a value of 1, and the worst choice taking a -1, with the rest of the impact variables taking values of 0. The rest of the level scale values are effects coded. (See guidelines for paired estimations in Flynn et al., 2007)

Table 3-2. Attributes and attribute variable 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

As seen in Figure 3-2, 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, WTP 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 hereafter) 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 (see Flynn et al., 2006). This study uses Paired estimation for BWS and random effects logit for Binary. An orthogonal main effects plan (OMEP) taken from Table 9 (Figure B-3) of

Street et al. (2005) was used to construct this survey, which resulted in 16 BWC scenarios (see Flynn et al., 2006).

Discrete-Choice Experimentation

Discrete-Choice Experimentation was first introduced by McFadden (1974), and it is among 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).

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). This study a 100% D-efficient design to construct choice sets of size three, with a “status quo” option. Following the guidelines of “Strategy 6” in Street et al. (2005), which uses software package SAS to generate a starting OMEP, used to create the first choice of each question 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 desired for this study, the choice sets were created using Table 9 from their study (Figure B-3). This process resulted in 16 questions, each with four choices.

This objectives of this chapter are to 1) use best-worst choice and discrete choice experimentation to test the hypotheses that several factors do not affect willingness-to-accept payments for carbon sequestration: (a) carbon contract revenue,

(b) institutional factors (risk tool, contract length, penalty for early withdrawal), and (c) respondent characteristics; 2) to contribute to the literature of forest carbon market research (Table 4-1), by implementing the first regional study of forest carbon markets in Florida using hedonic analysis of non-industrial private forest landowners; and 3) to contribute to the literature stated preference methods in applied economics and forestry, by implementing/introducing best-worst choice in the context of natural resource economics.

Methods

Survey Instruments

The electronic surveys were administered to participants 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 practices and barriers, organized into a reliable extension network, and likely be the group who would seriously consider participating in a forest carbon offset market.

Following the guidelines of Dillman et al. (2009), some key questions from the National Woodland Owners Survey[2] (NWOS) were adapted, to better compare the characteristics of the subpopulation of forest landowners in this study, 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 also followed Dillman (2001), and randomly select a portion (10-20%) of the

[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/

full sample of private owners in each state, 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 of survey respondent demographics of this study with those of 2002-2006 NWOS survey.

Coding

The DCE and Binary models were coded using effects coding for all independent variables. The dependent variable for DCE took 1 if chosen, and 0 otherwise, and Binary took 1 if profile was accepted and 0 if not. Effects coding works by coding all attribute levels, 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. Following Flynn et al. (2006), paired estimation instructions, all attributes of BWS were also coded using effects coding. (Table 3-3)

Table 3-3. Effects coding

Attribute	Effects coding	Effects coding	Effects coding
Contract length	10-years	40-years	100-years
5-years	-1	-1	-1
10-years	0	0	1
40-years	0	1	0
100-years	1	0	0
Revenue	$10	$20	$30
$5 acre-per-year	-1	-1	-1
$10 acre-per-year	0	0	1
$20 acre-per-year	0	1	0
$30 acre-per-year	1	0	0
Penalty for early withdrawal			
No Penalty	1	-	-
Penalty	-1	-	-
Risk tool type			
Insurance	1	-	-
Risk Pool	-1	-	-

Estimation

BWC was estimated with two models, BWS and Binary. The data of the binary component of BWC, which asks respondents to “accept” or “reject” a hypothetical carbon offset program (Figure 3-2) was estimated using random effects logit (REL) to adjust for clustering of individuals’ responses (e.g. Coast et al., 2006). The statistical software STATA models REL by assuming that probability of choosing “accept” (or “reject”) is conditional on random effects of the observations that are assumed to be independently Bernoulli distributed (Rodriguez and Elo, 2003).

The “most preferred” and “least preferred” choice task of BWC (Figure 3-2), BWS, were estimated using paired estimation, which fits the data for use in statistical software STATA, under the conditional logit command, which allows for interaction of covariates (see Flynn et al., 2006). Given that the OMEP used for BWS was unbalanced namely, not all best-worst pairs were equally available for selection (Figure B-3), this study adjusted for this bias using the guidelines provided by Flynn et al. (2006). The adjustment is performed with frequency weights via a two step process: 1) divide the number of times each best-worst pair was chosen 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.

The DCE model was estimated using a conditional 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 3-4, 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 (National Woodland Ownership Survey in this case). The

NWOS is the most comprehensive survey of non-industrial private landowners in Florida. An alternative specific constant (ASC) was included in the model, which is a dummy variable that equals one when the “none of these” option was not choosen (e.g. Adamowicz et al., 1998).

Table 3-4. Characteristics of discrete choice experimentation, best-worst choice, and national woodland ownership survey respondents

Category	NWOS[b] (n=4900)	BWC (n=93)	DCE (n=85)
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%
NGO (Importance of having a “non-government carbon-credit program” vs a government program. Scale of 1 to 5, 1 having the least importance)	-	3.13[c] (1.37)[d]	-

[a] Percent of respondents falling in the respective category
[b] National Woodland Owners Survey results for Florida
[c] Mean
[d] Standard deviation

Both DCE and Binary models were estimated using multiple specifications of both quantitative and effects coded independent variables. The attributes “Revenue” and “Time” were quantitatively coded for some models to attain multiple estimations of marginal WTA.

BWS 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 level importance (relative importance of an attribute level as compared to other attribute levels on a common utility scale). 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. I 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 3.62, 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 model in Table 3-9 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 = very unimportant, 2 = somewhat important, …, 5 = very important), and it takes a value of 1 if the answer was “very unimportant,” and 5 if “very important.”

Choices and Variables

The general guidelines in Chapter 9 of Louviere et al. (2000) for stated preference choice modeling were used to develop this choice tasks. The attributes and levels for this study were selected from 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 during the Summer of 2011. A similar approach was taken to 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 with 24 participants with forestry, policy, and survey design backgrounds. The final survey was electronically implemented following the format and procedural recommendations of Dillman et al. (2009).

Results and Discussion

A total of 920 surveys were administered and 310 responded, for a 34% response rate, which is fairly high according to the studies from Table 3-1 (13% of surveys were completed in Shaikh et al., 2007; 20% in Li, 2010; and 43% in Markowski-

Lindsay et al., 2011). After accounting for filter questions, and participants who did not provide full answers to all demographic questions (with the exception of location questions, such as zip code and address of largest forest plot), the sample size was reduced to 178 (93 with a BWC task, and 85 with DCE). 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 US dollars per choice.

Table 3-5 presents the results of three estimations of DCE using a statistical software STATA's conditional logit model. Model 1 uses effects coding for all variables, Model 2 quantitatively codes "Revenue," and Model 3 quantitatively codes "Revenue" and "Time." The last two columns display marginal WTA estimates for Models 2 and 3.

The results in Table 3-5 are very consistent across models in terms of significance, expected sign, and magnitude. The coefficient of "Insurance" is insignificant, which implies that respondents had no significant preference for either risk pool or insurance. This may be the result of confusion regarding the use of "risk pooling," or simply the fact that participant preferences are driven by some of the other attributes in these hypothetical programs. As anticipated, "Penalty" is negative and significant at a 1% level for all models, and "No Penalty" 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 $6.46 acre-per-year in compensation for Model 2 and $6.44 in Model 3. Model 1 shows an insignificant relationship of the lower two levels of compensation ($5, $20, and $10), and positive and significant for the $30 acre-per-year. Models 1 and 2 reveal a significant (at a 5% level of significance) and positive (except for 5 year contract, which is -.09) preference

for the lowest three levels of “contract duration” (5, 10, and 40 years), and negative for a “100 years contract.” The highest preference is for a 5 year program, followed by 10 years, then 40. The WTA estimates of Model 2 show the same relationship in terms of sign and magnitude. The inclusion of a 100 year commitment in a program is estimated to increase $38.23 acre-per-year in compensation costs. The inclusion of other time commitments would elicit a decrease in compensation costs of $17.95, $15.07, and $5.2 acre-per-year, for 5,10, and 40 years contract, respectively.

Table 3-6 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 discrete choice experimentation models. 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 $43.43 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 “40 year contact” would give up $9.87 acre-per-year in compensation to move to a “10 year contract.” Moving to a carbon program with “no penalty” for withdrawal would elicit a decrease in compensation cost of $12.92 acre-per-year.

Table 3-5. Results from discrete-choice experimentation: conditional 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	-0.09 (0.06)[b]	-0.08 (0.06)	-0.08 (0.06)	$1.26	$1.17
Risk Pool	0.09[e]	0.08[e]	0.08[e]	-$1.26	-$1.17
No Penalty	0.35***[a] (0.07)	0.42* (0.07)	0.42* (0.07)	-$6.46	-$6.44
Penalty	-0.35[e]	-0.42[e]	-0.42[e]	$6.46	$6.44
Revenue Quantitative		0.06* (0.01)	0.06* (0.01)		
Time Quantitative			-0.03* (0.00)		$0.47
$5 acre-per-year	-0.09[e]				
$10 acre- per-year	-0.05 (0.13)				
$20 acre- per-year	0.13 (0.13)				
$30 acre- per-year	1* (0.1)				
5 year contract	-0.09[e]	1.17[e]		-$17.95	
10 year contract	0.94* (0.17)	0.98* (0.17)		-$15.07	
40 year contract	0.36** (0.18)	0.34* (0.18)		-$5.2	
100 year contract	-2.44* (0.42)	-2.48* (0.42)		$38.23	
ASC	-3.33* (0.16)	-4.35* (0.21)	-3.02* (0.17)		
Number of Respondents	85	85	85		
Number of Choices	5440	5440	5440		
Log Likelihood	-873.74	-8788.06	-880.66		
Chi-Square Statistic[c]	2156.33	2147.69	2142.48		

[a] One (*), two (**), and (***) asterisk represent 0.01, 0.05, 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 3-6. Differences in marginal willingness–to-accept ($/choice) for discrete choice experimentation (Model 2) estimates

Attribute	Difference in WTA	Absolute value	Order of impact
WTA to go from Insurance to Risk Pool	$2.52	$2.52	1
WTA to go from No Penalty - Penalty	-$12.92	$12.92	4
WTA to go from a 5 to 10 year contract	-$2.88	$2.88	2
WTA to go from a 10 to 40 year contract	-$9.87	$9.87	3
WTA to go from a 40 to 100 year contract	-$43.43	$43.43	5

Table 3-7 presents the results of three Binary models with the same effects coding used in DCE (Table 3-3). These estimates were similar in terms of sign and significance to the results of DCE from Table 3-5, except for the variables $20 and $10 acres-per-year, which became significant in Model 1, and the coefficient of “40 year contract” became positive in Models’ 1 & 2. The magnitudes of most coefficients in this table are slightly higher than those of their DCE counterparts. “Penalty” carries the same interpretation given for Table 3.6, but the WTA was estimated higher for models 2 and 3, at $10.14 acre-per-year, and $9.00 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 $28.53 acre-per-year. The most preferred, or lowest WTA estimate in Model 2 is “5 year contract” (-$31.47 years of contract) whereas DCE estimated this attribute level to be the second lowest in terms of WTA.

Table 3-7. 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	0.00 (0.08)	0.00 (0.08)	-0.05 (0.08)	$0.02	$0.83
Risk Pool	0.00[e]	0.00[e]	0.05[e]	-$0.02	-$0.83
No Penalty	0.72*[a] (0.09)[b]	0.61* (0.08)	0.54* (0.08)	-$10.14	-$9.00
Penalty	-0.72[e]	-0.61[e]	-0.54[e]	$10.14	$0.50
Revenue Quantitative		0.06* (0.01)	0.06* (0.01)		
Time Quantitative			-0.03* (0.00)		$0.83
$5 acre-per-year	-0.41[e]				
$10 acre- per-year	-1.3* (0.18)				
$20 acre- per-year	1.15* (0.15)				
$30 acre- per-year	0.56* (0.16)				
5 year contract	2.05[e]	1.89[e]		-$31.47	
10 year contract	0.89* (0.15)	0.75* (0.14)		-$12.48	
40 year contract	-1.02* (0.15)	-0.93* (0.14)		$15.42	
100 year contract	-1.92* (0.18)	-1.71* (0.16)		$28.53	
Constant	-0.23*** (0.39)	-1.2* (0.38)	0.2 (0.36)		
Number of Respondents	97	97	97		
Number of Choices	1552	1552	1552		
Log Likelihood	-609.24	-639.29	-669.39		
Chi-Square Statistic[c]	225.68	226.43	199.82		

[a] One (*), two (**), and (***) asterisk represent 0.01, 0.05, 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 3-8. 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	-$0.04	$0.04	1
WTA to go from No Penalty to Penalty	$20.28	$20.28	4
WTA to go from a 5 to 10 year contract	$18.99	$18.99	3
WTA to go from a 10 to 40 year contract	$27.90	$27.90	5
WTA to go from a 40 to 100 year contract	$13.11	$13.11	2

Table 3-8 presents the same analysis of WTA estimates and "order of impact" for Binary Model 2, seen in Table 3-5. These estimates significantly different than those of DCE. The magnitudes are higher, and the order of impact is different. For these estimates, it would require a $13.11 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 $43.43 acre-per-year. The most noticeable change came from the WTA required to have participants switch from a "40 year contract" to a "10 year contact," which went from -$9.87 acre-per-year in DCE, to $27.9 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.

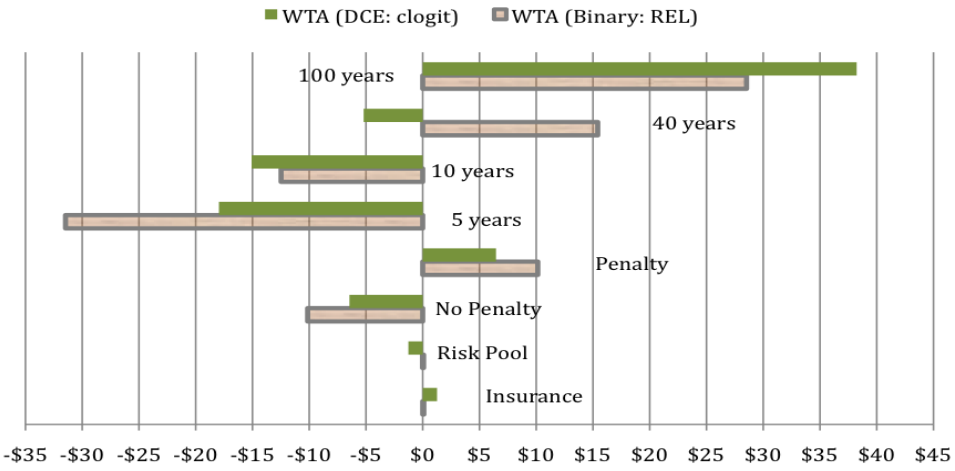


Figure 3-3. Willingness-to-accept ($/choice): discrete-choice experimentation (Model2) vs. binary (Model2)

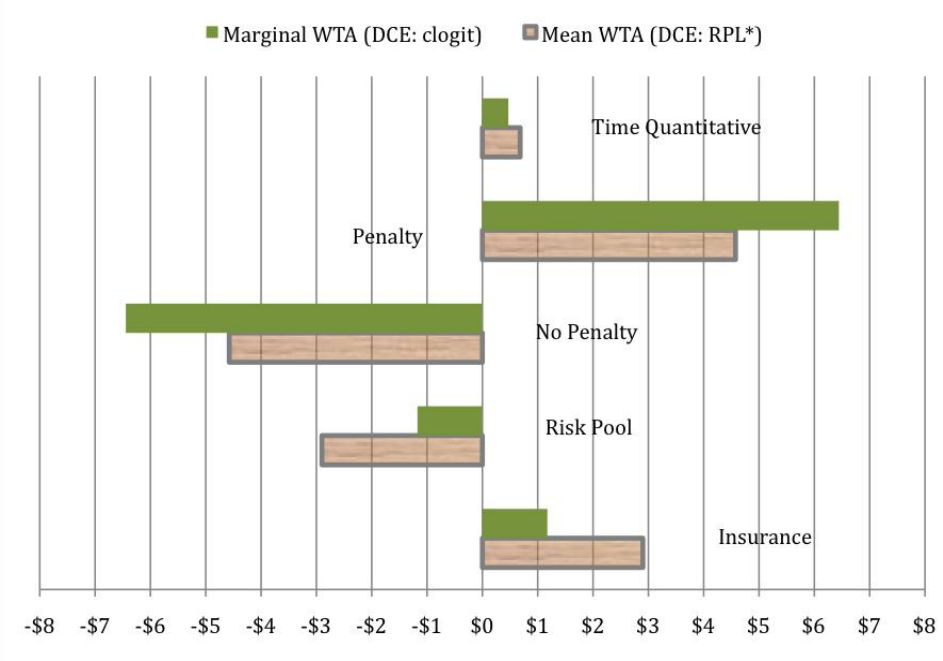


Figure 3-4. Willingness-to-accept ($/choice): discrete-choice experimentation (Model3) vs. binary (Model3)

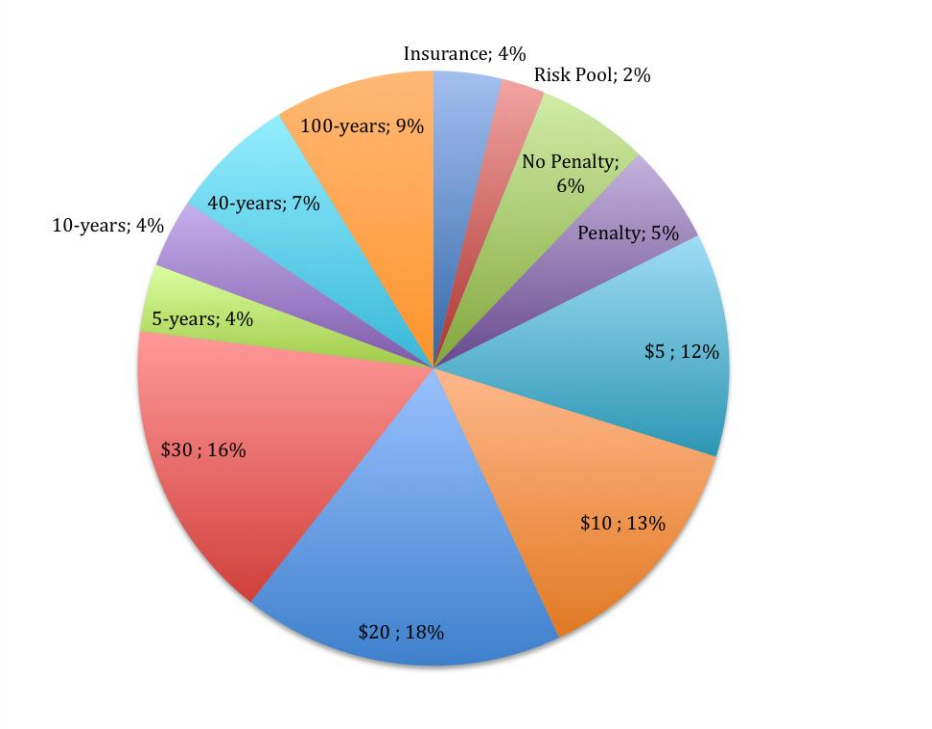


Figure 3-5. Frequencies of “best” attribute choices divided by the number of times they were available for selection

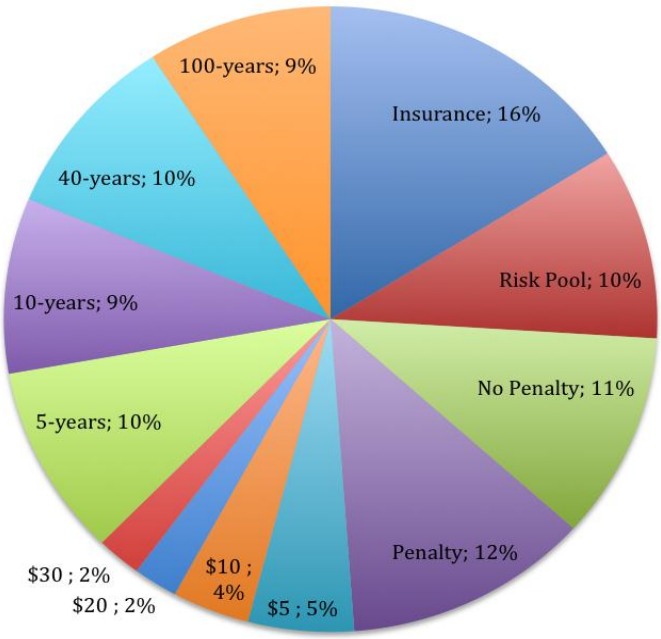


Figure 3-6. Frequencies of “worst” attribute choices divided by the number of times they were available for selection

All of the choice outcomes in Table 3-9 are significant to a 1% level. Ten covariate interactions were insignificant to a 10% level, and five were significant at a 5% level. The type of risk tool is significant to a 1% level, and it indicates a preference for “Risk Pool” over “Insurance.” “Revenue” is the most important attribute, followed by “Risk Tool,” which is slightly less important than “Penalty for Withdrawal.” “Time” was the least important. The level scale values (average effect of an attribute level) indicate preferences similar to those found in the previous models (DCE and Binary). That is, “Penalty” (the level scale value) is less important than “No Penalty,” and the higher levels of “Revenue,” “$20 acre-per-year” “10 acre-per-year” are more important than the lower two. The lower two levels (5 and 10 years) of the attribute “Contract length” are more important than the higher two (40 and 100 years).

Table 3-9. Results from best-worst scaling: clogit estimates adjusting for covariates

Attribute Impacts	Coefficient	Rank
Time	0 (reference)	1
Risk Tool	0.78* (0.04)	3
Penalty	0.38* (0.04)	2
Revenue	3.62* (0.05)	4
Age * Risk Tool	0.12* (0.01)	
Age * Penalty	0.1* (0.01)	
Age * Revenue	0.08* (0.01)	
Education * Risk Tool	-0.34* (0.01)	
Education * Penalty	-0.14* (0.01)	
Education * Revenue	-0.36* (0.01)	
Male * Risk Tool	-0.26* (0.01)	
Male * Penalty	-0.29* (0.01)	
Male * Revenue	-0.2* (0.01)	
Income * Risk Tool	0.05* (0.00)	
Income * Penalty	-0.04* (0.00)	
Income * Revenue	0.08* (0.00)	
Acres * Risk Tool	-0.0003358* (0.00)	
Acres * Penalty	-0.0002792* (0.00)	
Acres * Revenue	-0.0000956* (0.00)	
NGO * Risk Tool	0.01** (0.01)	
NGO * Penalty	-0.02* (0.01)	
NGO * Revenue	-0.25* (0.01)	
Level Scale Values	Coefficient	
Insurance	-0.19* (0.03)	
Risk Pool	0.19* (0.00)	
No Penalty	1.31* (0.03)	
Penalty	-1.31* (0.00)	
$5 acre-per-year	-0.04* (0.00)	
$10 acre- per-year	-0.53* (0.07)	
$20 acre- per-year	0.32* (0.07)	
$30 acre- per-year	0.25* (0.07)	
5 year contract	0.94* (0.00)	
10 year contract	0.92* (0.06)	
40 year contract	-0.96* (0.06)	
100 year contract	-0.19* (0.03)	

[a] One (*), two (**), and (***) asterisk represent 0.01, 0.05, 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 3-9. Continued

Attribute Impacts	Coefficient
Age * Insurance	-0.06* (0.00)
No Penalty	-0.08* (0.00)
Age * $10 acre- per-year	0.01* (0.01)
Age * $20 acre- per-year	-0.05* (0.01)
Age * $30 acre- per-year	-0.02** (0.01)
Age * 10 year contract	0.06 (0.01)
Age * 40 year contract	-0.04* (0.01)
Age * 100 year contract	-0.11* (0.01)
Education * Insurance	0.07* (0.01)
Education * No Penalty	-0.03* (0.01)
Education * $10 acre- per-year	0.0033933* (0.01)
Education * $20 acre- per-year	0.04 (0.01)
Education * $30 acre- per-year	0.08* (0.01)
Education * 10 year contract	-0.14* (0.01)
Education * 40 year contract	0.05* (0.01)
Education * 100 year contract	0.23* (0.01)
Male * Insurance	0.09* (0.01)
Male * No Penalty	-0.07* (0.01)
Male * $10 acre- per-year	0.08* (0.02)
Male * $20 acre- per-year	0.05** (0.02)
Male * $30 acre- per-year	0.07* (0.02)
Male * 10 year contract	-0.15* (0.02)
Male * 40 year contract	0.1* (0.02)
Male * 100 year contract	0.4* (0.02)
Income * Insurance	-0.0001787 (0.00)
Income * No Penalty	-0.03* (0.00)
Income * $10 acre- per-year	0.01 (0.01)
Income * $20 acre- per-year	0.02 (0.01)
Income * $30 acre- per-year	-0.03* (0.01)
Income * 10 year contract	-0.08* (0.01)
Income * 40 year contract	0.01 (0.01)
Income * 100 year contract	0.05* (0.01)
Acres * Insurance	0.00000583** (0.00)
Acres * No Penalty	-0.00000829* (0.00)
Acres * $10 acre- per-year	-0.0000217* (0.00)
Acres * $20 acre- per-year	0.0000375* (0.00)
Acres * $30 acre- per-year	0.00000699 (0.00)

[a] One (*), two (**), and (***) asterisk represent 0.01, 0.05, 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 3-9. Continued

Attribute Impacts	Coefficient
Acres * 10 year contract	-0.0000266* (0.00)
Acres * 40 year contract	0.0001* (0.00)
Acres * 100 year contract	0.0001* (0.00)
NGO * Insurance	-0.0012896 (0.00)
NGO * No Penalty	-0.07* (0.00)
NGO * $10 acre- per-year	0.05* (0.01)
NGO * $20 acre- per-year	-0.02 (0.01)
NGO * $30 acre- per-year	-0.08* (0.01)
NGO * 10 year contract	0.01 (0.01)
NGO * 40 year contract	0.18* (0.01)
NGO * 100 year contract	0.01 (0.01)
Number of Respondents	93
Number of Choices	17856
Log Likelihood	-197552.99
Chi-Square Statistic[c]	156458.72

[a] One (*), two (**), and (***) asterisk represent 0.01, 0.05, 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 3-9 also indicates that the upper two levels of attribute “Revenue” are highly significant (at 1% level), but “$20 acres-per-year” has a higher importance than “$30 acres-per-year,” but the relative difference is .07 units of the common utility scale, whereas the relative difference between $20 and $10 is .85 units. This implies that upper two levels of “Revenue” are fairly similar in importance. This estimate differs from the results of the previous other two models. The three models agree that the lower two levels of compensation are the least preferred within this attribute. The highest importance among the “Time” attributes was the “5 year contract,” and “40 year contract” was the lowest, followed very closely by “100 year contract.”

The results of this study are similar to the general findings of attribute influence from the Massachusetts study by Markowski-Lindsay et al. (2011). Their study indicates that participants prefer higher net revenue, no penalty for withdrawal, and shorter contractual commitments. The range of the compensation values in their study ($10, $100, $1000) and its emphasis on supply analysis (willingness to participate) of specific carbon-offset programs (amount of required enrolled acreage and whether the program was administered by the public or private sector) did not produce comparable WTA estimates. Their study analyses the probability of participation of three carbon offset program scenarios; “Scenario 1,” which includes a 30 year commitment period, penalty for withdrawal, and $10 acre per year compensation, is the only scenario that includes attribute levels similar this study (the other two scenarios included compensations of $100 and $1000 acres per year). The participation rates for this scenario are low (between 2% and 5%), which is relatively similar to the results from this study that finds a negative and significant influence of a $10 acre per year compensation, but a positive and low WTA (-$5.2 acre per year) for a 40 year contract.

Another Massachusetts study by Fletcher et al. (2009), finds average participation percentage estimates of 5% for $15 acre per year compensation, 13% for $30, and 33% for $50, which generally agree with the results of this study. Namely, this study finds negative and significant estimates for compensations that are less than $20 acre per year, and positive and significant for $20 or $30.

The Texas study by Li (2010) considered contract durations of 1 year, 5 years, and the designation of “conservation easement status.” His study estimated average WTA of $15.15 acre per year for 1 year, $19.92 acre per year for 5 years, and $27.36

acre per year for conservation easement. His estimates of WTA for a 5 year contract fall within range of WTA estimates ($17.95 to $31.47 acre per year) from my study. Shaikh et al. (2007) surveyed Canadian landowners and estimated an average WTA of $33.59 acre per year to get farmers to “plant blocks of trees” for 10 year contract durations. My study finds lower WTA estimates ($12.48 or $15.07 acre-per-year) for a 10 year contractual commitment. The difference in WTA estimates between my study and Shaikh et al. (2007) may be due to the fact that my study did not include specific land management requirements for carbon market programs, or attributed to regional and cultural differences between Florida and Canadian landowner preferences.

Alternative Model Specifications

The estimated parameters of Binary (Model 1) and DCE (Model 1) were graphed against their attribute levels, and a non-linear relationship was visually detected for the attribute “contract duration” (Appendix A). A quadratic specification of the quantitatively coded “contract duration” attribute was analyzed, but was found to lack significance at a 10% level in Binary, and in the case of DCE, the linear version of the variable (which was estimated along with the quadratic specification) lost significance at a 10% level. Non linear specifications are the source of future work, but I suspect that the problem may stem from the attribute levels ranges used for “contract duration,” namely, there is a “drastic” change from 40 year to 100 years contract. (Table 3-2)

An effort was made to adjust the random effects logit estimation of Binary to “represent” the population of landowners in Florida, by using the same approach applied to the conditional logit estimation of DCE, but the parameter estimations were drastically changing in sign and significance. This is the subject of future research, but I suspect that using a random effects model logit, which adjusts for the clustering of individual

characteristics, may be conflicting with the population “adjustment weights” that force marginal totals of sample proportions to conform with population totals.

As seen in Figure 3-3 and Figure 3-4, WTA estimates for both Binary and DCE models seem to produce similar results, but the most drastic difference in WTA came from “40 year contract” seen in Figure 3-4, which has a relatively similar magnitude, but with opposite sign. The sign difference may be due to the tipping point in which “contract duration” goes from a positive association with participation, to a negative.

Summary

In this study I have used three different models to analyze the preferences of a subpopulation of Florida landowners towards different aspects of contemporary carbon markets in North America. This study indicates that landowners are not very affected by use of risk-pooling, where they deposit carbon credits to address project uncertainty, or insurance type that is typically used in crops. Using measurements of marginal willingness-to-accept, this study estimates that including a penalty for early withdrawal in this type of program would increase the cost of participation by approximately $6.46 to $10.14 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 a program that offers $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 $28.53 to $37.78 acre-per-year, while a 10 year commitment would lower cost by $12.48 or $15.07 acre-per-year. Overall, 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 my knowledge in the field of applied economics using this model, and the potential of this method to accurately estimate wiliness-to-accept (or WTP), as well as measuring attribute impact, makes it appealing to applied researchers interested in binary discrete-choice experimentation. The results seem to indicate that the estimates of WTA from this model are higher in magnitude than those of the traditional discrete-choice experimentation (with more choice options), but they generally correlate in sign and relative magnitude.

CHAPTER 4
COMPARISON OF BEST-WORST SCALING AND DISCRETE CHOICE EXPERIMENTATION

There is little consensus in definition or measurement of product attribute importance (Louviere and Islam, 2008). The increase in use of best-worst scaling methodologies in the fields of Forestry, Healthcare, and Applied Economics (e.g. Loureiro and Arcos, 2012; Lusk and Parker, 2009) using various estimation methods (e.g. multinomial logit, random parameters logit, frequency scores), raises an empirical question of what is being measured and how it compares to well-established or traditional measurements of utility. This study uses discrete-choice experimentation for external validity, and performs a cross-validation/comparison of best-worst choice. The latter model produces binary observations akin to DCE as well as BWS observations. Each of these models measures utility in a different manner, namely BWC measures direct tradeoffs of attribute level differences, whereas DCE measures indirectly via the choosing of profiles composed of attribute levels. Yet, both models elicit tradeoffs between attribute/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 my knowledge, this study is the first comparative study of BWC and DCE. A recent study by Potoglou et al. (2011) implemented an empirical comparison of BWS and DCE, and found evidence of estimates that reveal similar patterns in preferences. Their experiment did not include price (or cost), which facilitates estimation of WTA/WTP, thereby potentially cancelling unknown confounding factors of this latent class models (see Flynn et al., 2007). 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. This chapter 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 applied differently, using paired models of conditional logit and random parameters, as well as the aggregate measure of frequency scores. However, the former allows for inferences about the effects of respondent-level covariates (see Flynn et al., 2008). This chapter also compares the marginal WTA estimates of BWC-Binary and DCE. The separation of “importance” and “utility” mentioned in Chapter 3 is not address in this chapter, but is the subject of upcoming research (as explained in Chapter 3, the additional survey with alternating instructions is required for this separation, which I am currently designing and exploring its feasibility).

Background

For the past two decades, economists working on environmental issues have been using conjoint analysis, and attribute based methods in the study of “stated preferences.” Non-market valuations are typically examined with these tools, which require participants to rank, choose, or rate a particular scenario 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, forestry, health, and applied economics (e.g. Marley et al., 2008; Flynn et al., 2008; Lusk and Briggeman, 2009). The approach measures the maximum-difference between attribute-levels, while offering an alternative over some of the shortcomings of the previously mentioned methods.

BWS models offer participants a set of items or attribute levels and instruct them to choose the two items with the largest perceptual difference on an underlying scale, namely, one of “most concern” and another of “least concern.” This process is repeated with varying sets of three or more choices, until an experimentally designed number of choice sets are complete (for a complete background of BWS see Flynn et al., 2007).

While comparing the advantages of BWS and ratings, Lusk and Briggeman (2009) explain that in rating-scales, participants are not forced to make trade-offs of relative importance, while in the real world, trade-offs between choices are made on a daily basis. Another deficiency of ratings comes from the notion that different people are likely to use the same scale differently, leaving the interpretation of ratings to an ordinal scale at best (Lusk and Bgriggeman, 2009). BWS minimizes the chances of introducing assumptions about human decision-making, by forcing respondents to consider only the extremes of the utility space (Flynn et al., 2007).

This chapter takes advantage of the well-documented empirical record of DCEs, to "reasonably assume that DCE-derived measures accurately reflect importance in actual market choices” (Louviere and Islam, 2008). DCE’s require few statistical assumptions and the nature of their estimates represent conditional demands, but BWS enables the “impact” (average utility across levels) estimation of all attributes (except one), a task that traditional DCE’s cannot do (Flynn et al., 2007). However, by asking a traditional accept/reject question along side BWS, the strengths of both can be drawn upon (see Flynn et al., 2007). This approach is commonly used in the field of applied economics, given that it provides an option to estimate one of the most important measurements in their field, willingness to pay (e.g. Lusk and Parker, 2009). Another

method includes an additional instruction commonly provided by BWS, which asks respondents if they would be willing to “buy” or “not buy” (Chapter 3) the particular profile of attribute-levels (e.g. Coast et al., 2006, Marley et al., 2008).

Binary answers to non-market goods are common in the field of environmental economics, which allow for the estimation of random utility models (RUM) with referendum type questions (e.g. Hanemann, 1984; Shaikh et al., 2007). BWC elicits such responses, along side direct estimates of BWS. The DCE used for external validity in this study has also been shown to approximate RUM estimates (McFadden and Train, 2000) using mixed logit with approximate choice of variables and mixing distribution. This chapter also compares estimates DCE mixed logit (RPL from now on) with measurements of BWS and Binary estimates contained in BWC.

There is increased importance in weights and WTA measures in the field of applied economics, as well as the “current absence of guidelines for defining sample sizes for BWS”(Flynn et al., 2007), and evidence that increasing sample sizes of choice-based conjoint experiments yield more accurate estimates of WTA (Lusk and Norwood, 2005). So, this study aims to provide cross-validation/comparison to the results of Louviere and Islam (2008), which suggest DCE measures can be systematically impacted by what is included/excluded, thus inference measures from this model will appear sensitive to context effects. By adding a price attribute, and controlling for other survey design elements, I also aim to augment the analysis of Potoglou et al. (2011). The inclusion of an accept/reject question to the BWS profiles will be the first empirical comparison of BWC to DCE.

Research Objective and Methodology

BWS and The Effects of Ambiguity for Empirical Researchers

As explained the previous chapter, BWS estimates of BWC produce measurements of $b(z_i) = \tilde{b}(z_i)^{\beta_i} / \tilde{b}(z_j)^{\beta_j}$ using the following equation:

$$\mathrm{BW}_z(\mathrm{Z_i},\mathrm{Z_j}) = \frac{b(z_i) \ / b(z_j)}{\sum_{k,l \notin M, k \neq l} [\ b(z_k) \ / b(z_l) \ ]} \quad i \neq j \qquad (4\text{-}1)$$

Thus, estimates of $b(z_i)$ include the "weights" of β_i ("importance" weights), with the utility values of $\tilde{b}(z_i)$, which may elicit an erroneous or ambiguous interpretation of the impact that a variable has on judgment. This entanglement cannot be separately identifiable from a single design involving a finite set of profiles (see Marley et al., 2008), and the issue of BWS estimation and interpretation becomes an empirical question in the applied field. The aim of this chapter is to estimate BWS using some of the most widely used procedures, and to empirically compare these measurements with two types of discrete-choice experimentation tools (DCE and Binary) that are common in the field of applied economics. A secondary goal is to compare the welfare estimates of BWC derived using Binary (Chapter 3) to examine the reliability of this technique in estimating WTA measurements.

External Validity

The use of DCE data to compare other limited dependent variable estimations has several advantages, and it is the tool of choice for most empirical studies examining the performance of BWS (e.g. Potoglou et al., 2011; Louviere and Islam, 2008; Lancsar et al., 2007). According to Louviere and Islam (2008), "this tool has a well-established

record of high correspondence of experimental measures with measures derived from real choices," and as such provides the market realism necessary to examine hypothetical carbon markets in Florida, which is the subject of this study.

Estimation and Research Design

The attributes in Table 3-2 were arranged using an OMEP for both BWC and DCE survey designs (e.g. Coast et al., 2006), to control for potential structural design factors that may affect this empirical comparison. The design from Figure B-3, was used in both models. BWC only implemented "Option 1" of optimal design for two 2-level attributes and two 4-level attributes. Options 2 and 3 of the OMEP were design by systematically varying the levels of "Option 1," which is ideal for the purposes of this chapter. Please refer to Chapter 2 and Chapter 3 for a detailed description of the qualitative methods used to select the current survey attributes and participants of this chapter.

The attribute levels of both surveys use effects coding, which is recommended for BWS by Flynn et al. (2007), and optional for DCE (see Louviere et al., 2002). Other aspects of design, such as context-dependent issues discussed in Louviere and Islam (2008) were addressed in equal manner for both surveys to control for the effects of ambiguity. (Appendix A includes examples of both surveys)

All models were constructed using a 100% D-efficient design. Following the guidelines of "Strategy 6" in Street et al. (2005), which uses software package SAS to generate a starting OMEP, used to create the first choice of each question 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

desired for this study, the choice sets were created using Table 9 from their study (Figure B-3). This process resulted in 16 questions, each with four choices.

The design was not balanced, but the appropriate balancing techniques recommended for BWS (see Flynn et al., 2007) were applied to the appropriate designs to make up for the fact that attributes 1 and 2 (risk tool and penalty for withdrawal) from Option 1 in appeared with more times in attributes 2 and 3 (contract length and revenue).

Best-Worst Scaling

The observations of direct attribute level tradeoffs from BWS can be estimated using a number of methods (see Flynn et al., 2007 for a detailed a description estimation procedures). These methods fall into two categories: 1) “paired” estimations, which, as the name suggests, use pairs of best and worst observations to make inferences about the latent utility scale; 2) “marginal” methods using aggregate choice frequencies or individual selections to approximate the paired estimations. I estimated two paired models (Conditional Logit and Random Parameters Logit) and one marginal method using sample level frequency scores of best and worst choices. The former approach is theoretically consistent with maximum distance choice models, but marginal estimations have been found to be in agreement with such paired models (see Flynn et al., 2008).

Paired Conditional Logit

For this model (BWS_clogit from now on) I follow the estimation specifications of Flynn et al. (2008), which allow for the inclusion of covariates (Chapter 3) representing additional impact a given attribute had upon the particular landowner-sociodemographic group. Given that marginal approaches are an approximation to the paired models, only

the latter was considered for covariate interactions. The results from the previous chapter were incorporated for this comparison, along with another specification excluding covariates (Table 4-2).

Paired Random Parameters Logit

The estimation of BWS from Chapter 3 assume that all individuals in the sample place the same level of importance on each value, this assumption is relaxed by allowing importance parameter β_i of best-worst choice *i* of individual *j* to be specified as $\tilde{\beta}_{ji} = \bar{\beta}_i + \sigma_i \mu_{ji}$, where $\bar{\beta}_i$ and σ_i are the mean and standard deviations of β_i in the population, and μ_{ji} is a normally distributed random component with mean zero and unit standard deviation (Lusk and Briggeman, 2009). The use of a reference case (omitting one attribute level or impact variable) to be normalized to zero is also used in this model to both avoid colinearity in effects coding, and to serve as a benchmark for comparing all other estimates. All attribute levels and impact variables were assumed to be independently normally distributed in the population. This approach will be referred to as BWS_RPL from now on.

Frequency Counts

Frequency Counts (BWS_Freq) is an approximation estimate of BWS, and it was used in a recent application of BWS to the field of forestry (see Loureiro and Arcos, 2012). Following the analysis of Louviere and Flynn (2010), these estimates were analyzed by assigning the most preferred attribute level a “1” and the least a “-1,” for each of the 16 profiles in our design, and aggregating their frequencies. These frequency counts of “most” – “least” were subtracted (most - least) and adjusted for the imbalance of the design of this survey. Namely, the “most – least” counts were divided

by the availability of each attribute level. For example, “penalty-for-withdrawal” and “no penalty” appeared 8 times in each survey, and therefore counts of “most - least” for each of these levels were divided by 8. Whereas frequency counts of “most - least” “100 year contracts” which appeared 4 times, were divided by 4.

Discrete-Choice Experimentation

The results from Chapter 3 using conditional logit estimates of DCE were incorporated in this analysis, along with the random utility estimations using RPL (see Train, 2003). All non-price attributes in DCE using RPL (DCE_RPL) were assumed to be independently normally distributed, and the price coefficient was not allowed to vary in the population to make sure that WTA estimates are normally distributed (e.g. Lusk et al., 2003; Train, 2003). The confidence intervals for WTA estimates of DCE_RPL were estimated using 10,000 repetitions of the Krinsky-Robb method (Krinsky-Robb, 1986). Other specifications such as adjusting the population proportions were similar to the ones applied to conditional logit estimations of DCE (DCE_clogit) from Chapter 3.

WTA measurements were estimated for DCE_clogit, DCE_RPL, and Binary (Chapter 3) models. Louviere and Islam (2008) elaborate on the significant advantages using WTA for model comparison purposes. Attribute utilities in discrete choice models are measured on interval scales unique to each attribute and individual. These estimates of utilities are confounded by the magnitudes of estimated attribute parameters with error variances of individuals. WTA estimates cancel these effects by offering a common utility scale in terms of price/choice, which allows for the appropriate comparison of attributes. All DCE measurements of WTA (see Louviere et al., 2000, Chapter 12) were assumed to come from a linear indirect utility function. For example, a 2 level attribute, such as penalty for withdrawal would have a WTA given by the ratio of

the attribute's coefficient to that of the price coefficient, $\beta_{Pen} / \beta_{\$}$, where the units of β_{Pen} are utility per level, and $\beta_{\$}$ are utility per dollar. BWS has the advantage of producing level scale parameter estimates with a common utility scale.

The purpose of estimating DCE using random parameters logit is to make use of the WTA estimates to evaluate the performance of BWS, and to compare them to the Binary WTA estimates from Chapter 3. The same method used in Chapter 3 to adjust population proportions to match those of the National Woodland Ownership Survey results from Florida were used for these estimations.

An alternative specific constant (ASC) was included in the model, which is a dummy variable that equals one when the "none of these" option was not choosen. ASC controls for (or represents) the utility associated with moving away from "none of these" option. Adamowicz et al. (1998) utilized a similar ASC for a similar orthogonal desing using multiple conjoint estimations, and explain that a lack of inclusion of ASC may result in "status quo" bias. In their study, they elaborate on the ambiguity surrounding the interpretation of this parameter, namely, if negative and significant, this may be considered so form of "status quo" bias (in the case of this study, this could entail lack of insitutional trust or understanding of carbon market programs), but it may also indicate a form of "protest response." This study specified the ASC option as "non of these" (instead of "status quo"), the parameter estimate of ASC does not carry a clear (although survey instructions explicitly asked respondents to consider each choice set in isolatin from the following or previous questions sets) behavioral interpretation.

Results

The results from Table 4-1 were estimated using the same procedure as Chapter 3, but omitted the interaction of covariates. All attribute impacts and scale parameters were significant to a 1% level, with the exception of “Penalty,” which was significant at a 5% level. Risk Tool was used as the reference case, and the most valued attribute was Revenue, while Penalty the least valued. The attribute impacts produced a different order of rank than the one found in the previous chapter (the BWS clogit estimation with individual covariates from Chapter 3 will be referred to as BWS_clogit_demo from now on). The least preferred attribute of contract length was “40 year contract,” and the most was “100 year contract.” This result differs from Chapter 3, and may be a result from of adjusting for covariates, namely, most of the interaction of contract length with individual covariates found in Table 3-10 were significant, which suggests that the effects of this attribute on utility varies within subpopulations of participants. The rest of the estimates produce similar results to Chapter 3, in terms of a preference for no penalty for withdrawal, the two higher levels of Revenue. The attribute level scale parameters of Risk Tool were significant in this model, and show a preference for the use of Risk Pool.

Table 4-1. Results from best-worst scaling: clogit estimates

Attribute Impacts	Coefficient	Rank
Risk Tool	0	2
Time	0.44* (0.01)	3
Penalty	-0.01** (0.01)	1
Revenue	1.89* (0.01)	4

[a] One (*), two (**), and (***) asterisk represent 0.01, 0.05, 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 4-1. Continued

Level Scale Values	Coefficient
Insurance	-0.05* (0.01)
Risk Pool	0.05
No Penalty	0.32* (0.01)
Penalty	-0.32
$5 acre-per-year	-0.39
$10 acre- per-year	-0.16* (0.01)
$20 acre- per-year	0.3* (0.01)
$30 acre- per-year	0.24* (0.01)
5 year contract	0.11
10 year contract	-0.04* (0.01)
40 year contract	-0.21* (0.01)
100 year contract	0.36* (0.01)
Number of Respondents	93
Number of Choices	17856
Log Likelihood	-207100.15
Chi-Square Statistic[c]	137364.39

[a] One (*), two (**), and (***) asterisk represent 0.01, 0.05, 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

The estimation results of BWS_RPL are displayed in Table 4-2, which produce measurements of importance for level scale values and attribute impacts. These estimates are relative to Risk Tool, and most mean estimates were significant at a 1% level, except for “$10 acre-per-year,” which was significant at a 5% level, and “insurance,” which turned out insignificant. Only the standard deviations of the attribute impacts were significant at a 1%, while none of the level scale values had a significant at 10%. The most important attribute was “Revenue,” and the least was “Risk Tool.” The rank order was also differs in this model from the results of BWS_clogit and BWS_clogit_demo. These results will be further analyzed in the subsequent comparison analysis section.

Table 4-2. Results from best-worst scaling: random parameters logit model estimations

Attribute Impacts		Coefficient	Rank	Share of preference
Risk Tool	Reference Case	0	1	9.07%
Contract Length	Mean	0.61* (0.11)	2	16.65%
	St. dev.	0.97* (0.11)		
Penalty for Withdrawal	Mean	0.97* (0.09)	3	24.05%
	St. dev.	0.64* (0.09)		
Revenue	Mean	1.71* (0.08)	4	50.23%
	St. dev.	-0.33* (0.09)		
Level Scale Values		Coefficient		
Insurance	Mean	-0.03 (0.05)		6.56%
	St. dev.	0.09 (0.06)		
Risk Pool	Effects coded	0.03		7.00%
No Penalty	Mean	0.2* (0.05)		8.29%
	St. dev.	-0.01 (0.05)		
Penalty	Effects coded	-0.2		5.54%
$5 acre-per-year	Effects coded	-0.96		2.60%
$10 acre-per-year	Mean	-0.76** (0.09)		3.16%
	St. dev.	0.03 (0.07)		
$20 acre-per-year	Mean	1.37* (0.12)		26.78%
	St. dev.	-0.07 (0.1)		
$30 acre-per-year	Mean	0.35* (0.1)		9.61%
	St. dev.	0.04 (0.08)		
5 year contract	Effects coded	-0.18		5.64%
10 year contract	Mean	-0.2* (0.08)		5.52%
	St. dev.	0.02 (0.09)		

[a] One (*), two (**), and (***) asterisk represent 0.01, 0.05, 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.

Table 4-2. Continued

Level Scale Values		Coefficient	Share of preference
40 year contract	Mean	-0.39* (0.09)	2.74%
	St. dev.	0.12 (0.09)	
100 year contract	Mean	0.77* (0.08)	8.76%
	St. dev.	0.04 (0.05)	
Number of Respondents	93		
Number of Choices	17856		
Log Likelihood	-2482.26		
Chi-Square Statistic[c]	228.06		

[a] One (*), two (**), and (***) asterisk represent 0.01, 0.05, 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.

The importance of the levels of contract length show a similar order of importance found in BWS_clogit, with the “100 year contract” having the most preference and the “40 year contract” the least. These results also show a preference for “no penalty,” at a 1% level, and “insurance” was insignificant.

Table 4-3 shows another model specification for BWS_RPL excluding impact variables (BWS_RPL_levels). The level scale value of “100 year contract” was significant at 1%, but in contrast with the results of Table 4-2, the standard deviation of this level was also significant at 10%. The mean was .28, and the standard deviation was .21, which shows a drastic variation from the estimated mean of “100 year contract.” The most important level of “contract duration” was “100 year contract,” while the least important was “5 year contract,” the other two levels were insignificant. The lower two levels of revenue were insignificant, and the “$20 acre-per-year” level was the

most important of this attribute. The most important overall significant level was “100 year contract” and the “Penalty” was the least.

Lusk and Briggeman (2009) allude to the fact that “one of the difficulties in evaluating the importance of each value that results from MNL and RPL models is that the estimates themselves have no natural interpretation.” Their research comparing BWS estimations using multinomial logit and RPL remedy this problem by computing “shares of preferences.” This calculation is performed by plugging the estimated parameters into the logistical equation. (Column four of Table 4-3)

The shares of preference were (which add up to one given the nature of the logistical equation) are presented Figure 4-1, and they show that on average, 13% of people believe that “100 year contract” and “$20 acre per year” are the most important attribute levels. Whereas 11% believed that “No Penalty” was most important. Shares of preferences were not estimated for BWS_clogit, because it was a conditional estimation of BWS.

Table 4-3. Results from best-worst scaling: random parameters logit model estimations excluding impact variables

Attribute Impacts		Coefficient	Share of Preference
Insurance	Reference Case	0	-
No Penalty	Mean	0.08** (0.04)	10.67%
	St. dev.	0.06 (0.1)	
Penalty	Effects coded	-0.08	9.05%
$5 acre-per-year	Effects coded	-0.31	7.21%

[a] One (*), two (**), and (***) asterisk represent 0.01, 0.05, 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.

Table 4-3. Continued

Attribute Impacts		Coefficient	Share of Preference
Insurance	Reference Case	0	-
No Penalty	Mean	0.08** (0.04)	10.67%
	St. dev.	0.06 (0.1)	
Penalty	Effects coded	-0.08	9.05%
$5 acre-per-year	Effects coded	-0.31	7.21%
$10 acre-per-year	Mean	-0.10 (0.06)	8.88%
	St. dev.	0.00 (0.09)	
$20 acre-per-year	Mean	0.26* (0.06)	12.81%
	St. dev.	0.00 (0.08)	
$30 acre-per-year	Mean	0.15** (0.06)	11.38%
	St. dev.	0.00 (0.13)	
5 year contract	Effects coded	-0.22	7.87%
10 year contract	Mean	-0.09 (0.07)	8.98%
	St. dev.	0.01 (0.08)	
40 year contract	Mean	0.03 (0.07)	10.13%
	St. dev.	0.22** (0.12)	
100 year contract	Mean	0.28* (0.07)	13.03%
	St. dev.	0.21*** (0.12)	

[a] One (*), two (**), and (***) asterisk represent 0.01, 0.05, 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.

The shares of preference were also estimated for BWS_RPL and presented in Table 4-2. Figure 4-2 uses estimates from the RPL model using impact weights. An advantage of BWS is that it allows for the separation of impact weights and scale values (Flynn et al., 2007).

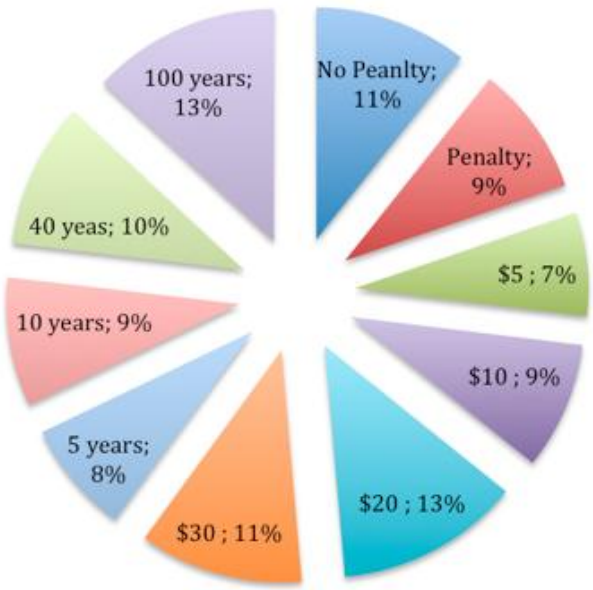


Figure 4-1. Relative desirability of carbon offset institutional elements: estimated with BWS_RPL excluding impact variables.

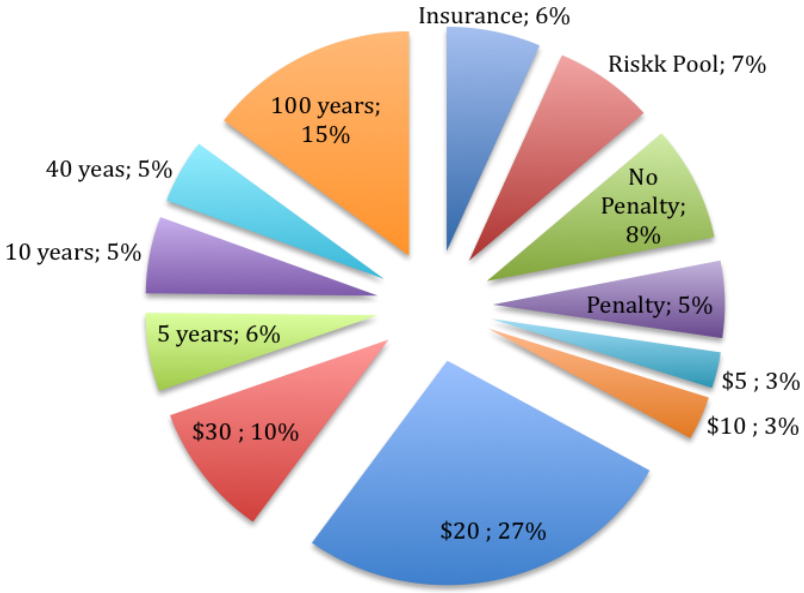


Figure 4-2. Relative desirability of carbon offset institutional elements: estimated with BWS_RPL

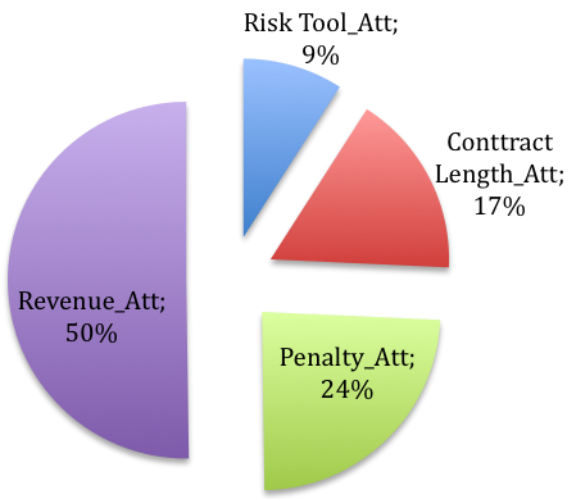


Figure 4-3. Relative desirability of carbon offset institutional attributes: estimated with BWS_RPL

In Figure 4-2 I see that 15% of this sample finds “100 year contract” to be the most important, and 8% “No Penalty.” Figure 4-3 illustrate the share of preference of attribute impacts, which show that 50% of respondents find the attribute “Revenue” the most important, while 20% “Penalty for withdrawal.”

Table 4-4 presents the results from a BWS Frequency Count model (BWS_Freq). Given that BWC elicits direct responses of “most preferred” and “least preferred” elements of a carbon offset program via the use of BWS, these methods allows us to explore the data from this study without pairing the most and least responses. The mean of “most – least” estimates of this procedure adjusts for the availability of individual attribute levels. The analysis of these frequency counts typically evaluates estimates by subgroups and categories (e.g., Loureiro and Arcos, 2012), but in this chapter I restrict the scope of this study to the aggregate population of respondents. Each respondent answered 16 questions and 97 participants completed the entire

survey, which came out to 1504 observations of “most preferred” and “least preferred” attribute levels.

Table 4-4. Results from best-worst scaling: frequency counts

Attribute level	N[a]	Most[a]	Least[a]	Most - Least[a]	Mean[b]
Insurance	1504	63	258	-195	-0.02 (0.06)[c]
Risk Pool	1504	81	269	-188	-0.02 (0.06)
No Penalty	1504	157	217	-60	0.00 (0.06)
Penalty	1504	132	251	-119	-0.01 (0.06)
$5 acre/year	1504	156	46	110	0.02 (0.12)
$10 acre/year	1504	179	40	139	0.02 (0.12)
$20 acre/year	1504	228	22	206	0.03 (0.11)
$30 acre/year	1504	220	24	196	0.03 (0.11)
5 years	1504	46	94	-48	-0.01 (0.12)
10 years	1504	46	89	-43	-0.01 (0.12)
40 years	1504	84	96	-12	0.00 (0.12)
100 years	1504	112	98	14	0.00(0.12)

[a] The number of times an attribute level was chosen across all choice sets and respondents.
[b] Total most – least counts divided by the availability of each principle (calculated as the number of times it appeared across the design, see Figure B-3 Option 1 in Appendix B for availability design).
[c] Standard deviations from the adjusted mean.
[e] Effects coding: negative sum of the above level scale values corresponding to this attribute

Figure 4-4 illustrates the frequencies of “most preferred” minus “least preferred.” The analysis of this study focuses on the adjusted mean estimates from column 6 on Table 4-4, which are graphically displayed in Figure 4-5. Figure 4-4 shows the mean frequency scores before adjustment. From Figure 4-5 I see that the relative estimate of “$20 acre-per-year” seems to have the most importance, closely followed by “$30 acre-per-year.” “Risk pool” and “insurance” seem to have the least relative importance, followed by “penalty.” The lowest levels of “contract length” were found to have the less relative importance than the “100 year contract” level.

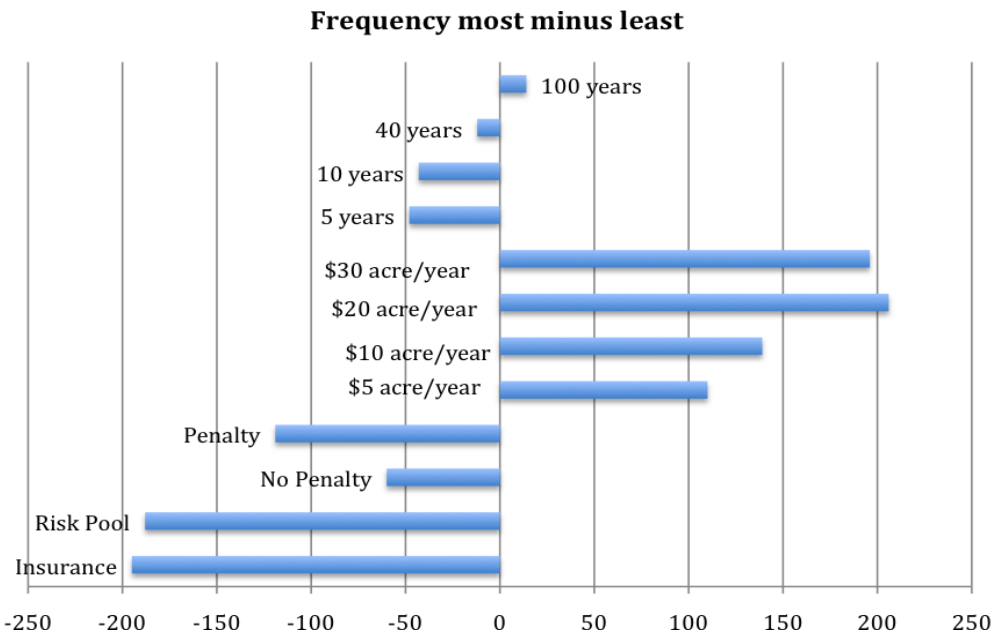


Figure 4-4. Best-worst scaling: frequency of "most -least" scores for the 12 attribute levels of carbon-program institutional components

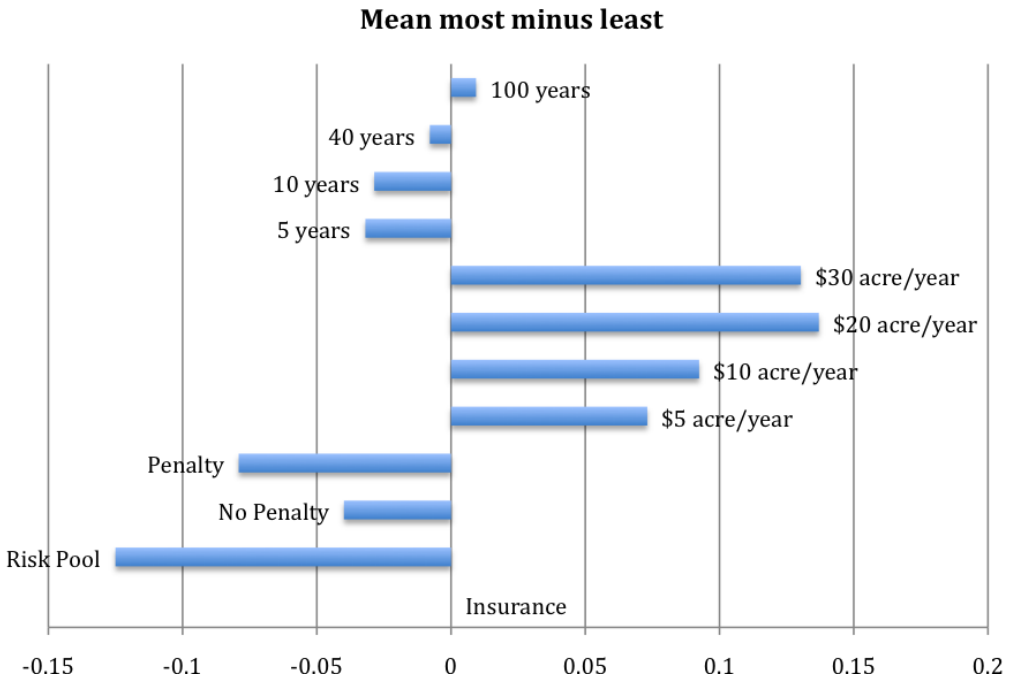


Figure 4-5. Best-worst scaling: mean of "mean-least" scores for the 12 attribute levels of carbon-program institutional components

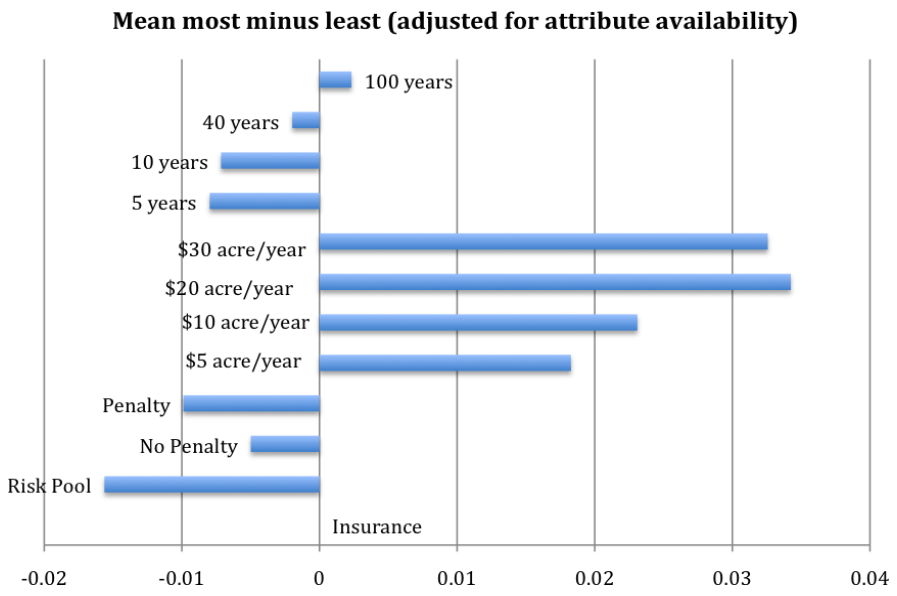


Figure 4-6. Best-worst scaling: mean of "mean -least" scores for the 12 attribute levels of carbon-program institutional components, divided by the number of times they were available

Table 4-5 presents the results of DCE using random parameters model. As previously discussed, the model was specified to assume that all non price attibutes were independently normally distributed, and the revenue was not allowed to vary. The specification was similar to the logistical analysis of DCE in Chapter 3, but the model is respecified to allow for the coefficients to vary in th population rathan being fixed within the conditional logit (see Train, 1998). Fixing the price coefficient enables the estimation of WTA measurements that are ensured to be normally distributed, and it forces respondents to have a positve revenue coefficient, which could not happen under a normally disttributed parameter of "Revenue" (Lusk et al., 2003). Revenue was quantitatively coded for all estimates, and two different specification are presented in Table 4-5. Model 1 in this table uses effects coding for all attribute levels (expect revenue), and Model 2 quantitatively codes Revenue and Contract Length (Time).

Table 4-5. Results from discrete-choice experimentation model: random parameters logit model estimations

Attribute	Specification	Model 1 Revenue quantitative	Model 2 Revenue & Time quantitative
Revenue Quantitative	Fixed	0.19*[a] (0.02)	0.18* (0.02)
Insurance	Mean	-0.01 (0.13)	-0.51* (0.12)
	St. dev.	-0.54* (0.11)	-0.66* (0.15)
Risk Pool	Effects coded	0.01	0.51
No Penalty	Mean	0.81* (0.17)	0.81* (0.28)
	St. dev.	-0.83* (0.24)	0.64** (0.3)
Penalty	Effects coded	-0.81	-0.81
Time Quantitative	Mean		-0.12* (0.01)
	St. dev.		0.08* (0.01)
5 year contract	Effects coded	2.69	
10 year contract	Mean	1.81* (0.25)	
	St. dev.	-1.02* (0.23)	
40 year contract	Mean	-0.99* (0.3)	
	St. dev.	-1.07* (0.13)	
100 year contract	Mean	-3.51* (0.51)	
	St. dev.	-0.64** (0.26)	
ASC	Mean	-22.47* (3.23)	-10.84* (1.06)
	St. dev.	17.21* (3.18)	11.88* (1.23)
Number of Respondents		85	85
Number of Choices		5440	5440
Log Likelihood		-305.79	-328.40
Chi-Square Statistic[c]		1144.54	1104.52

[a] One (*), two (**), and (***) asterisk represent 0.01, 0.05, 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.

The majority of estimates from Model 1 were significant at a 1% level, except for the standard deviation of “100 year contract” that attained significance at a 5% level, and the mean of “Insurance,” which was insignificant at a 10% level. All means and standard deviations from Model 2 were significant at a 1% level, execpt for the standard deviation “No Penalty.” Both models produce similar and postive estimations of the means of “Revenue” and “No Penalty,” showing that on average, more revenue and the absence of a penalty for withdrawal would increase participation in carbon offset markets. The lower two levels of contract length from Model 1 have an association with participation, while the lower two are negative at the mean values. The estimate of “Time Quantitative” is negative and has large and significant standard deviation of .08 from an estimated mean of -0.12. The ASC paramter estimate was negative and significant to a 1% level. This may indicate the presense of the protest answers to this survey, or a “non of these” (“status quo”) bias. If this study would have indicated that the fourth option in each DCE question set was to be interpreted as the “status quo” management of their forest land, then ASC would have a clearer behavioral interpretation.

Table 4-6. Mean willingness–to-accept ($/choice) estimates for discrete-choice experimentation: random parameters logit (Model 1)

Attribute	Mean WTA	Median WTA	[95% Confidence Interval]	
Insurance	0.06	0.06	[-1.41	1.29][b]
Risk Pool	-0.06	-0.06		
No Penalty	-4.27	-4.24	[2.57	6.18]
Penalty	4.27	4.24		
5 year contract	-14.24	-14.04		
10 year contract	-9.53	-9.46	[6.61	12.9]
40 year contract	5.18	5.13	[-8.67	-1.91]
100 year contract	18.59	18.36	[-25.67	-12.9]

[b] Number in parentheses are confidence intervals, estimated using 10,000 repetitions of the Krinsky-Robb Method

Table 4-7. Mean willingness–to-accept ($/choice) estimates for discrete-choice experimentation: random parameters logit (Model 2)

Attribute	Mean WTA	Median WTA	[95% Confidence Interval]	
Insurance	2.9	2.83	[-5.34	-0.91]
Risk Pool	-2.9	-2.83		
No Penalty	-4.58	-4.51	[3.69	5.86]
Penalty	4.58	4.51		
Time Quantitative	0.68	0.67	[-2.15	0.71]

[b] Number in parentheses are confidence intervals, estimated using 10,000 repetitions of the Krinsky-Robb Method

The confidence intervals from Table 4-6 and Table 4-7 were estimated using 10,000 repetitions of the Krinsky-Robb Method. The WTA estimate of “10 year contract” in Table 4-6 indicates that the inclusion of this attribute is associated with a $18.59 acre per year mean increase in costs of enrollment, whereas a program with “5 year contract” would see a $14.24 decrease in mean compensation needed for participation. The exclusion of penalty for withdrawal would decrease participation costs by an average of $4.27 acre per year. This estimate of WTA for “Penalty” is similar in Model 2 ($4.58). Table 4-7 estimates that the overall effect of a one-unit increase in contract length is an associated mean increase of $0.68 acre per year in enrollment costs.

Table 4-8. Differences in mean willingness–to-accept ($/choice) for discrete-choice experimentation: random parameters logit (Model 1) estimates

Attribute	Difference in WTA	Absolute value	Order of impact
WTA to go from Insurance to Risk Pool	-$0.12	$0.12	1
WTA to go from No Penalty – Penalty	$8.54	$8.54	3
WTA to go from a 5 to 10 year contract	$4.71	$4.71	2
WTA to go from a 10 to 40 year contract	$14.71	$14.71	5
WTA to go from a 40 to 100 year contract	$13.41	$13.41	4

Table 4-8 details differences in mean WTA across attribute levels for Model 1 of DCE_RPL. These results indicate that it would take an average of $13.41 acre per year to have a landowner accept a change from a 40-year contract to a 100-year contract, but it would only take an average of $14.71 acre per year to go from a “10 year contract”

to a “40 year contract.” The results of “order of impact” show that the biggest absolute difference between levels came from highest levels of contract length and the lowest (of the significant estimates) came from also from this attribute.

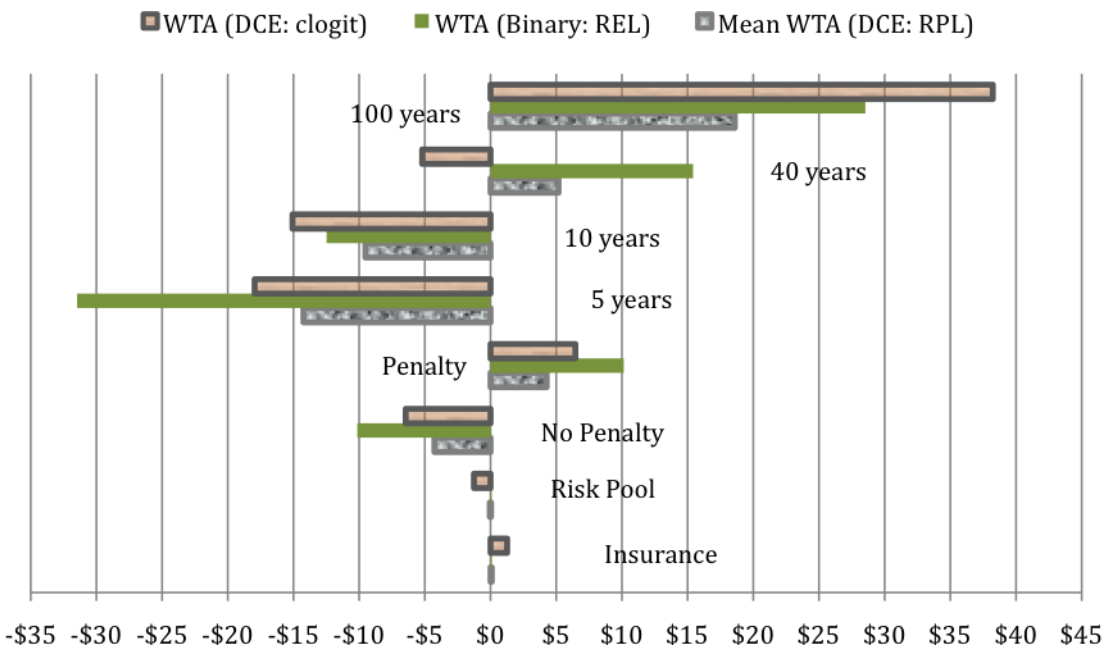


Figure 4-7. Willingness-to-accept estimates for models with the variable “Revenue” quantitatively coded

Figures 4-8 compares WTA estimates of Binary and DCE_clogit from Chapter 3, with DCE_RPL and finds relative agreement from all models. For the most part, Binary appears to be over estimating WTA measurements in 3/8 attribute levels, while estimates of DCE_RPL seem to be in between the estimates of the other two models. The quantitatively specified DCE_RPL was compared in Figure 4-8, and finds similar results as Figure 4-7, but seems to have more agreement with DCE_clogit.

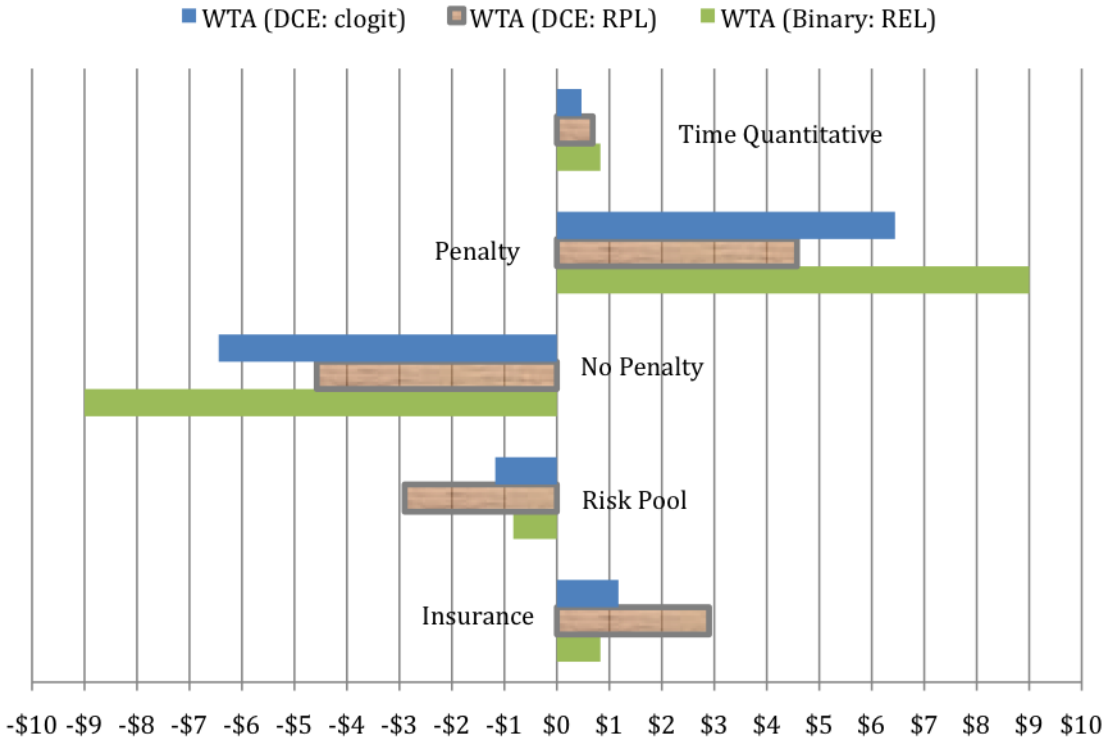


Figure 4-8. Willingness-to-accept Estimates for models with “Revenue” & “Contract Length” variables quantitatively coded

Comparisons of Importance Measures

Figure 4-9 compares the estimates of BWS using Random Parameter Logit, Conditional Logit Model, and Adjusted Mean Frequency Counts (the upper horizontal axis corresponds to the adjusted Mean of Frequency Counts). This figure shows more agreement between estimations of BWS_clogit and BWS_RPL, and slightly less with BWS_freq. The latter model does not estimate impact weights and therefore seems absent in the lower part of this Figure. There is strong disagreement among models regarding “insurance” and “risk pool,” estimates of relative importance, but this attribute overall did not carry a lot of significance. There is strong agreement with dominant importance of the highest two levels of revenue, and some disagreement between BWS_Freq and the other two models. There is general agreement of the relative

importance of the levels within the attribute contract length, which generally state that "100 years contract" is of higher importance than the other three levels. BWS_clogit and BWS_RPL of the impact value of the attribute "revenue" and "risk tool," but somewhat differ with "penalty." The same can be said of BWS_clogit_demographics, which are compared in Figure 4-10.

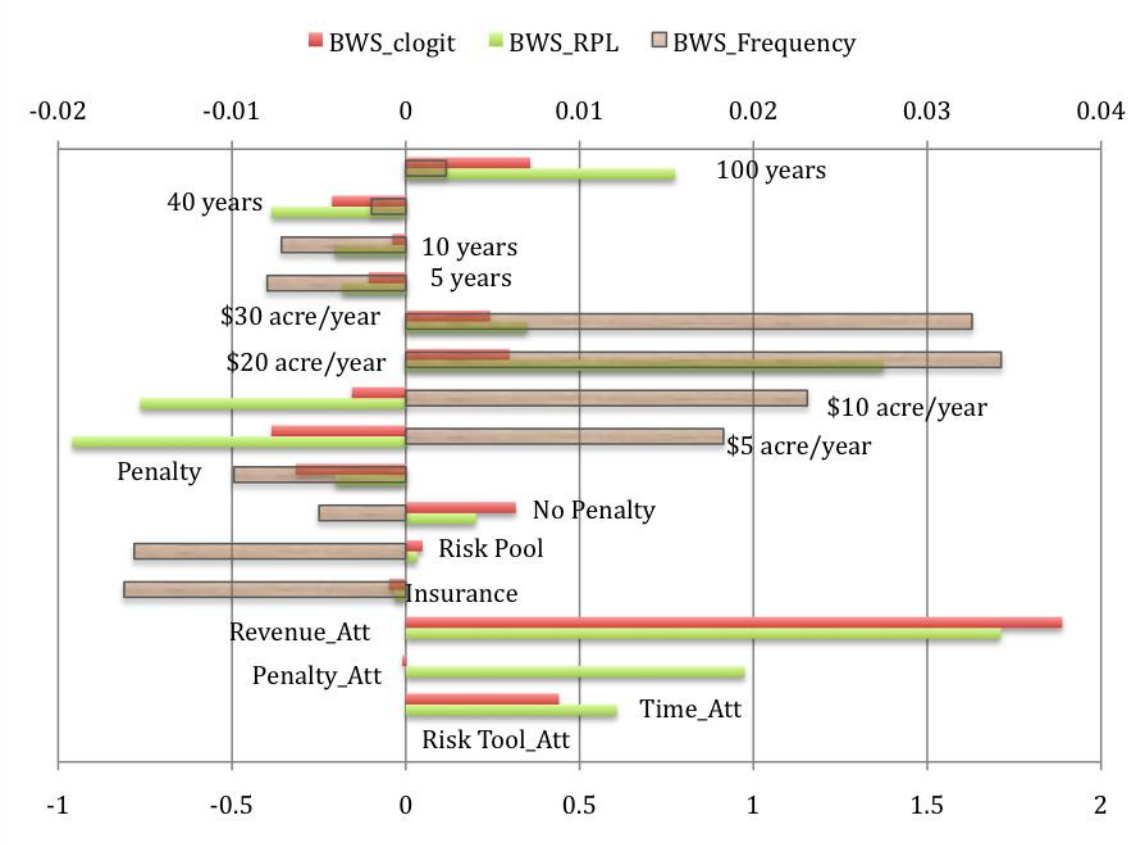


Figure 4-9. Best-worst scaling model comparison: estimated using random parameter logit, conditional logit model, adjusted mean frequency counts (the upper horizontal axis corresponds to the adjusted mean of frequency counts, and the lower to the paired BWS estimations of clogit and RPL)

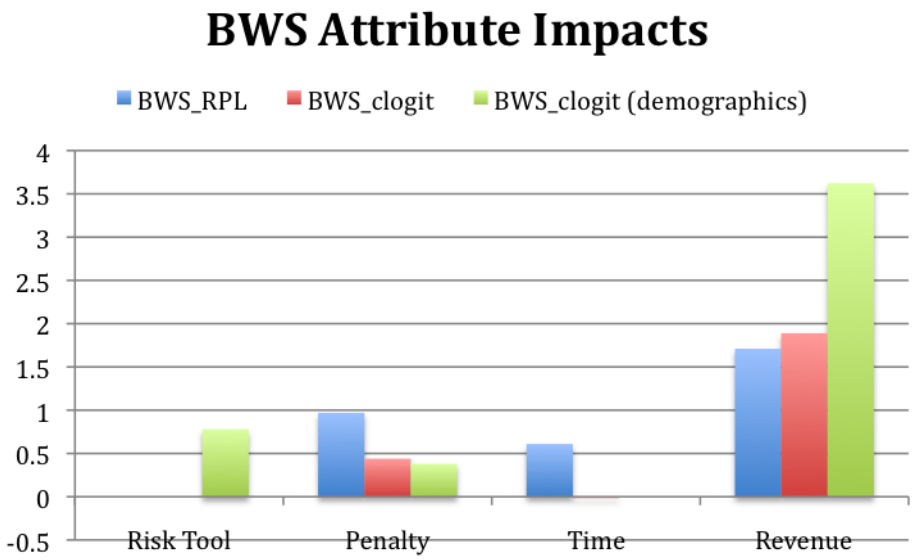


Figure 4-10. Best-worst scaling attribute impact estimate comparison of random parameter logit and conditional logit models

Table 4-9. Order of differences between best-worst scaling level scale attributes for BWS_clogit, BWS_RPL, and BWS_Freq (1 having the lowest distance)

Level Scale Attribute	Order of difference between levels (difference)		
	BWS_RPL	BWS_clogit	BWS_Freq.
Difference between Insurance to Risk Pool	6	5	1
Difference between No Penalty - Penalty	1	6	6
Difference between $5 to $10 acre-per-year	7	1	5
Difference between $10 to $20 acre-per-year	3	7	8
Difference between $20 to $30 acre-per-year	2	3	3
Difference between 5 to 10 year contract	5	4	2
Difference between 10 to 40 year contract	8	8	7
Difference between 40 to 100 year contract	4	2	4

Table 4-9 presents the differences between BWS level scale values and orders them according to their magnitude (1 having the least magnitude). Results show there is almost general agreement between the three models that the biggest difference between levels came from the attribute “10 to 40 year contract,” which is not the most important attribute with respect to the estimations of impact values. Figure 4-11

graphically displays this ordinal comparison, and shows more agreement between BWS_RPL and BWS_clogit.

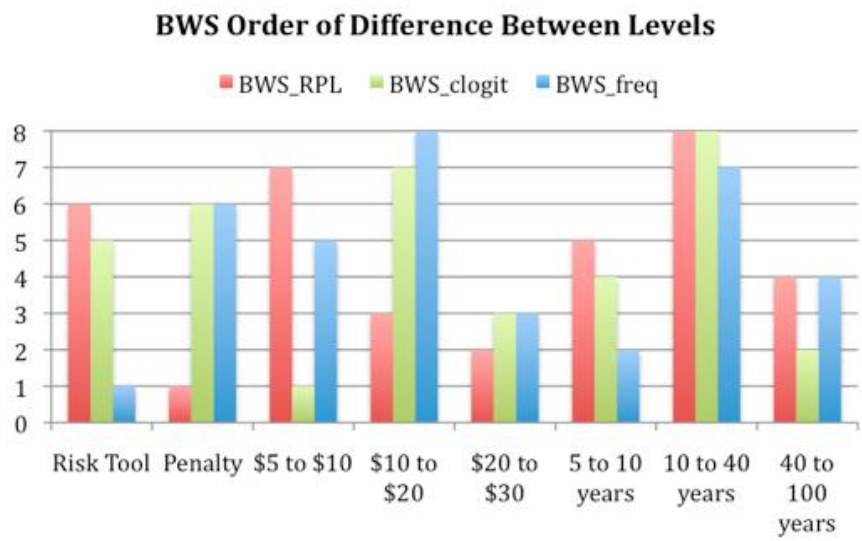


Figure 4-11. Best-worst scaling order of difference between attribute levels of random parameter logit and conditional logit models

Table 4-10. Ordering of relative impact of attribute/scale level ranges across best-worst scaling models estimated using random parameter logit, conditional logit, adjusted mean frequency counts (1 having the least impact)

Level Scale Attribute	Order of relative impact (range)		
	BWS_RPL	BWS_clogit	BWS_Freq
Risk Tool	1 (0.07)	1 (0.1)	1 (0.00)
Penalty	2 (0.4)	3 (0.63)	3 (0.00)
Time	3 (1.16)	2 (0.57)	2 (0.01)
Revenue	4 (2.33)	4 (0.69)	4 (0.02)

Table 4-10 presents the ordering of relative impact of attribute/scale level ranges across methods BWS estimations (1 having the least impact). This table illustrates a general agreement between methods regarding the ranking of the attributes with the biggest and shortest ranges, but shows disagreement on the rankings in between. Figure 4-12 displays these ordinal rankings and shows relative agreement between the three models, but more between BWS_freq and BWS_RPL.

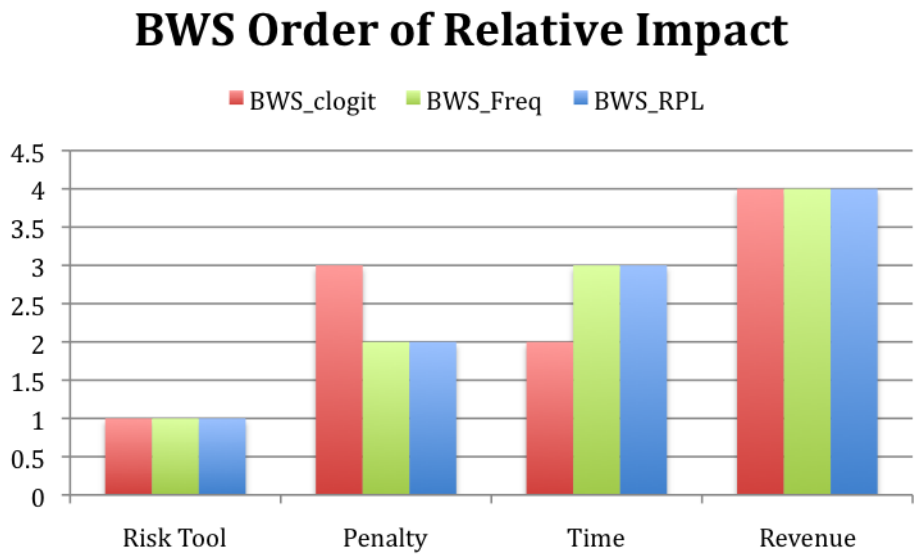


Figure 4-12. Best-worst scaling order of relative impact of attribute/scale level ranges across methods

Table 4-11 presents a comparative display of relative "impacts" of attribute/scale level ranges across methods. The values from the last third columns correspond to the ordering of WTA ranges of DCE models, and Binary Model 1, respectively; the middle three columns reflects the hierarchy of level scale value range in BWS. These values range from 1 to 4, where 4 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. By design, using WTA limits us from producing a rank order estimates for "revenue."

Table 4-11. Comparison between rank and ordering of relative impact of attribute/scale level ranges across all methods used in Chapter 3 and Chapter 4 (1 having the least impact)

Attribute	BWS Rank and "(impact value)"			Order of relative impact and "(WTA attribute range)"					
							Using WTA attribute range		
	BWS (RPL)	BWS (clogit)	BWS_clogit (demographics)	BWS (RPL)	BWS (clogit)	BWS (Freq)	DCE (RPL)	DCE Model 2 (clogit)	Binary Model 2 (REL)
Risk Tool	1 (0)	2 (0)	3 (0.78)	1	1	1	1 (0.12)	1 (2.52)	1 (0.04)
Penalty	3 (0.97)	3 (0.44)	2 (0.38)	2	3	3	2 (8.54)	2 (12.92)	2 (20.28)
Time	2 (0.61)	1 (-0.01)	1 (0)	3	2	2	-	-	-
Revenue	4 (1.71)	4 (1.89)	4 (3.62)	4	4	4	3 (32.83)	3 (56.19)	3 (60.00)

Table 4-12. Comparison of order of differences between levels across all methods used in Chapter 3 and Chapter 4 (1 having the least impact)

Level Scale Attribute	Order of differences between levels (1 having the lowest magnitude)						
	BWS (RPL)	BWS (clogit) demographics	BWS (clogit)	BWS (Freq)	DCE (RPL)	DCE Model 2 (clogit)	Binary Model 2 (REL)
Difference between Insurance to Risk Pool	6	8	5	1	7	8	1
Difference between No Penalty - Penalty	1	1	6	6	2	1	4
Difference between $5 to $10 acre-per-year	7	5	1	5	1	6	7
Difference between $10 to $20 acre-per-year	3	6	7	8	6	2	2
Difference between $20 to $30 acre-per-year	2	3	3	3	3	3	5
Difference between 5 to 10 year contract	5	4	4	2	4	4	3
Difference between 10 to 40 year contract	8	2	8	7	5	7	8
Difference between 40 to 100 year contract	4	7	2	4	8	5	6

Table 4-11 shows general agreement between all models indicating that "revenue" is the most important attribute in terms of order of rank and order of relative importance, whereas "risk tool" is the least important in all models except BWS_clogit_demographics and BWC_clogit, which place "Time" as the attribute with least importance. It is important to note that "Risk tool" was insignificant in DCE_RPL and DCE_clogit. The exclusion of covariates from the model BWS_clogit produces a slightly different order of impact than BWS_clogit_demographics, but if the impact values are relatively similar, namely, "Penalty" is 0.44 for the former and 0.38 for the later, "Time" is -0.01 for the former and 0 for the later; the similarity differs in "Revenue" and "Risk tool." The impact values of BWS_clogit are in more agreement with DCE_clogit. The ranges estimated using WTA attribute measurments seem to be similar for all DCE, but the magnitudes of DCE_RPL apper slightly smaller than DCE_clogit and DCE_REL. Overall, BWS Rank appears to producing similar measurements of order of relative impact of DCE using WTA and BWS using level scale values.

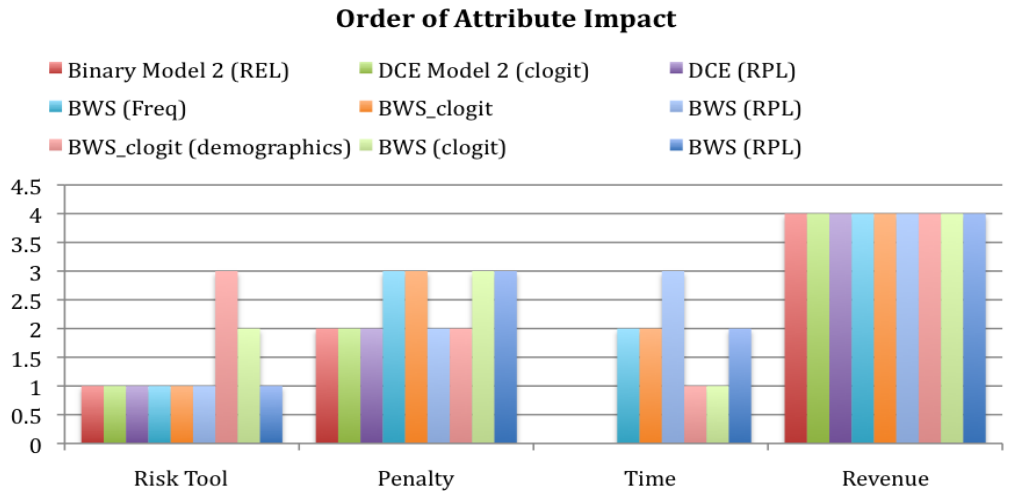


Figure 4-13. Order of attribute impact

Figure 4-13 shows the order of impact from all models. BWS_clogit using demographics seems to be the only model assessing the second importance to “risk tool.” The adjustment for covariates may be influencing the estimate of impact values.

Table 4-12 compares the “order of differences” between levels across all methods used in Chapters 3 and 4. The differences were ranked from 1 to eight, based on the largest magnitude differences between levels, where 1 indicates the lowest difference. Figure 4-14 graphically displays these ordinal comparisons. This figure shows a general disagreement of between all models, which concurs with the BWS comparison of these ordering indicators shown in Figure 4-11.

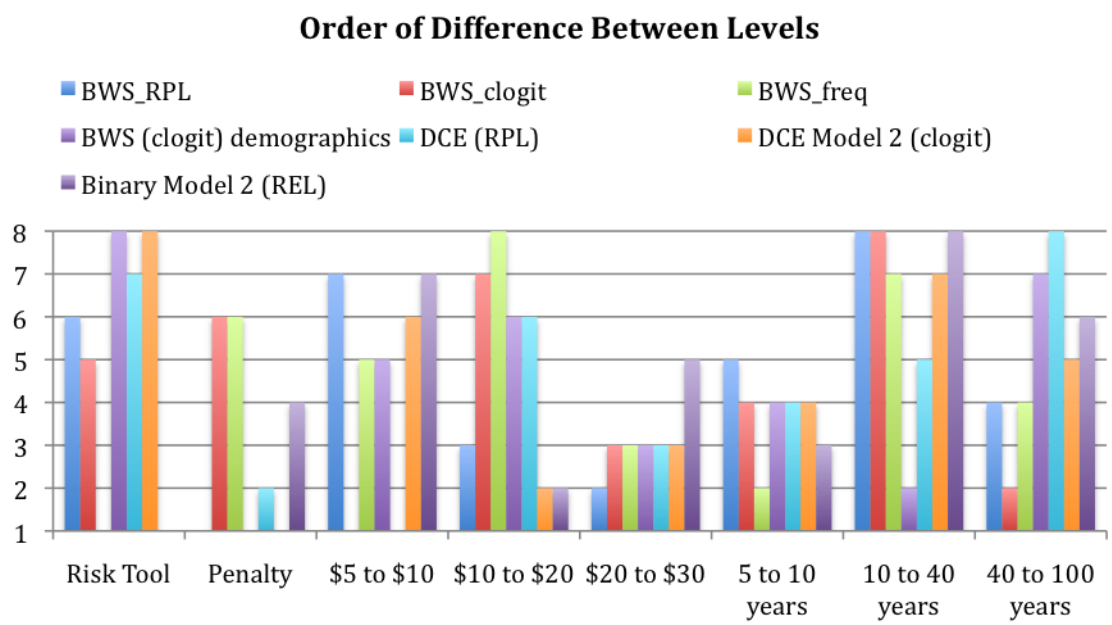


Figure 4-14. Order of difference between levels

Limitations

This comparison chapter did not include other BWS estimations, such as weighted least squares, and other marginal methods proposed in Flynn et al. (2007). Further analysis of covariates would have provided more information regarding the

influence of their interaction with level scale values and impact variables in the BWS. The analysis of sub-populations, which are common in the use of Frequency Counts, was not factored into these comparisons, which may also limit the scale of this analysis.

Discussion and Summary

To better select the most appropriate discrete choice experiment, Louviere et al. (2000) advise researchers to consider the following design objectives: identification, precision, cognitive complexity, and market realism. For some applications, such as referendum type questions, BWC may provide the necessary market realism to estimate welfare measures and BWS analysis importance. The identification and precision of BWS estimates from BWC have been found to be sensitive to model specification and estimation, but to generally agree with the paired estimations of conditional logit and random parameters logit. There was also general agreement with the ordering of attribute impacts, especially with regards to the highest and lowest ordered attributes across most DCE, BWS, and Binary models, but not within the middle range areas. Most BWS specifications (including the use specifications using demographic covariates) did agree fully with this ordering. This study did not determine the reason for these differences, but this is the subject of further research exploring the effects of relaxing some assumptions of conditional logit using random parameters logit in BWS estimations, as well as potential problems of price endogeneity and non-linearity in BWS.

The welfare estimates of Binary from BWC were found to be in general agreement with all DCE estimations in regards to sign and significance, but they seem to be overestimating some (about 37%) of the WTA measurements of attribute levels of carbon offset programs institutional components. Train (2003) explains the fact that

binary logit models that fail to account for other available (or expected) choices have fewer parameters in the denominator of the probabilistic equation, which is estimated with the same numerator that assumes only two options (yes/no), may affect the probability of choosing a carbon program.

The overall results of this study suggest that analysts in Forestry and Applied Economics exploring areas of market realism that resemble binary choices (i.e. referendum type studies), will significantly benefit from using best-worst choice, which produces best-worst scaling measurements, along with consistent welfare estimates from a binary discrete choice experimentation tool.

CHAPTER 5
ESTIMATING THE SUPPLY OF FOREST CARBON OFFSETS: STATED PREFERENCE MEASUREMENTS OF CARBON SEQUESTRATION IN FLORIDA

An improvement of forest management practices (IFM) in Florida has been estimated to yield an additional $116.8 million[1] to producers of pine plantations who engage in forest carbon markets (Mulkey et al., 2008). The use of stated preference methodologies to estimate willingness-to-accept (WTA) compensation for producing forest carbon-offsets has been successfully applied to predict participation in these programs, and to examine the supply elasticity for various prices of carbon (Markowski-Lindsay, 2011; Kline et al., 2000; Fletcher et al., 2009). In this chapter I apply a Linear logit model (see Louviere et al., 2000) to estimate the "supply of carbon-offset production" of Forest Stewardship Program (FSP) participants, using measured field plot data from the Forest Inventory Analysis (FIA) of the USDA Forest Service.[2]

From a policy perspective, it is useful to present the findings of stated preference (SP) research in a manner that allows for policy makers to assess the influence of attributes on aggregate participation or adoption rates. Recent studies of hypothetical carbon-offset programs in the US have used this format to present their results of multiple scenarios with fewer or greater institutional requirements (see Markowski-Lindsay et al., 2011). Kline et al. (2000) estimated the potential supply of NIPF land enrolling in 10-year forest conservation reserve programs in Western Oregon and Western Washington, by using a random utility framework (RUM) to estimate WTA, compute the probability of enrollment, and multiplying this probability by the estimated

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

[2] http://www.fia.fs.fed.us/

area of NIPF forestland in these regions. A recent study focusing on land-conversion, surveyed Florida FSP members to elicit responses to bids offering compensation for renting their woodlands for corn production. This study used similar methods to measure WTA and estimate a hypothetical supply curve of NIPF forested land corn production in Florida (Pancholy et al., 2011). This approach may suffer from over generalizations of survey results from subpopulations, but if appropriately implemented, this method has shown to offer an interesting policy interpretation of stated preference research.

Several studies have used revealed preference (RP) data to estimate marginal costs to supply carbon sequestration in the US, based on landowner behavior (see Stavins, 1999). Lubowski et al. (2006) use RP micro-data of landowner behavior to model six major private land uses in the US, by treating commodity prices as endogenous, and predicting carbon storage changes with carbon optimization models. Their simulation results from their study, which introduces a subsidy/tax rate ranging from $0 to $350 per acre to estimate a baseline and policy scenario for multiple land uses, finds lower marginal costs of carbon sequestration when timber harvesting is prohibited on lands enrolled in this type of subsidy/tax program. Their findings show that land use preferences of NIPF landowners would be responsive to incentives (e.g. subsidy and more), and that institutional components, such as taxes for carbon leakages, and restrictions are relevant considerations in RP simulations. Stainback and Alavalapati (2002) also focused on similar carbon sequestration subsidy/taxation policy in the southern US, using Land Expectation Values (LEV) from timber benefits. Their

estimations suggest that a carbon sequestration benefits and emissions cost policy would benefit private forest landowners.

The use of simulation tools is often required in carbon sequestration certification programs to evaluate current carbon stocks and future sequestration rates. The Climate Action Reserve (Chapter 2) for example, under the forest protocol of IFM, requires a qualitative characterization of likely vegetation conditions and activities that would have occurred without the project (including laws, statutes, regulations or other legal mandates), along with 20 sample plots to perform a computer simulation for 100 years.

This chapter extends the results from previous chapters by augmenting the analysis of carbon market preferences with measured forest plot data of current carbon sequestration rates from Florida Forests (USDA Forest Services Forest Inventory Analysis). The probability of participation in multiple carbon offset program scenarios is used to estimate the carbon sequestration supply of respondents who are assumed to enroll in either an IFM program or reducing emissions from deforestation and degradation (REDD).

Conceptual Framework

Following the framework from Louviere et al. (2002), I implement a linear logit model to estimate the probability of choosing to participate in multiple carbon-offset certification programs. Using the Binary data from BWC, I estimate the participation probabilities as follows: Let the probability of choosing to enroll equal to $P_1 = \exp V_{1q} / (\exp V_{1q} + \exp V_{2q})$, where V_{1q} and V_{2q} are the linear characteristic associated with alternative 1 (enroll) and 2 (not enroll). Then,

$$\ln\left(\frac{P_{1q}}{1-P_{1q}}\right)=\sum_{k=1}^{K}\beta_k X_{kq} \tag{5-1}$$

where X_k is the value of the explanatory variables and β_k the parameter estimates. The left hand side is known as the logit of the probability of choice, and it represents the logarithm of the odds that individual q will choose to (enroll) 1. Given that I have observations of repeated choices for each attribute, this approach will yield consistent parameters (Louviere et al., 2002).

This study estimates the probabilities of enrollment for 82 survey respondents who correctly reported their zip code and/or address of their largest forest plot in Florida using BWC. A range of $5 to $130 acre-per-year carbon prices was used to trace the probability of enrollment. All of the programs were specified to use “risk pooling” (Chapter 2) to deal with uncertainty, and supply shifts were estimated using the presence and absence of a penalty for withdrawal (Chapter 3). Three programs were considered to match contract durations of currently available carbon-offset certification programs for Florida landowners (Chapter 2): Program 1 used a 5-year contract (e.g. OTC), Program 2 used a 40-year contract (ACR and VCS), and Program 3 used 100-year contract (e.g. CAR).

Estimating WTA Compensation for Producing Carbon Offsets

This study continues the work from Chapter 3, where two survey elicitation methods were implemented to elicit responses of BWC and DCE (Figure 3-1 from Chapter 3). Survey participants were randomly assigned to either survey type, differing only in terms of the conjoint questions (Chapter 3). Table 5-1 describes the results from a logistical estimation of the binary BWC (Binary_logit from now on) survey responses

using the attributes described in Table 3-2 from Chapter 3. Table 3-4 from Chapter 3 presents a comparison of survey respondents from BWC, DCE, and the most recent (2006) National Woodland Ownership Survey[3] (the most comprehensive NIPF landowners survey in Florida). As seen in Table 3-4, BWC and DCE respondents were properly randomized into each survey, and their demographic responses were very similar. The results from Table 5-1 included observations who responded to a question regarding the location of their biggest plot of land, and who provided identifiable information (e.g. zipcode, address, etc). The BWC data was reduced by 15 observations, and the map of these plots is shown in Figure 5-1.

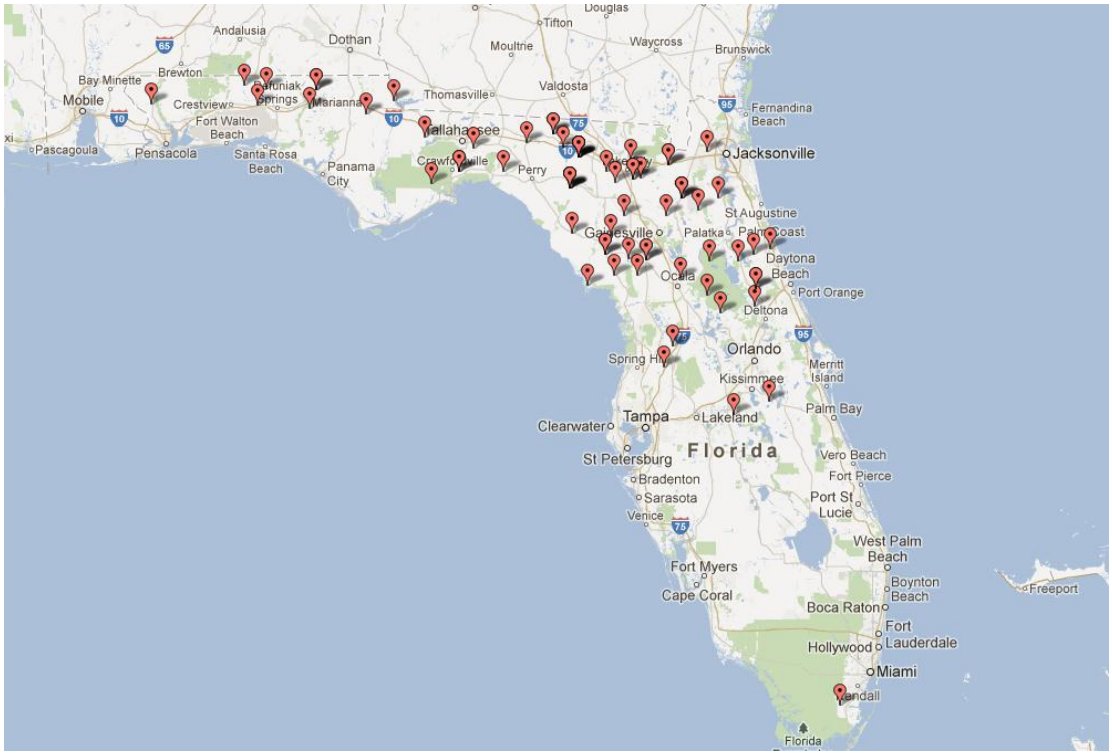


Figure 5-1. Map of biggest forestland plot owned by BWC survey participants.

[3] http://www.fia.fs.fed.us/nwos/

The results from Table 5-1 use effects coding for qualitative attributes ("Risk Tool" and "Penalty for Withdrawal") and quantitative coding for "Contract Duration (time quantitiave) and "Revenue" (Revenue Quantitative) (Chapter 3 details effects coding). The results were very similar to Chapter 3 in terms of sign and significance. Namely, the two levels of attribute "Risk Tool" (insurance and risk pool) were insignificant to a 10% level, while the rest were significant to a 1% level. As expected, "no penalty" and "revenue quantitative" had a positive influence in participation, while "time quantitiave" was negative. The marginal WTA estimates were also similar to their counterparts from the previous chapters, they indicate that an inclusion of "penalty" would increase the costs of enrollment in a carbon-offset program by $10.07 acre-per-year, while an increase of one year of contract duration would increase marginal WTA by $0.69 acre-per-year.

Table 5-1. Results from binary choice model: logit model estimations for survey respondents who reported a correct with address and/or zip code

Attribute	Coefficient	WTA
Insurance	-0.03 (0.06)	$1.04
Risk Pool	0.03[e]	-$1.04
No Penalty	0.29* (0.06)	-$10.07
Penalty	-0.29[e]	$10.07
Revenue Quantitative	0.03* (0.01)	
Time Quantitative	-0.02* (0)	$0.69
Constant	0.13 (0.13)	
Number of Respondents	82	
Number of Choices	1312	
Log Likelihood	-831.10	
Chi-Square Statistic[c]	156.17	
Pseudo R^2	0.09	

[a] One (*), two (**), and (***) asterisk represent 0.01, 0.05, 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.

Figure 5-2 presents a comparative graph of WTA estimates from all discrete choice experimental models of this study, using the coding described for the measurements of Table 5-1. This figure shows that Binary_logit estimates of this sample are in agreement with all other models, especially with Binary_REL, but they seem to estimate higher values of WTA for “penalty” and “no penalty.” The “time quantitiave” estimates are very similar in all models.

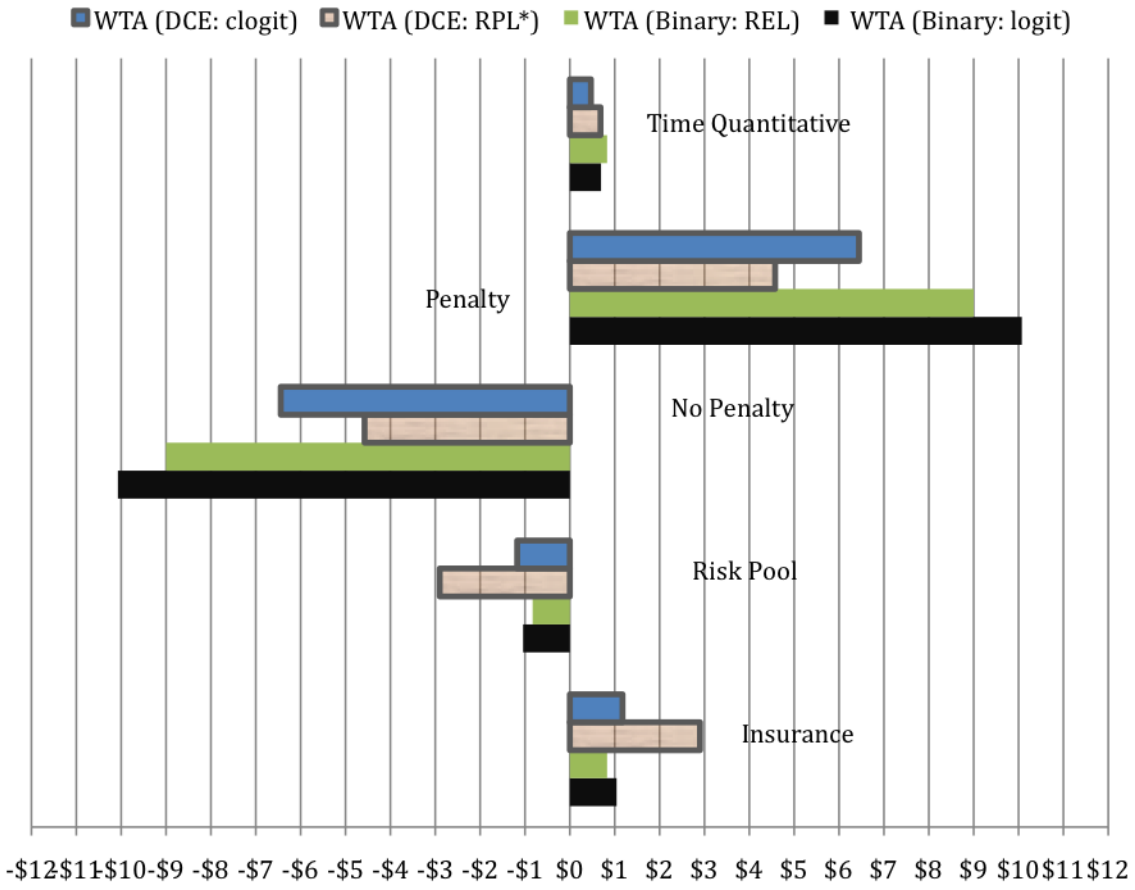


Figure 5-2. Willingness-to-accept ($/attribute level) comparison of various models from all chapters: “time quantitiave” stands for contract length, “pen” is penalty for withdrawal, “no pen” is no penalty for withdrawal, and “risk pool” and “insurance” are the risk abatement tools.

Estimating the Probability of Enrollment

Figure 5-3 shows the estimated supply response by a landowner, with a 95% confidence interval, using Binary_logit for a program with a 5-year contract duration, the use of “Risk Pool,” and “No Penalty” for withdrawal. The scatter plot in this figure shows the supply response for “revenue” values that range from $5 to $130 acre-per-year. The blue diamond points in this figure are the estimated probabilities of enrollment and the red and green lines show the upper and lower bounds of the 95% confidence interval. The figure shows that 95% of this sample would be predicted to participate within these bounds, which lie very close to the estimated participation probability line. Hence, there is not a lot of dispersion from the estimated probability “line.” The supply response line seems fairly elastic for the revenue range of $5 to $70 acre per year, and somewhat inelastic for higher revenues.

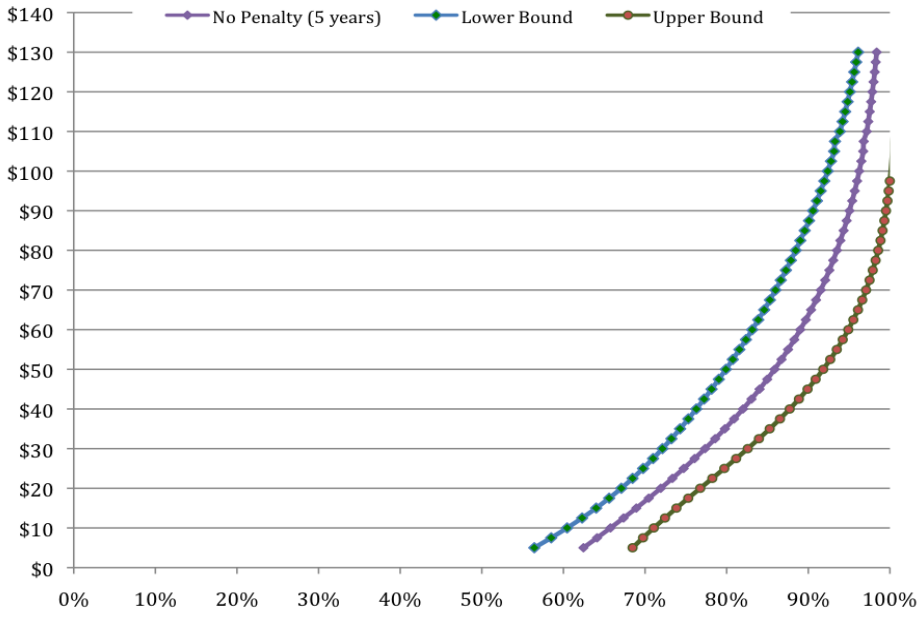


Figure 5-3. Supply response with 95% confidence interval. Supply response by landowner using Binary_logit for a program with 5-years contract duration, the use of “Risk Pool,” and “No Penalty” for withdrawal.

Figure 5-5 illustrates the supply response for Scenario 1 (5 year contract, risk pool), which compares a change of “penalty” to “no penalty” for withdrawal. The green line shows a “no penalty,” which shifts to the left and changes elasticity by introducing a “penalty” for withdrawal. The elasticity results from Figure 5-3 seem to be consistent in this graph, namely, lower estimates of participation probability seem to be more elastic for revenue that is less than $70 acre per year.

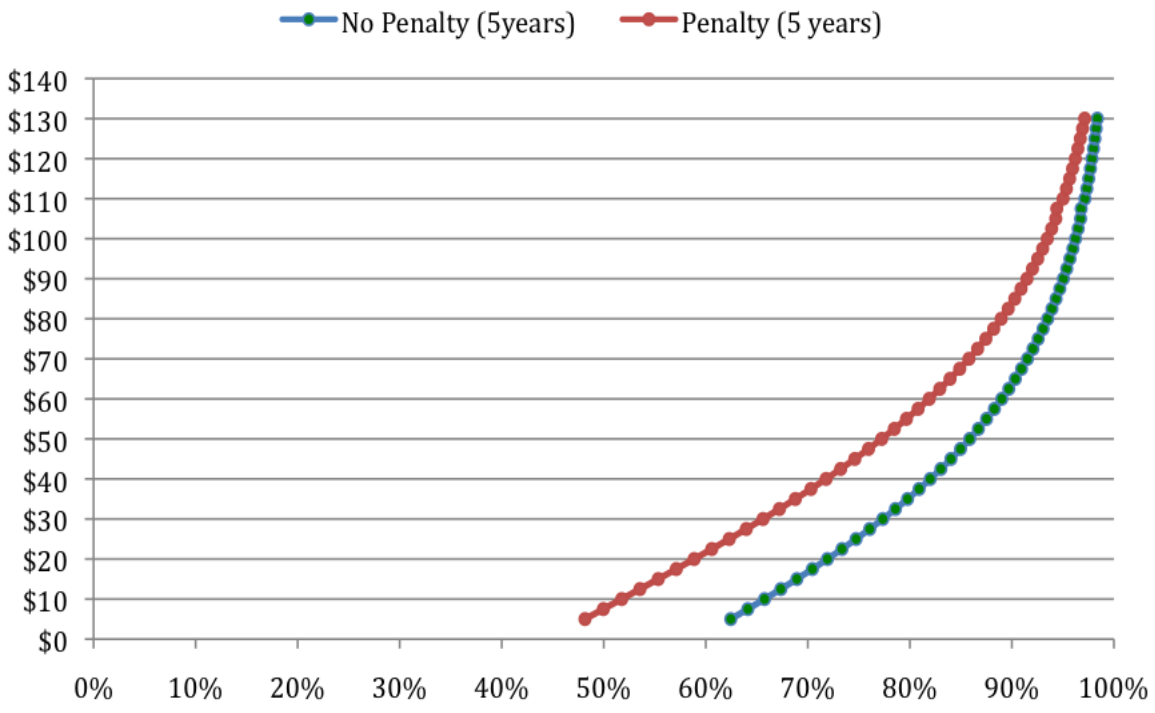


Figure 5-4. Scenario 1 supply response. Supply response by landowner using Binary_logit for a program with 5-year contract duration, the use of “Risk Pool,” and different levels of “Penalty” for withdrawal.

Figure 5-5 shows Scenario 2 (40 year contract with risk pool), which seems to be more elastic than Scenario 1, and the supply shift of a change from “no penalty” (green line) to “penalty” (red line) appears to be greater. This indicates that higher contractual commitments are more decrease sensitive to the inclusion of a penalty for withdrawal.

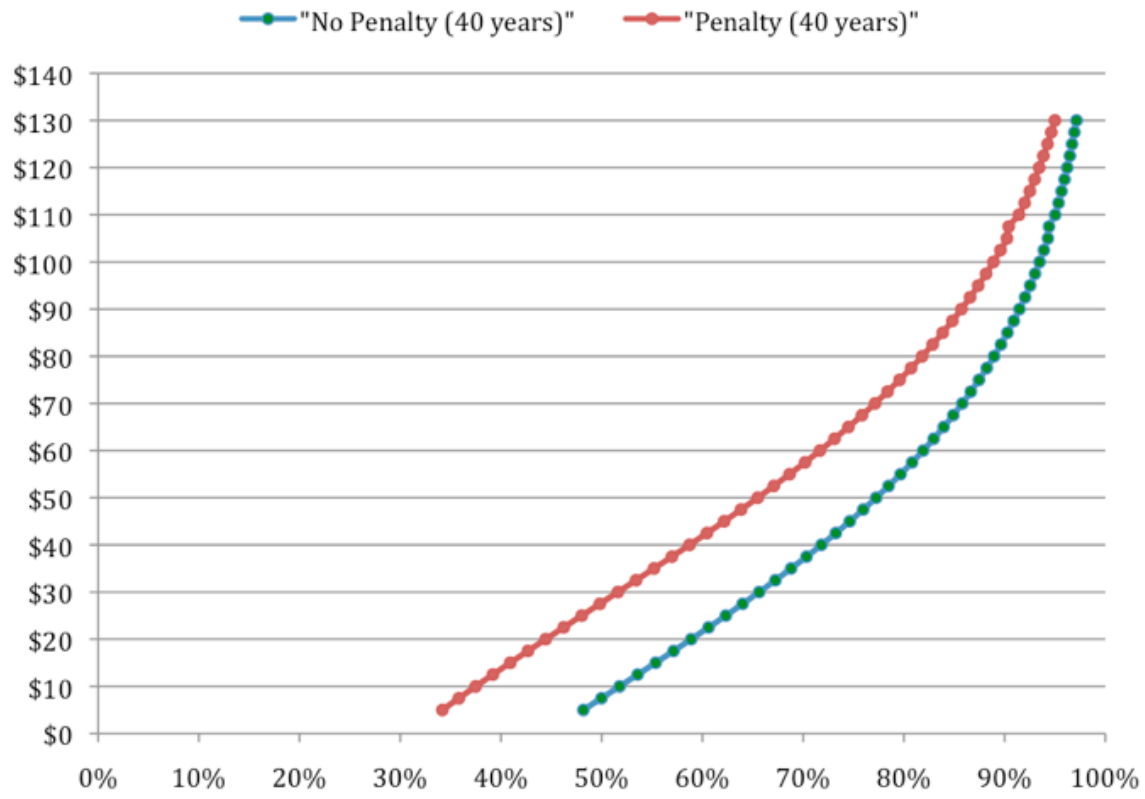


Figure 5-5. Scenario 2 supply response. Supply response by landowner using Binary_logit for a program with 40-year contract duration, the use of "Risk Pool," and different levels of "Penalty" for withdrawal.

Figure 5-6 shows the supply response for Scenario 3 (100 year contract with risk pool). This scenario is less elastic than scenarios 1 and 2. The supply shift of inclusion of a penalty for withdrawal is significantly greater than scenario with lower contractual commitment. The lower revenue values of $5 to $50 acre per year are less elastic for "penalty," and become slightly more elastic for higher values. At $30 acre per year revenue, the shift from the addition of a "penalty" seems to contract the probability of participation by almost 13%. This figures illustrates the sensitivity of enrollment to changes in contract restrictions (penalty), which appear to be far greater for programs with higher contract durations.

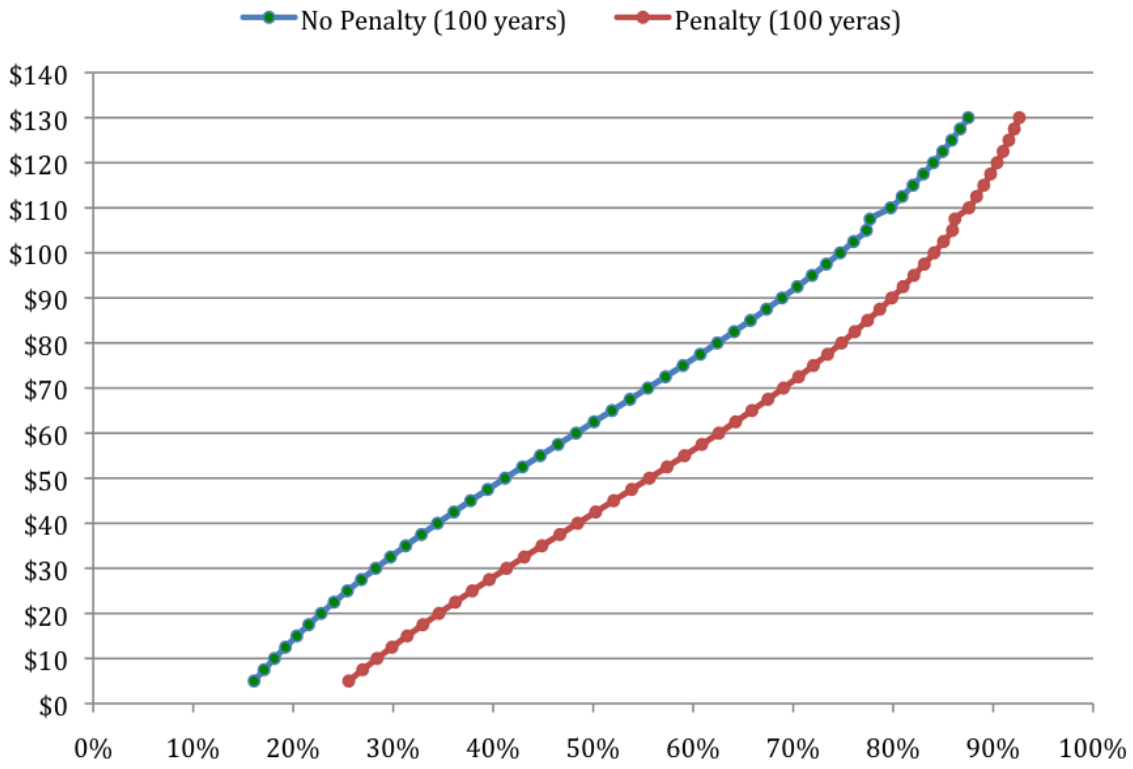


Figure 5-6. Scenario 3 supply response. Supply response by landowner using Binary_logit for a program with 100-year contract duration, the use of "Risk Pool," and different levels of "Penalty" for withdrawal.

Figures 5-7 and 5-8 compares four scenarios with different contract durations (5,30,40, and 100 years). These graphs examine the shifts arising contract duration. Figure 5-7 compares the supply response lines with "no penalty" for withdrawal. This figure indicates a 100-year contract elicits a significant shift to the left of other supply response curves. The 100-year contract supply curve seems to be more elastic than the other time commitments of 5 to 40 year contracts. At the revenue price of $30 acres per year, a commitment of 100 years is estimated to enroll about 28% of participants, while 40 years would enroll 65%, 30 years 68%, and 5 years 78%. There seems to be a 50% difference in estimated participation rates of 5 to 100 years of contract commitment.

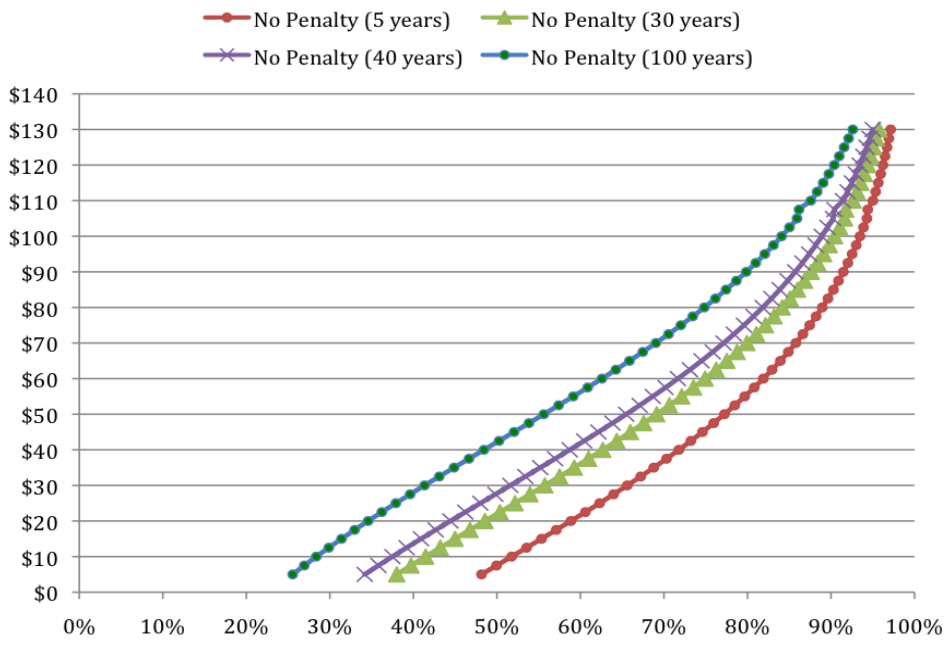


Figure 5-7. Multi-cenario supply comparison. Supply response by landowner using Binary_logit for programs with several levels of contract duration, the use of "Risk Pool," and "No Penalty" for withdrawal.

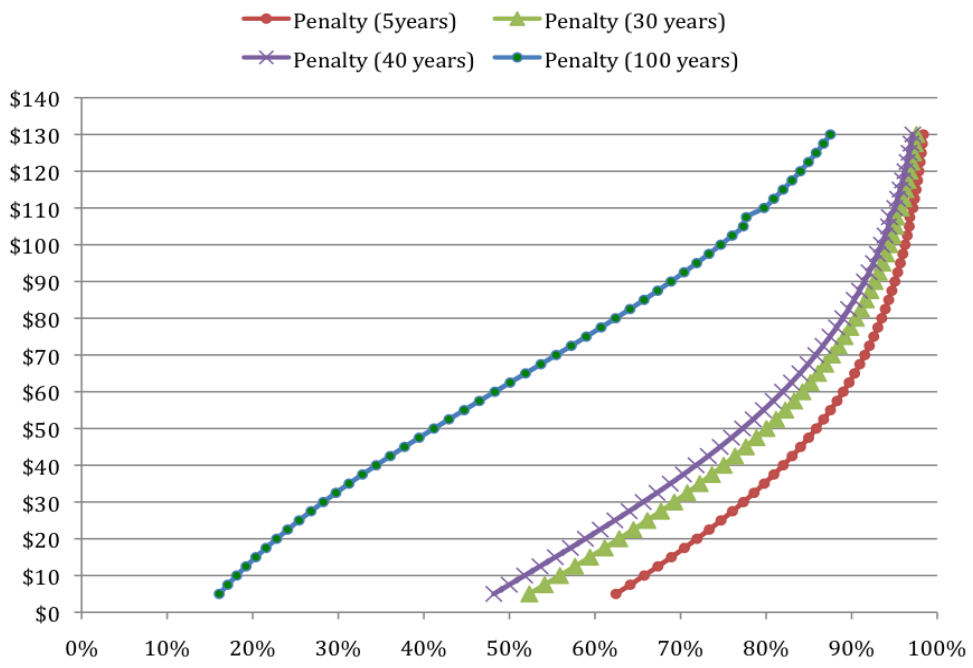


Figure 5-8. Multi-scenario supply comparison. Supply response by landowner using Binary_logit for programs with several levels of contract duration, the use of "Risk Pool," and "Penalty" for withdrawal.

Figure 5-8, compares the four different time commitments for supply response curves with “penalty” for withdrawal. The supply shift from this figures indicate fairly similar elasticities for contract duration of 5 to 100 years. The shifts are progressively going to the right with less contract commitments. At the revenue price of $30 acres per year, a commitment of 100 years is estimated to enroll about 42% of participants, while 40 years would enroll 51%, 30 years 55%, and 5 years 68%. There was a difference of almost 26% in estimated participation rates of 5 to 100 years of contract commitment. Figures 5-7 and 5-8 seem to indicate that at high prices, program features do not appear to be influencing participation probabilities, but at lower prices they become very significant in determining the participation.

Figures 5-8 and 5-9 show programs with higher time commitments tend to shift the supply response curves or probability of enrollment to the left, which decrease participation. The inclusion of “penalty” for withdrawal tends to decrease the over all shifts to the left of the supply response curves, arising from higher commitment contracts by approximately 24% at a $30 acre per year revenue from producing carbon offsets.

Combining BWC and DCE Survey Data with FIA Sample Plots

In this section I described the augmentation of the survey data from BWC and DCE with field plot data from the USDA Forest Services Forestry Inventory Analysis program. The FIA is a nationwide continuous forest census, designed to evaluate current forest management practices. The surveys described in Chapter 3 included demographic and institutional questions to identify landowner preferences, and a question regarding the percentage of their Florida forestland they would be willing to enroll in a specific carbon offset program (Q17 from now on). The sample population

used to estimate the WTA and supply response curves in this chapter, come from landowners who reported either the zip code or address of their biggest plot of forest. In this section I combine both DCE and BWC data to estimate current carbon sequestration rates of all participants, using matched data from FIA.

In Table 5-1 presents the summary statistics of the combined responses for both BWC and DCE (Combined from here on). Survey participants were randomly distributed to BWC and DCE and Table 3-4 from Chapter 3 shows that they are very similar in characteristics. Table 5-2 shows the summary statistics of demographic and institutional questions for the Combined dataset.

Table 5-2. Summary statistic of variables from carbon program survey: mean and "(standard deviation)."

Variable	Definition	Mean (std dev)
Acresf	Number of forest acres owned in Florida	837.80 (3885.63)
Q17	Percent of FL forestland willing to enroll in a program with: either Insurance or Risk Pool, No penalty for early withdrawal, $30 acre-per-year, 5 year contract	0.79 (0.34)
Q17_acres	Interaction of variables acresf & Q17	603.54 (2691.26)
Survey type	If data collected in BWC =1, DCE=0	0.52 (0.5)
NGO	Importance of having a "non-government carbon-credit program" vs a government program 1 = Very Unimportant 2 = Somewhat Unimportant 3 = Neutral 4 = Somewhat Important 5 = Very Important	3.13 (1.37)
Verifier	Importance of having a "non-government program verifier" to verify a forestland owner's monitoring report, vs a government verifier 1 = Very Unimportant 2 = Somewhat Unimportant 3 = Neutral 4 = Somewhat Important 5 = Very Important	3.12 (1.4)

Table 5-2. Continued

Variable	Definition	Mean
Cost-share	1 = if ever used a state or federal sponsored cost-share program 2 = otherwise	0.39 (0.53)
Type of CS	1= if ever used a State cost-share program 2= if ever used a Federal cost-share program 3= if ever used both State and Federal cost-share program 4= none (Follow-up question to “Cost-share,” n=84)	2.14 (1)
Home	1 = if primary residence within one mile from any of their forestland 2 = if primary residence is not within one mile from any of their forest land 3 = Not applicable	1.59 (0.59)
Income	1 = less than $25,000 2 = $25,000 to $49,999 3 = $50,000 to $99,999 4 = $100,000 to $199,999 5 = $200,000 or more	3.99 (1.7)
Sex	1 = Male; 2 = Female	1.25 (0.61)
Age	1 = under 25 years 2 = 25 to 34 years 3 = 35 to 44 years 4 = 45 to 54 years 5 = 55 to 64 years 6 = 65 to 74 years 7 = 75 years or over	5.09 (1.21)
Education	1 = Less than 12th grad 2 = High school graduate or GED 3 = Some college 4 = Associate or technical degree 5 = Bachelor’s degree 6 = Graduate degree	4.86 (1.3)

Using the zip code of their biggest reported plot of land, FIA data was used to pair these observations with estimates of two observations of compiled for the 2009 FIA report and the 2010 FIA data (Tables 5-3 and 5-4), with measurements periods of

roughly 7 years apart. These Combined data resulted in 136 observations (Figure 5-9). There were multiple FIA plot observations per zip code for some the survey data, and the systematic rule for these situations was to take the average per zip code of the values provided for a given plot.

FIA data included aboveground and belowground carbon stocks for two measurement periods. The above and belowground sequestration (units tons/ha) per plot was estimated by taking the annualized difference between these two observation periods for above and below ground carbon stock, and dividing them by the amount of years between observations. (Tables 5-3 and 5-4)

Figure 5-9 shows the map of the biggest reported plot of forestland from the Combined dataset. As seen in this figure, this survey sample appears to be evenly distributed in the Northeast, Northwest, and North Central areas of Florida.

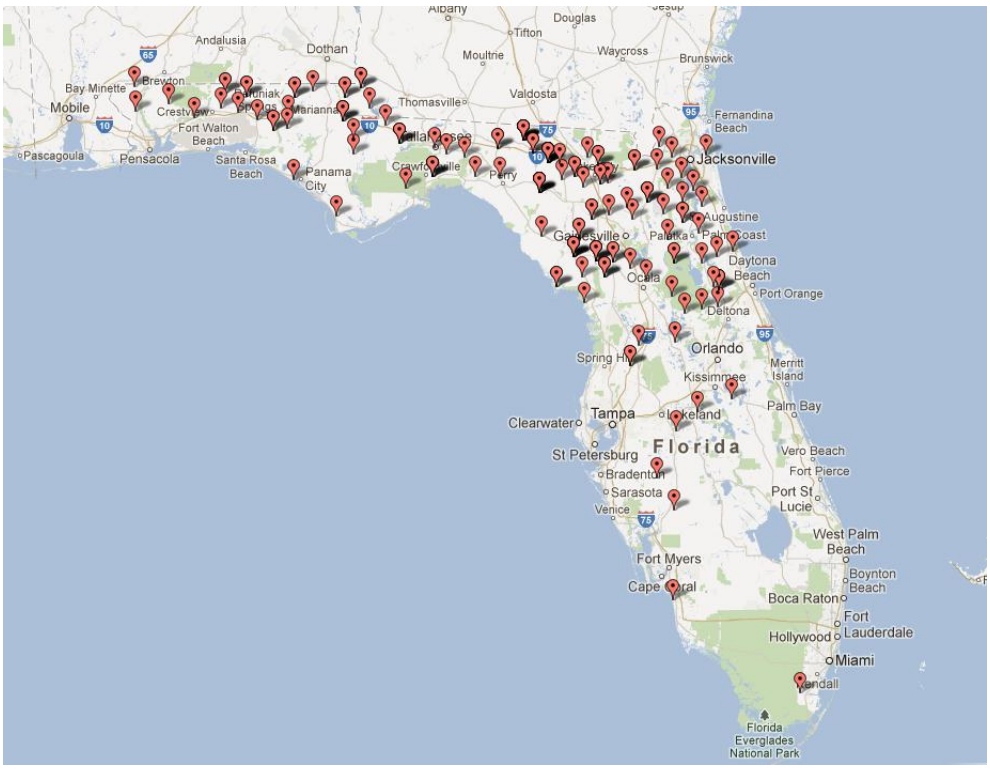


Figure 5-9. Map of the biggest reported plot of forestland from Combined data

The third columns of Table 5-2 shows that 65% of Combined matched (FIACombined from hereafter) observations had no observable management treatments of their land during the two observations periods, 42% applied “cutting” (e.g. clearing, slash burning, chopping, disking, bedding), or other practices clearly intended to prepare a site for either natural or artificial regeneration, and 4% had used some type of site preparation (e.g. clearing, slash burning, chopping, disking, bedding, or other practices) clearly intended to prepare a site for either natural or artificial regeneration.

Table 5-3. Forest Inventory Analysis “Treatment” code descriptions.

Code	DCE-Model 2: Ordered by absolute WTA range	Frequency
0	No observable treatment.	88 (65%)
10	Cutting – The removal of one or more trees from a stand.	42 (31%)
20	Site preparation – Clearing, slash burning, chopping, disking, bedding, or other practices clearly intended to prepare a site for either natural or artificial regeneration.	6 (4%)
30	Artificial regeneration – Following a disturbance or treatment (usually cutting), a new stand where at least 50 percent of the live trees present resulted from planting or direct seeding.	0
40	Natural regeneration – Following a disturbance or treatment (usually cutting), a new stand where at least 50 percent of the live trees present (of any size) were established through the growth of existing trees and/or natural seeding or sprouting.	0
50	Other silvicultural treatment – The use of fertilizers, herbicides, girdling, pruning, or other activities (not covered by codes 10-40) designed to improve the commercial value of the residual stand, or chaining, which is a practice used on western woodlands to encourage wildlife forage.	0

Table 5-4, shows that 68 of observations were slash pine forest types, 21 loblolly, 38 mixed forest, 6 longleaf, and 2 southern scrub oak. The average difference between measurements was 6.95 years, the mean stand age was about 39 years, and the average site productivity was close to 85 cubic feet/acre/year. The “RESERVCD” variable in this table indicates that the vast majority of observations came from areas that were not reserved or withdrawn by law(s) prohibiting the management of the land

for production. The “OWNCD” variable informs us that 93% of these plots were from “undifferentiated private” owners (i.e. not part of national forests system, state, local, etc.).

Table 5-4. Summary statistics of variables from Forest Inventory Analysis. Means and “(standard deviations).”

Variable	Definition	Mean
Tree	1 = Slash Pine (n=68) 2 = Longleaf (n=6) 3 = Loblolly (n=21) 4 = Mixed (n=38) 5 = Southern Scrub Oak (n=2)	-
Year Diff	Difference between plot measurments (years)	6.95 (0.6)
Stand Age	Stand Age (years)	38.72 (16.95)
C_AG_Seq	Annual above-ground carbon sequestration. Estimated by taking the annualized difference between above ground carbon stock measurements of FIA data (2009-2010). The observations were annualized by dividing the corresponding differences in carbon stock, by the variable “Year Diff” (tons/ha)	2.61 (12.88)
C_BG_Seq	Annual below-ground carbon sequestration. Estimated by taking the annualized difference between above ground carbon stock measurements of FIA data (2009-2010). The observations were annualized by dividing the corresponding differences in carbon stock, by the variable “Year Diff” (tons/ha)	0.39 (2.82)
SITECLCD	Site productivity class code. A classification of forestland in terms of inherent capacity to grow crops of industrial wood. 1 = 225+ cubic feet/acre/year 2 = 165-224 cubic feet/acre/year 3 = 120-164 cubic feet/acre/year 4 = 85-119 cubic feet/acre/year 5 = 50-84 cubic feet/acre/year 6 = 20-49 cubic feet/acre/year 7 = 0-19 cubic feet/acre/year	4.69 (0.58)
RESERVCD	Reserved land is land that is withdrawn by law(s) prohibiting the management of the land for the production of wood products. 0 = if not reserved 1 = if reserved	0.01 (0.04)

Table 5-4. Continued

Variable	Definition	Mean
OWNCD	Owner class code:	5.76
	1 = National Forest System (n=3)	(0.88)
	2 = Bureau of Land Management (n=1)	
	3 = Department of Defense/Energy (n=1)	
	4 = Other federal (n=1)	
	5 = State (n=3)	
	6 = Undifferentiated private (n=120)	
Treatment	10 = if cutting since last measurement (5 years if new plot)	3.97
	20 = Site preparation (clearing, slash burning, etc)	(5.75)

Carbon Sequestration Estimates

Table 5-4 indicates that average above ground carbon sequestration for these plots is 2.61 tons/ha/year, with standard deviation of 12.88 tons/ha, and belowground average carbon sequestration is 0.30 tons/ha, with a standard deviation of 2.82 tons/ha. These numbers indicate a very large dispersion in this data.

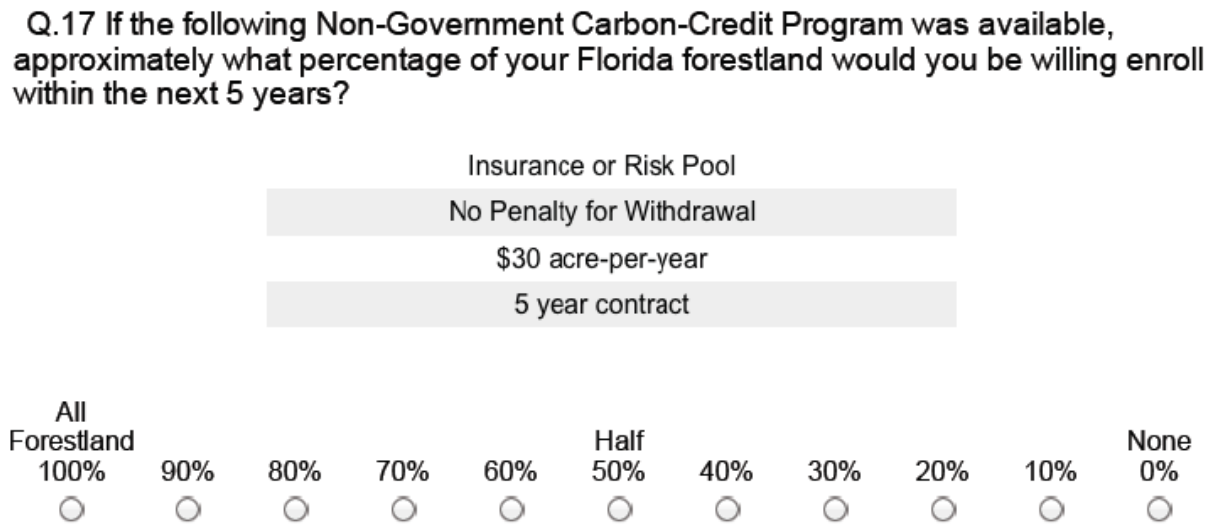


Figure 5-10. Example of Question 17 of survey.

Each of the respondents in the BWC and DCE surveys were asked to respond to the question in Figure 5-10. Their responses to Question 17 (Q17) of the survey are graphed in Figure 5-11. This horizontal axis of this figure displays the percent of their

Florida forestland willing to enroll in the carbon program described in Figure 5-10. Close to 60% of respondents were willing to enroll 100% of their land in Q17, which is Scenario 1 at Revenue $30 acre-per-year with “no penalty” for withdrawal. The mean of Q17 was 79% of land willing to enroll in Scenario 1, with a standard deviation of 34%. (Figure 5-11)

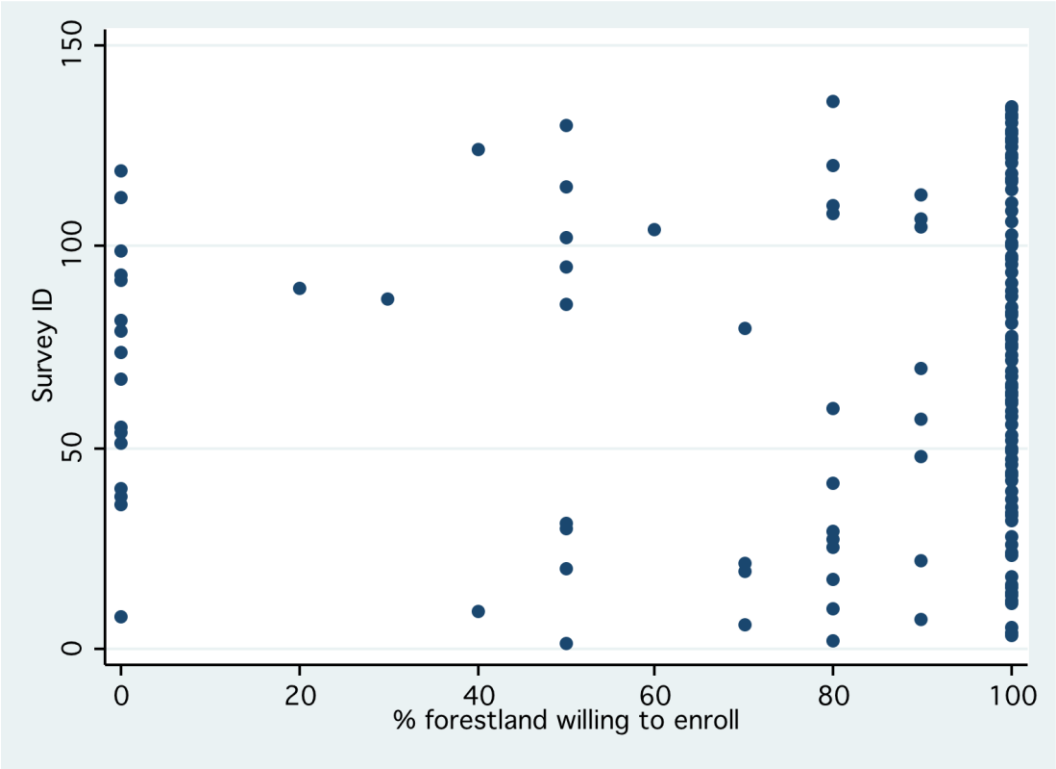


Figure 5-11. Answers to Question 17 of the BWC and DCE surveys: the horizontal axis displays the percent of their Florida forestland willing to enroll in a carbon program described in Figure 5-6.

Figure 5-12 displays the interaction between reported forest acreage with Q.17, which indicates the amount acres of Florida forestland willing to enroll in Q.17. This figure shows that the majority of respondents would enroll less than 2,000 acres.

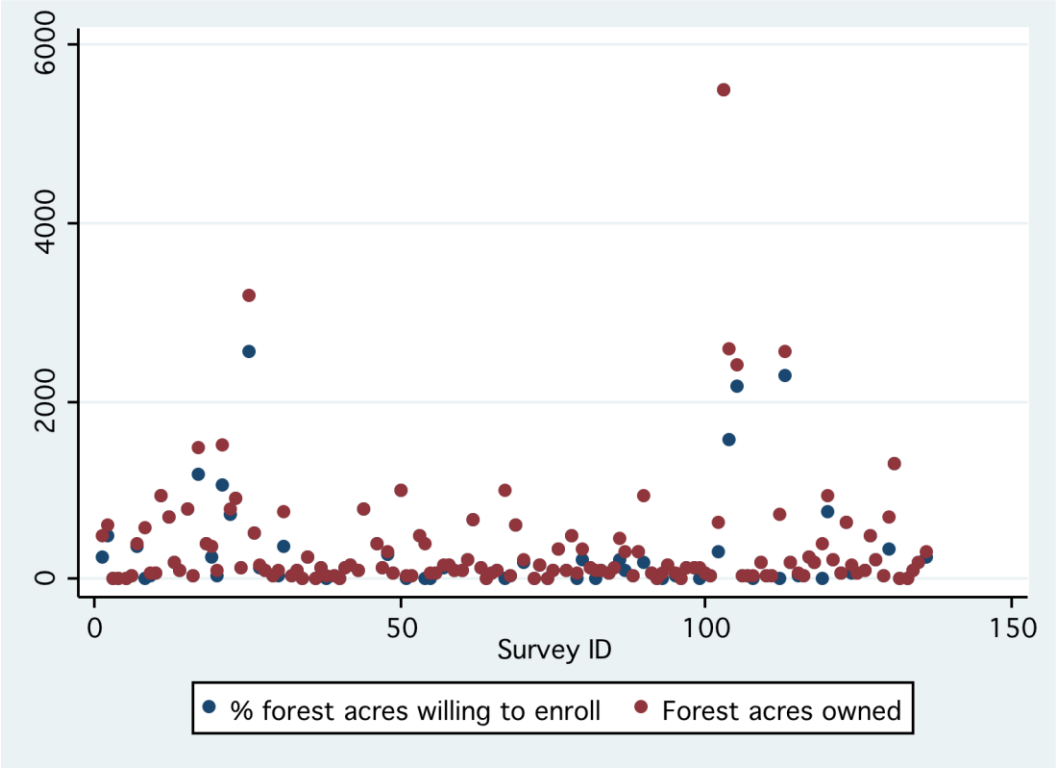
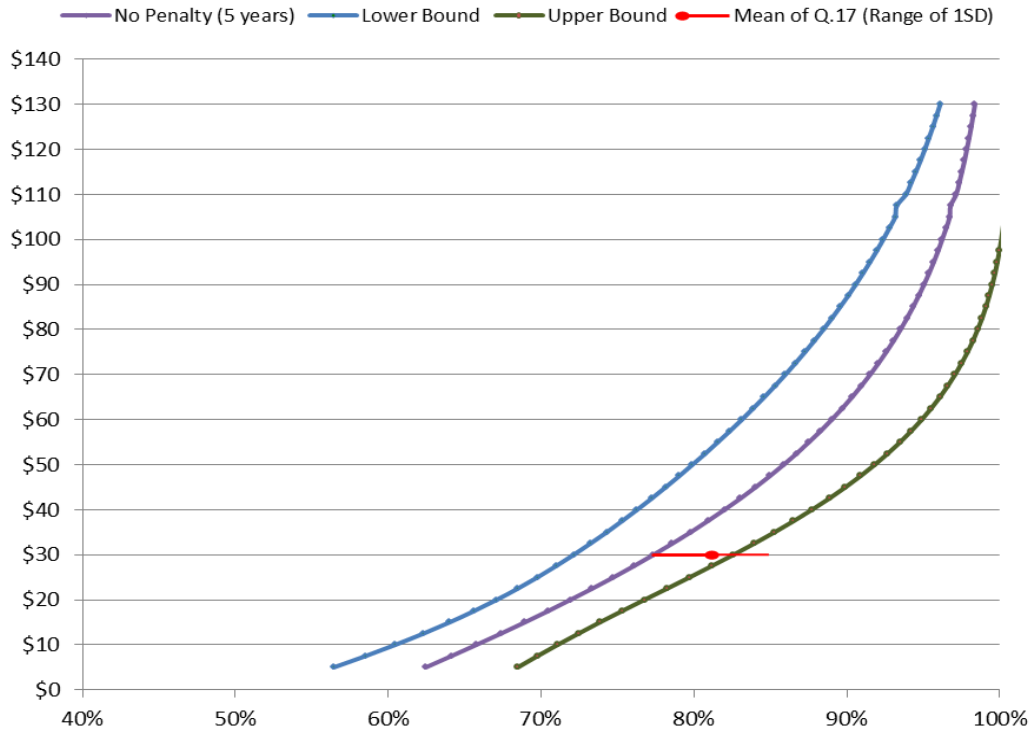


Figure 5-12. Interaction between forest acreage reported and the percent of forestland willing to enroll in Scenario 1

Figure 5-13 displays the supply response for Scenario 1 (5-years contract duration, the use of “Risk Pool,” and “No Penalty” for withdrawal) with a 95% confidence interval, using the same method from the previous section. If I assume that Q.17 implies percent participation in this program, then the mean of Q17 would fall within the 95% CI of Scenario 1 supply response curve (Figure 5-13). The purple line indicates predicted probability of enrollment and the blue and green lines are the 95% confidence interval. The red dot in this figure is the mean of Q17, with a range of one standard deviation (red line).

The red dot in Figure 5-13 representing Q17 indicates that 79% (mean of Q17) of Florida forestland reported in this survey (FIACombined) would have been enrolled at this program for $30 acre-per-year. If I were to assume that prediction enrollment curve

implied a supply of acres enrolled in this particular program (Scenario 1), then, at $30 acre-per-year, the estimation would have been very close to the mean acreage reported in Q17. Continuing with this assumption, and looking at the first standard deviation of Q17 displayed on this graph (red line), at least 34.1% of Q17 (half of the standard deviation) falls within the 95% confidence interval (CI) of the predicted probability of enrollment (within the red and blue lines). The rest is arguably either inside of the 95% CI of this curve, or to the right of the upper bound, which means that if I were to assume a one-to-one relationship between predicted enrollment and acreage enrollment, not only would this be fairly accurate assumption for Q17 in Scenario 1 at $30 acres-per-year, but a slightly conservative one.



Figuer 5-13. Supply response with 95% confidence interval. Supply response by landowner using Binary_logit for a program with 5-years contract duration, the use of “Risk Pool,” and “No Penalty” for withdrawal.

Given these results, this analysis will assume that the supply response curves imply a percent of acres enrolled in the particular program for the respondents in the FIACombined data set.

Additionality

Figure 5-14 shows the total aboveground and belowground carbon sequestration (Ctot) estimates of the sum of C_AG_Seq and C_BG_Seq estimates from Table 5-4, for respondents in the FIACombined dataset. The horizontal axis is the survey ID (ordered by Ctot) and the units of the vertical axis are in metric tons per year. This figure shows that almost 50 plots have a negative rate of carbon sequestration.

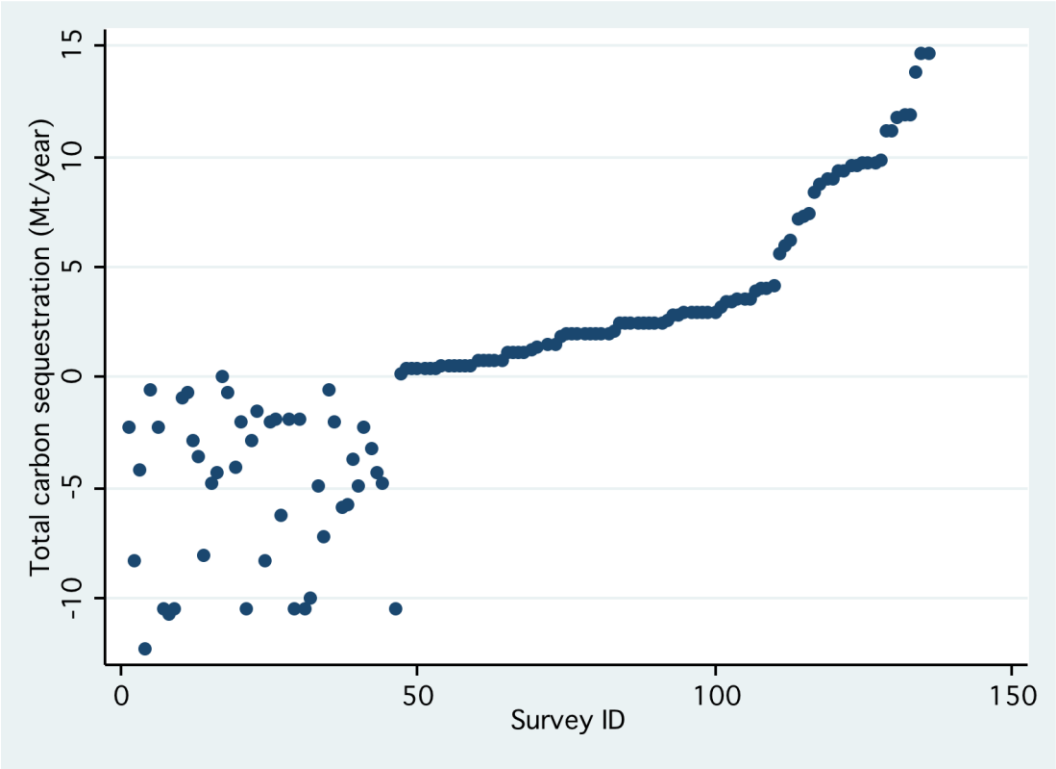


Figure 5-14. Total carbon sequestration estimates for respondents in FIACombined. The horizontal axis is the survey ID and the units of the vertical axis are in metric tons per year.

The analysis of the previous section indicates that most of the plots in this study are not “reserved,” hence their land is not withdrawn by law(s) prohibiting the

management of the land for the production of wood products. Thus, I model additionality for the participants with positive carbon sequestration rates with an Improved Forest Management (IFM) carbon certification protocol (which in this case assumes that landowners manage their land for commercial wood products) and the rest using a reduce deforestation and degradation protocol. (Chapter 2 defines and analyzes IFM and REDD)

IFM Additionality Estimation

As noted in the introduction of this chapter, the CAR certification program, requires the use of simulation models in their protocols of IFM (Chapter 2). To estimate IFM additionality, I employ the results from Mulkey et al. (2008), which simulate changes in management intensities in commercial pine plantations in Florida. Their study simulated slash pine and loblolly forest, which comprise represent 66% (another 28% are “mixed forest,” which include loblolly, slash pine, and other forest types) of forest types in this data (Table 5-4).

Mulkey et al. (2008) assume that management activities and intensities in Florida can range from “little intervention on low quality lands,” to “greater intervention on high quality lands” involving fertilizing and thinning.” The authors also assume that these practices are implemented in private forestlands. Average volume harvested per unit area is estimated by aggregating the combination of site productivity and management intensity. Their simulation models changes from low to medium management intensity, and from medium to high management intensity. They also assume that fertilizer is only applied for medium to high changes in IMP. The high management intensity scenario is assumed to use fertilizer every 4 years on sites with a rotation age of 25 years, whereas the medium scenario uses fertilizer at years 2 and 16. To estimate aboveground carbon,

their study assumes that carbon in stem is 50% of “stem biomass,” and in branches is 21% of stem biomass. Carbon in roots was estimate as twice the annual carbon production in roots.

Table 5-5 shows carbon pool simulation estimates in commercial pine plantations in Florida (Mulkey et al., 2008). This figure “implies that every acre switched could potentially yield 0.39 tonnes (MMt) carbon per acre per year. Namely, going from medium to high intensity would increase sequestration by approximately 35% per acre per year, and 29.4% for a low to medium switch.

Table 5-5. Carbon pool in commercial pine plantations in Florida.

Management intensity	% of land under each intensity	# of acres (millions)	Biomass $acre^{-1}$ (MMt)	Carbon $acre^{-1}$ (MMt)	Rotation age (years)	Carbon $acre^{-1}$ $year^{-1}$ (MMt)
Low	0.37	5	63.5	25.42	30	0.85
Medium	0.58	5	68.5	27.42	25	1.10
High	0.05	5	92.8	37.14	25	1.49

Note: 1.4 cubic meters equals 1 MMt; in converting biomass to carbon, the authors assumed that moisture content would be 20% and 50% of dry biomass is carbon. [Table adapted from Mulkey S., J. Alavalapati, A. Hodges, A.C. Wilkie and S. Grunwald (2008), Opportunities for greenhouse gas reduction by agriculture and forestry in Florida (Page 17, Table 4). University of Florida, School of Natural Resources and Environment - Department of Environmental Defense, Washington D.C.]

To estimate additionality for IFM, I assume a baseline scenario of current carbon sequestration rates based on Figure 5-14, and I make the assumption that, these lands would be producing commercial timber, and that a change in IFM for low productivity lands would yield a 29% increase in carbon sequestration (addtionality) and from medium to high a 35% increase in carbon sequestration. As seem in Table 5-4, the variable SITECLCD provides an estimate of site productivity. The FIACombined data was classified this data in three groups: 1) low productivity if the land produces 0 to 49 cubic feet/acre/year, 2) medium if 50 to 164 cubic feet/acre/year, and 3) high

productivity if greater than 165 cubic feet/acre/year. In all 96.32% of observations were of medium productivity, and 3.68% were low productivity, and none were highly productive.

"Additionality" estimates for IFM are calculated in three steps: 1) baseline consists of multiplying acres of forest by current carbon sequestration rates, 2) if classified as medium productivity, assume that a 35% increase in sequestration occurred by switching to from a medium to high management intensity, and 29% for switching from low to medium, and 3) subtract the new rate of carbon sequestration by the baseline.

REDD Additionality Estimation

REDD estimations for areas currently having a negative sequestration rate are assumed to be engaging in deforestation, that will be "reduced" by the incentives of REDD (Chapter 2). A sensitivity analysis is performed for different rates of REDD.

Figures 5-15 and 5-16 show the maps of forestlands assumed to be under IFM and REDD, respectively. Figure 5-15 shows a map of forestland assumed to be under IFM. This map indicates that the majority of forestland assumed to be enrolled under IFM, appears to be in North Florida. Figure 5-16 shows the forestland areas assumed to be under REDD do not seem to be clustering in any particular region of Florida. Figures 5-15 and 5-16 do not visually indicate a particular clustering around major Florida cities, but Jacksonville appears to have more IFM present than REDD.

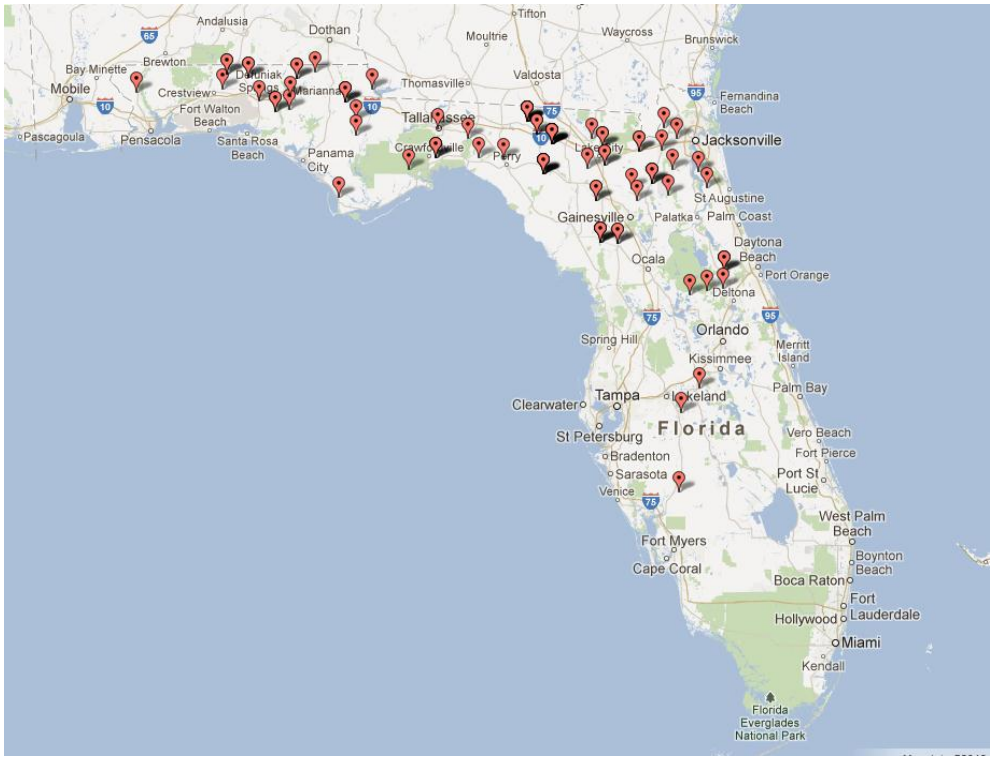


Figure 5-15. Map of forestland assumed to be under IFM

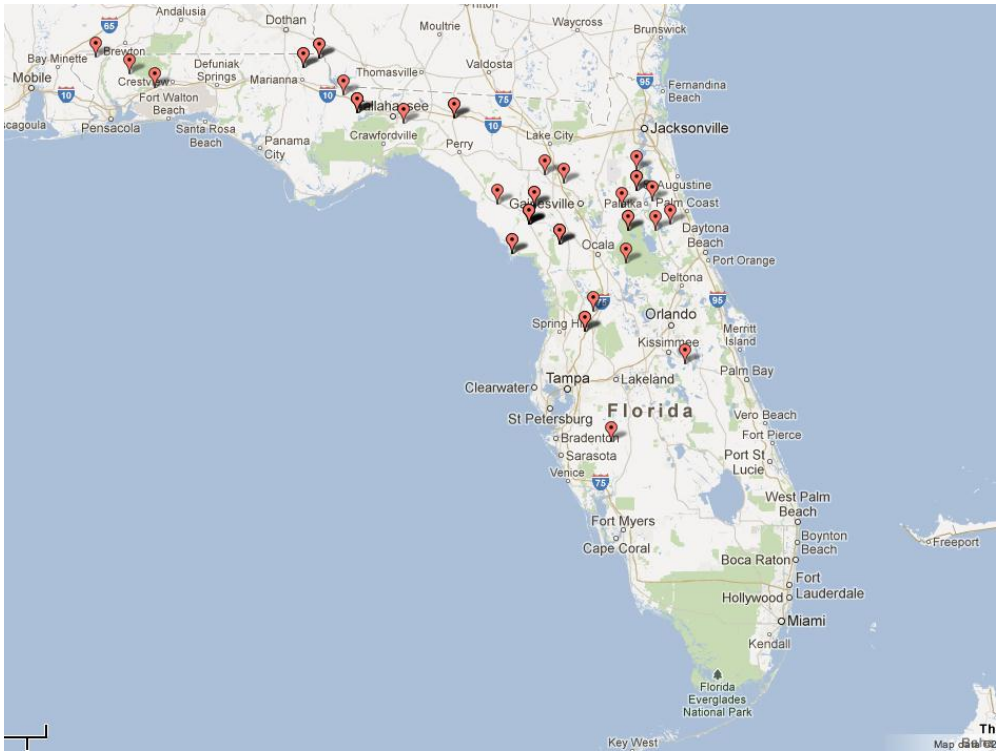


Figure 5-16. Map of forestland assumed to be under REDD

Results

Figures 5-18 to 5-20 show IFM estimates of carbon additionaly with varying levels of REDD. The blue lines indiate the increase in management intensity implemented for the purpose of IFM and REDD, and the maroon lines are the base line or current sequestration rates. The observations of approximately the first 50 individuals in these graphs show a negative sequestration for the current sequestration rate, which is assumed to come from deforestation. The blue dots corresponding to these obserervations become positive by assuming they stop deforestation by participation in REDD. Figure 5-16, shows REED participation at 10%, Figure 5-17 at 20% and Figure 5-18 at 50%. The rest of blue curve comes from the IFM estimates described in the previous section.

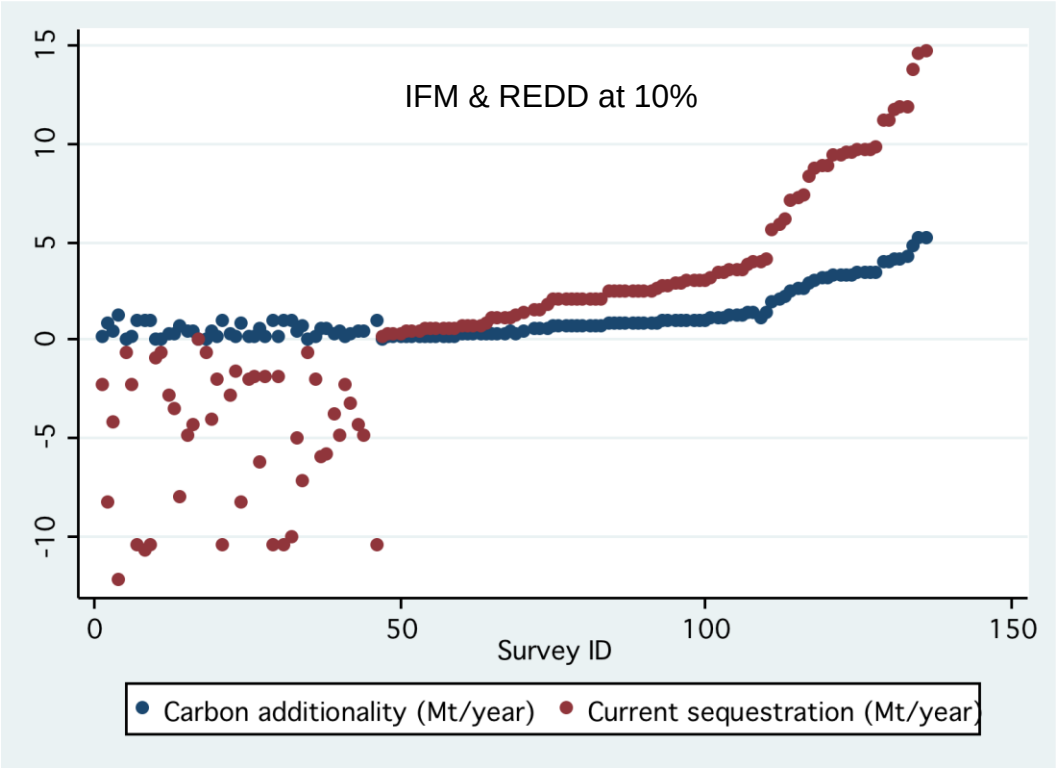


Figure 5-17. Carbon sequestration and additionality for IFM and REDD at 10%

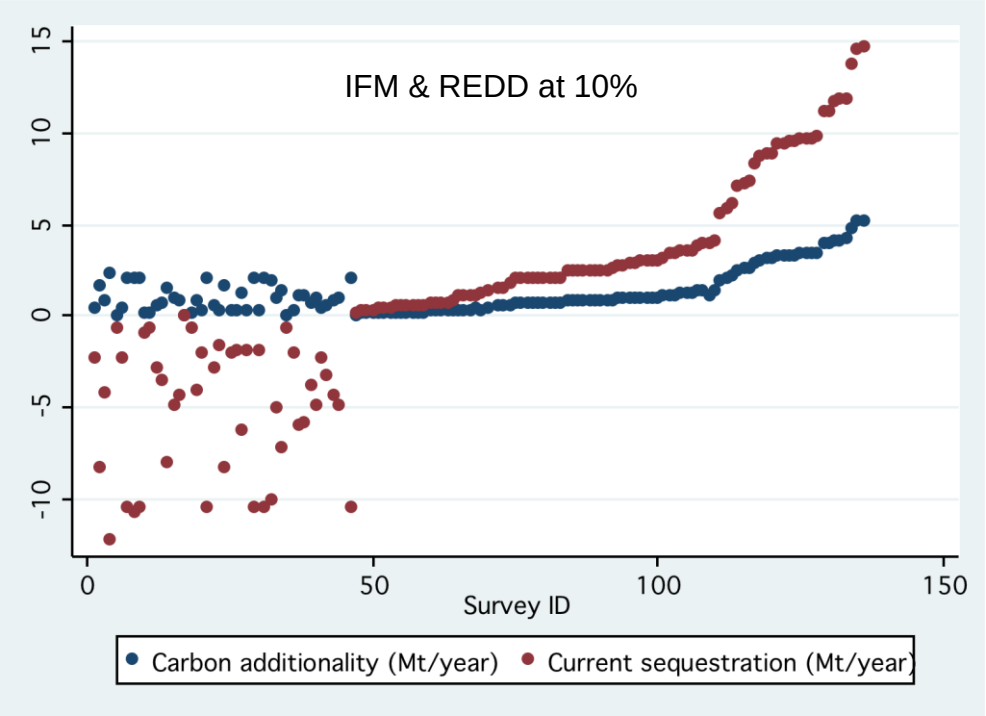


Figure 5-18. Carbon sequestration and additionality for IFM and REDD at 20%

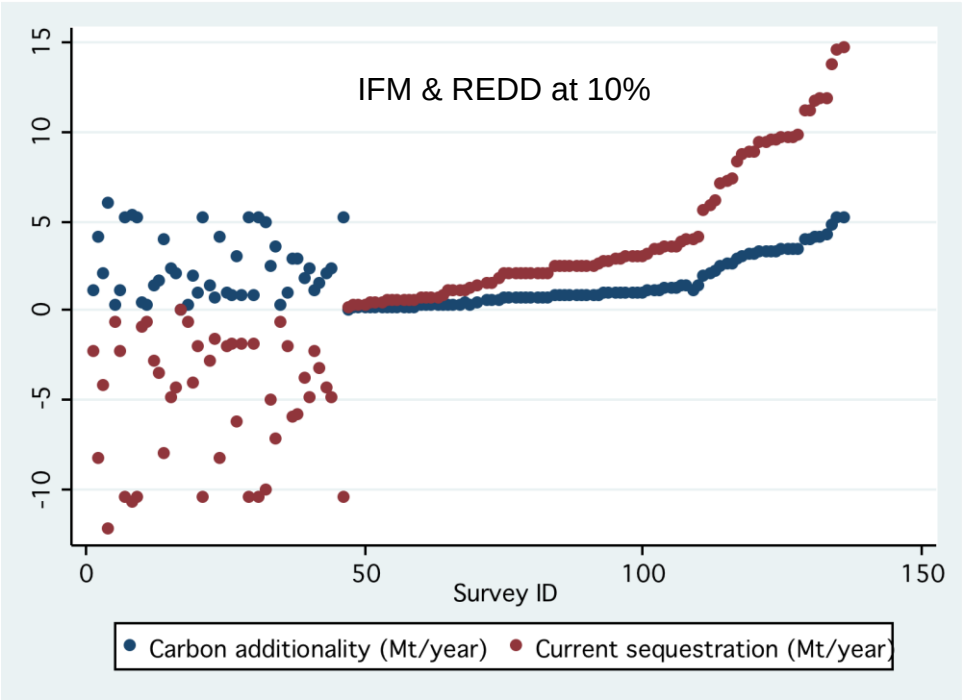


Figure 5-19. Carbon sequestration and additionality for IFM and REDD at 50%

By subtracting the baseline in Figure 5-17, with the estimated changes in management intensity and REDD at 10%, I estimate an aggregate carbon additionality of 19,776 tons per year. This additionality was multiplied by the supply response scenarios from the previous sections to estimate the supply curves in metric tons (MMt) of carbon per year shown in Figures 5-21 to 5-23. These figures produce the same elasticity framework discussed in the previous sections.

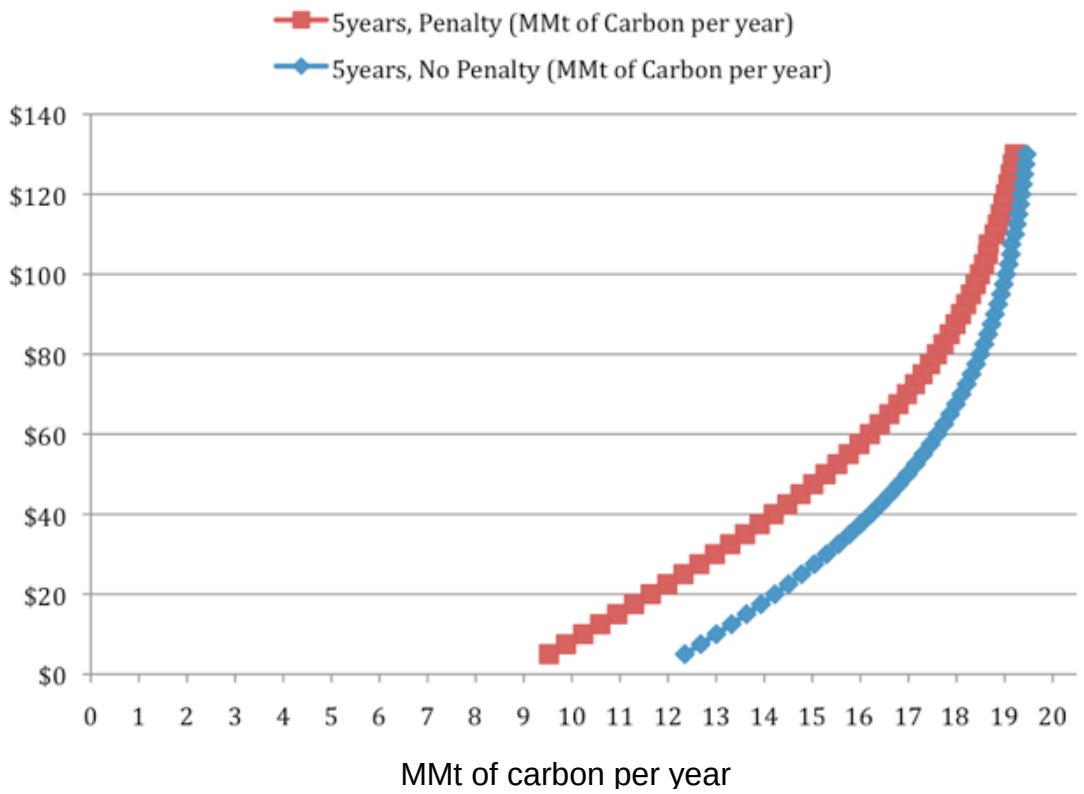


Figure 5-20. Supply of carbon additionality for Scenario 1 using IFM and REDD at 10%

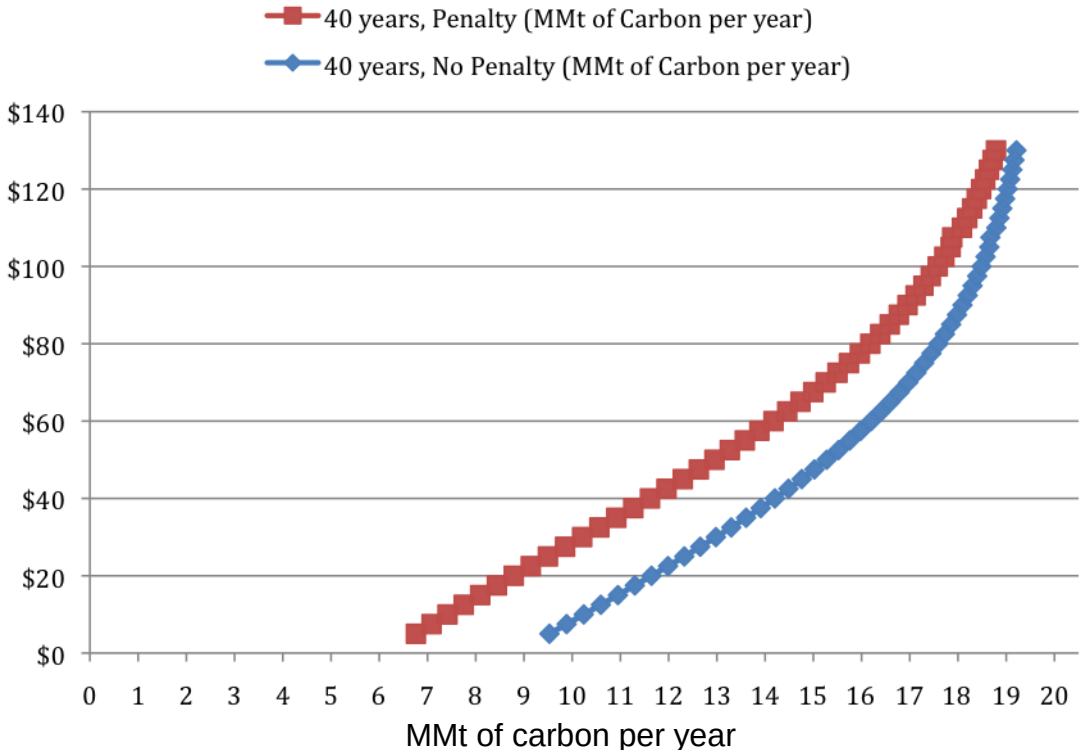


Figure 5-21. Supply of carbon additionality for Scenario 1 using IFM and REDD at 10%

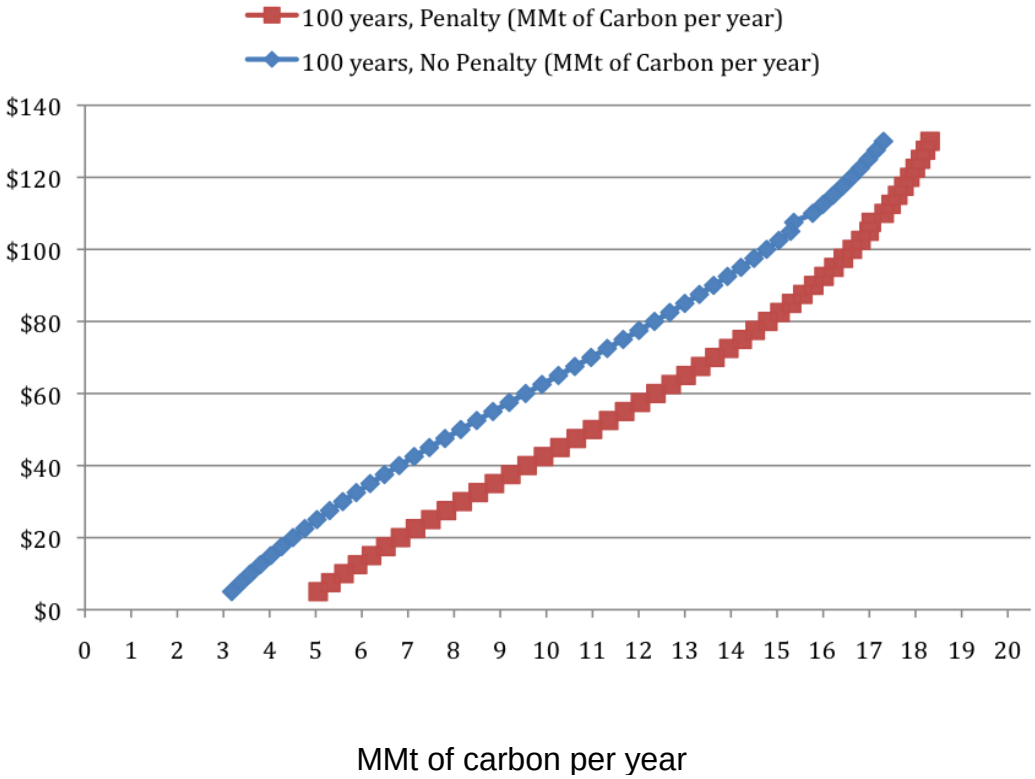


Figure 5-22. Supply of carbon additionality for Scenario 1 using IFM and REDD at 10%

Discussion and Summary

This chapter provided an approximation of the supply of carbon sequestration for survey participants using direct forest plot measurements from the Forest Inventory Analysis, and the predicted participation probabilities of hypothetical carbon offset programs. The simulation estimates from Mulkey et al. (2008) provided a way to estimate additionality from a change in improved forest management intensity, but the simulation of land expectation values can be used to model carbon policy scenarios that may be more suitable for the stated preferences elicited in the BWC and DCE surveys (e.g. Stainback and Alavalapati, 2002). The supply response curves from 5-20 to 5-23 show that respondents to this survey can potentially provide up to 19.78 MMt per year of carbon, and they may serve as an interesting reference for policy makers examining effects of various institutional factors of carbon sequestration programs.

CHAPTER 6
CONCLUSIONS

This dissertation characterized forest carbon-offset markets in Florida using a hypothetical carbon program survey, administered to one the most comprehensive lists of non-industrial private landowners. In December 2011, 920 Florida Forest Stewardship Program affiliates were surveyed to eliciting response to different carbon offset programs that varied according to composition of institutional components. The survey was administered electronically and 310 responded to the requests, of which 189 completed the entire survey. Additionally, Chapter 2 of this dissertation provided an analysis of current available carbon-certification options for Florida forestland owners, and reviewed their institutional compositions to qualitatively identify potential barriers to participate. Results from Chapter 2 indicated a lack of access to regional cap-and-trade markets in North America, but described specific options to engage in voluntary carbon markets. The dissertation in Chapter 3 quantitatively analyzed the results from Chapter 2 by examining the influence of four particular attributes of carbon market program references: Contract Duration, Revenue, Penalty for Early Withdrawal from a program, and the use of different Risk Tools to reduce the risks associated with producing offsets. The results from this chapter indicate that landowners in this study prefer programs with compensations of $20 to $30 acres-per-year, contract durations of 5 to 20 years, no penalty for withdrawal. Next, Chapter 4 implemented an empirical comparison of a relatively new stated preference tool that elicits responses using best-worst scaling and binary discrete choice experimentation. The results from this chapter indicated a general agreement among estimations of best-worst scaling, and identified potential measurements of disagreement. Finally, Chapter 5 provided an estimation of current

carbon sequestration rates for survey respondents, and estimated the supply of carbon additionality for various scenarios that approximate current existing carbon certification programs, using stated preference and available forest plot data from the Forest Inventory Analysis.

APPENDIX A
THE SURVEYS

Introduction and Filter Questions Survey

Filter and Introduction

Carbon Offset Production in Florida's Forest Lands

The purpose of this study is to determine private landholders' preferences for potential carbon credit programs.

You are one of about 500 non-industrial private forest landowners in Florida being asked to take the survey. Your responses will help us better understand landowner preferences for carbon credits.

The survey will take approximately 15-20 minutes to complete.

Note that this survey is 100% voluntary, and there is no penalty or compensation for participating. Also, note no anticipated risks of participation and no direct benefits to you. Your participation and responses to all questions will be kept strictly confidential, and no sensitive information will be asked. Note that you must be 18 years or older to participate in this study.

By clicking on the arrows of the bottom of this page, you agree to participate in this survey.

If you have questions about this study, please contact the principal investigator, José Soto:

José R. Soto (Ph.D. Candidate)
University of Florida Food and Resource Economics Department
1170 McCarty Hall
University of Florida
Gainesville, FL 32611-0410
Phone: (520) 664-8309
Email: josesoto@ufl.edu

If you have questions about your rights as a research participant, please contact the University of Florida IRB Institutional Review Board office at:

98A Psychology Building
University of Florida
P. O. Box 112250
Gainesville, FL 32611-2250
Telephone: (352) 392-0433
Fax number: (352) 392-9234
Email: irb2@ufl.edu

For the following questions, please provide answers for all of the forestland (or "woodland") that you own in Florida.

"Forestland" in Florida is defined as:
- Land at least one (1) acre in size, 120 feet wide, and with at least ten (10) well-spaced trees per acre; and
- Land, where at least trees would grow again if removed (not converted to another use, such as cropland, pasture land, or residential).

For our purpose, "forestland" does NOT include: Christmas tree farms, orchards, or nurseries.

Q.1 Do you own any forestland in Florida?

○ Yes

○ No

Q.2 How many of the management decisions have you made on this land?

○ All

○ Most

○ Some

○ Few

○ None

Thank you very much for your response. If you have any comments about the survey or carbon credits in Florida, please use the box below, or contact me directly.

José R. Soto (Ph.D. Candidate)
University of Florida Food and Resource Economics Department
1170 McCarty Hall

Instructions for Discrete Choice Experimentation

1) Trees store carbon:

Forests can both release and store carbon dioxide (CO_2), a greenhouse gas that contributes to climate change. Trees, through the process of photosynthesis, take CO_2 from the environment and store the gas as carbon in their trunk, leaves, branches, and roots. Carbon is also stored in the soils that support the forest, as well as plants and litter on the forest floor.

2) Carbon-credit programs:

A carbon-credit program encourages greenhouse gas (CO_2) reductions by documenting and registering forestlands that receive "credits" for the amount of CO_2 they capture, the landowner then receives an annual payment for these credits.

3) Carbon-credit program features:

There are different kinds of carbon-credit programs that use different tools to deal with risk, time-commitment, and payments, including:

- **Risk Management Options:**
  1. **Insurance:** Individual landowner insurance against events that release stored carbon, like wildfires, hurricanes, etc. (similar to crop-insurance).
  2. **Risk Pool:** Group carbon-credit Risk Pool, that acts as a general insurance against wildfires, hurricanes, etc. Each time you are given credits, a certain amount must go to the Risk Pool, depending on the project's risk rating. For example, if a forest project is issued 10 credits, and the project's risk rating is 10 percent, then 9 credits will be given to the forest owner and 1 credit must be put into the Buffer Pool.
- **Revenue:** Payments from the sale of carbon-credits; please assume revenue covers all costs such as risk insurance or the costs of a Risk Pool.
- **Contract Length:** The time you agree to remain in the project in order to maintain the project's CO_2 reductions.
- **Penalty for Withdrawal:** Fines for leaving the program early.

In the following pages you will see a series of potential carbon-credit programs. These programs will offer different amounts of carbon-credit payments, contract-lengths, penalties for withdrawal, and either risk-insurance or a Risk Pool to deal with risk.

Please assume that each of the programs are available in Florida, and then **choose one** from the following choices.

Example:

Of the Non-Government Carbon-Credit Programs below, which would you choose to participate in?

(Please check only one of the four options below)

Risk Pool	Insurance	Risk Pool	
No Penalty for Withdrawal	Penalty for Withdrawal	Penalty for Withdrawal	
$20 acre-per-year	$30 acre-per-year	$5 acre-per-year	None of these
100 year contract	5 year contract	10 year contract	
○	◉	○	○

Instructions for Best-Worst Choice

Penalty for Withdrawal	○	○
$20 acre-per-year	○	○
5 year contract	○	○

Would you enroll in this program? Yes ○ No ○

Non-Government Carbon Offset Program 4

(Check one option as the most important and one option as the least important)

	Most Important	Least Important
Insurance	○	○
No Penalty for Withdrawal	○	○
$20 acre-per-year	○	○
40 year contract	○	○

Would you enroll in this program? Yes ○ No ○

Non-Government Carbon Offset Program 5

(Check one option as the most important and one option as the least important)

	Most Important	Least Important
Insurance	○	○
No Penalty for Withdrawal	○	○
$5 acre-per-year	○	○
100 year contract	○	○

Would you enroll in this program? Yes ○ No ○

Non-Government Carbon Offset Program 6

(Check one option as the most important and one option as the least important)

	Most Important	Least Important
Insurance	○	○
Penalty for Withdrawal	○	○
$5 acre-per-year	○	○
10 year contract	○	○

Would you enroll in this program? Yes No

Demographic Questions

(Please check only one of the four options below)

Insurance
No Penalty for Withdrawal
$10 acre-per-year
10 year contract

Risk Pool
Penalty for Withdrawal
$20 acre-per-year
40 year contract

Insurance
Penalty for Withdrawal
$30 acre-per-year
100 year contract

None of these

Q.17 If the following Non-Government Carbon-Credit Program was available, approximately what percentage of your Florida forestland would you be willing enroll within the next 5 years?

Insurance or Risk Pool
No Penalty for Withdrawal
$30 acre-per-year
5 year contract

All Forestland 100%	90%	80%	70%	60%	Half 50%	40%	30%	20%	10%	None 0%

Demographics

Demographic Information:

We would like to know a little about you to help us understand who prefers carbon credits.

Please note that responses to all questions will be kept strictly confidential.

Q.1 In terms of your participation, how important is it to have a **non-government** carbon-credit program rather than a **government** carbon-credit program?

	Very Unimportant	Somewhat Unimportant	Neutral	Somewhat Important	Very Important
Importance of Non-Government Status					

Q.2 How important is it to have a **non-government** program **verifier** rather than a **government** program **verifier**? A program **verifier** visits the forest project site, to verify a forestland owner's monitoring report.

	Very Unimportant	Somewhat Unimportant	Neutral	Somewhat Important	Very Important
Importance of Non-Government Status					

Q.3 Cost-share programs provide landowners with money to help plant trees or manage their forestland.

Examples include Conservation Reserve Program, Stewardship Incentive Program, and Forestry Incentives Program.

Have you ever used a state or federal sponsored cost-share program to help you manage your forestland in Florida?

- Yes
- No
- Prefer Not To Answer

If yes, what cost-share program have you used?

- State
- Federal
- Both State and Federal
- None

- Prefer Not To Answer

Q.4 Is your primary residence within one (1) mile of any of the forestland that you own in Florida?

Yes	No	Not Applicable	Prefer Not To Answer
○	○	○	○

Q.5 Please indicate your household's annual income?

- Less than $25,000
- $25,000 to $49,999
- $50,000 to $99,999
- $100,00 to $199,999
- $200,000 or more
- Prefer Not To Answer

Q.6 What is your gender?

- Male
- Female
- Prefer Not To Answer

Q.7 What is your age?

- Under 25 years
- 25 to 34 years
- 35 to 44 years
- 45 to 54 years
- 55 to 64 years
- 65 to 74 years
- 75 years or over
- Prefer Not To Answer

Q.8 What is the highest degree or level of school that you have COMPLETED?
Check only ONE. If currently enrolled, mark the previous grade or highest degree received.

- Less than 12th grade
- High school graduate or GED
- Some college
- Associate or technical degree
- Bachelor's degree
- Graduate degree
- Prefer Not To Answer

Q.9 What is the Zip Code of your largest track of forestland in FL?

- Zip Code
- Prefer Not To Answer

Q.10 What is the address of the your largest track of **forestland** in Florida?

APPENDIX B
NON LINEAR CONSIDERATIONS

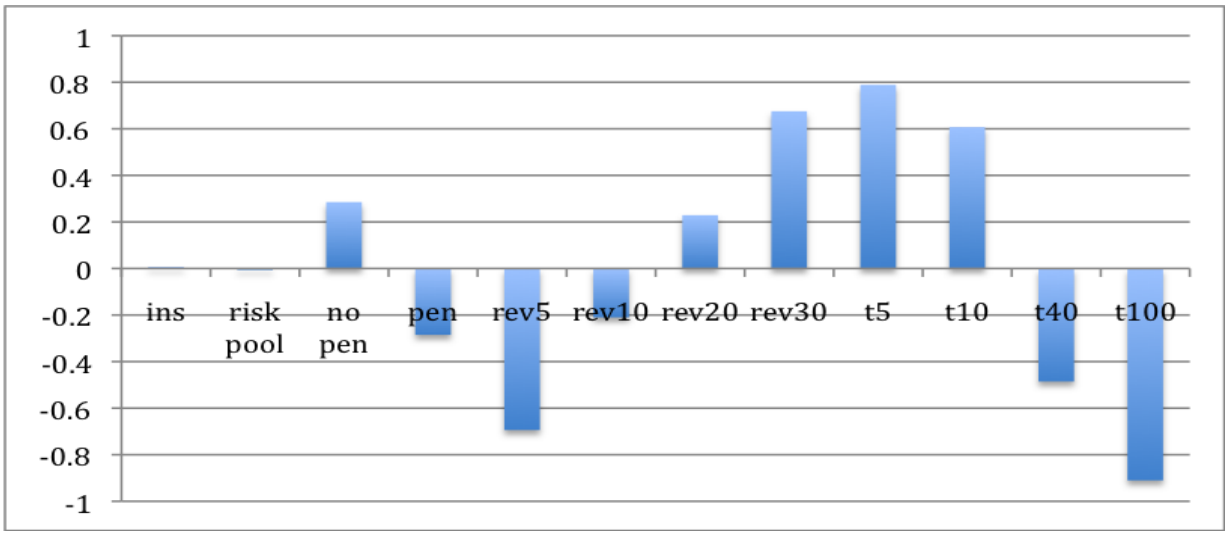


Figure B-1. Discrete choice experimentation estimates of Mode 1 vs. attribute levels

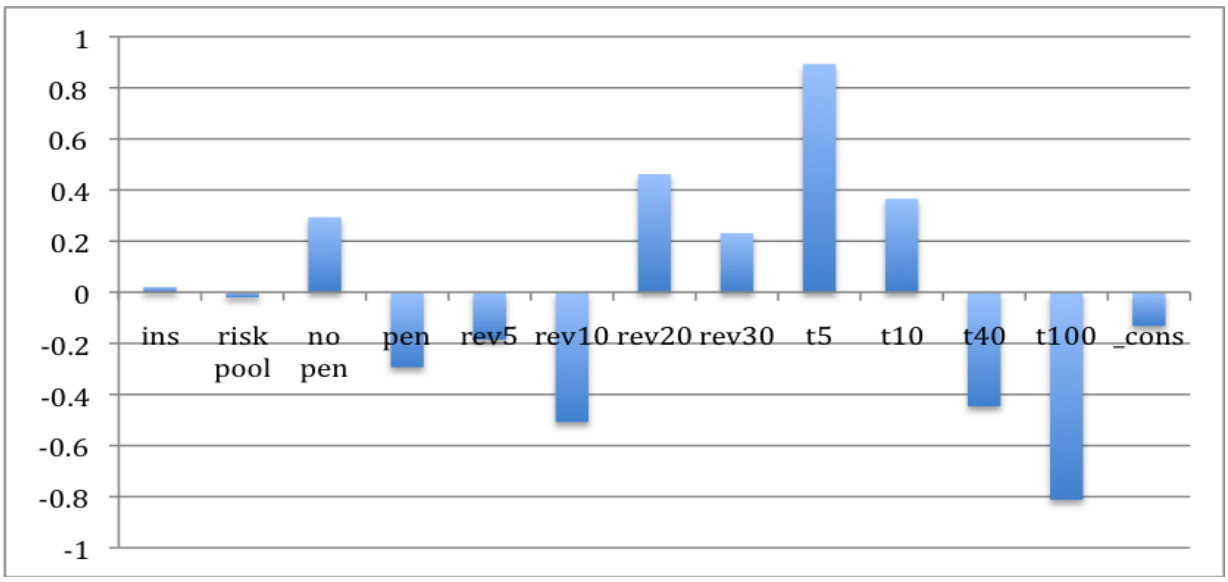


Figure B-2. Binary estimates of Mode 1 vs. attribute levels

Table 9
Optimal design for two 2-level attributes and two 4-level attributes

Set #	Option 1				Option 2				Option 3			
	A_1	A_2	A_3	A_4	A_1	A_2	A_3	A_4	A_1	A_2	A_3	A_4
1	0	0	0	0	1	1	1	1	0	1	2	2
2	0	1	0	2	1	0	1	3	0	0	2	0
3	1	0	2	0	0	1	3	1	1	1	0	2
4	1	1	2	2	0	0	3	3	1	0	0	0
5	1	1	0	3	0	0	1	0	1	0	2	1
6	1	0	0	1	0	1	1	2	1	1	2	3
7	0	1	2	3	1	0	3	0	0	0	0	1
8	0	0	2	1	1	1	3	2	0	1	0	3
9	1	1	3	0	0	0	0	1	1	0	1	2
10	1	0	3	2	0	1	0	3	1	1	1	0
11	0	1	1	0	1	0	2	1	0	0	3	2
12	0	0	1	2	1	1	2	3	0	1	3	0
13	0	0	3	3	1	1	0	0	0	1	1	1
14	0	1	3	1	1	0	0	2	0	0	1	3
15	1	0	1	3	0	1	2	0	1	1	3	1
16	1	1	1	1	0	0	2	2	1	0	3	3

Figure B-3. Orthogonal main effects design. [Figure adapted from Street, D.J., Burgess, L., and J.J. Louviere (2005), Quick and easy choice sets: constructing optimal and nearly optimal stated choice experiments (Page 465, Table 9), Int. J. Res. Marketing, 22 (2005), pp. 459–470.]

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BIOGRAPHICAL SKETCH

José R. Soto was born along the US/Mexico border in the town of Nogales, Sonora (Ambos Nogales). Throughout his life, he become a scientist or observer of the grand or small schemes of the economic realities and relations of the border. His personal growth was accompanied by a growing awareness of many disparities of the environmental, social, cultural, and economic interactions along the border. He therefore intuitively came to understand the politics of the border fence that preclude long lines of produce trucks and trains full of chemicals, as well as people waiting to cross official checkpoints. In addition the drug culture and undocumented migrants, all attempting to get to the “other side” of the divide. And yet –for him- it was just a fence. At 15, his family migrated to the US side of this wall. After that, he would sometimes climb up the Nogales hills in order to watch the traffic jams, listen to the sirens and look at the awesome disparity of two countries. He could see the *colonias* full of makeshift shacks where poor Mexican workers live around the industrial parks (*maquilas*). As a result of this vantage point, he came to understand the topology of dividing lines of many types and reasons. This contemplation invited him to think about that twenty-foot tall, corroded, metal wall dividing, while at the same time, organically making him a global citizen.

His interests and aspirations in economics are therefore not innate or superficially acquired. They stem from a need to know why or how it is that our natural resources, our workforce, our pollution, and our incentives are managed the way they are. But more importantly, a need to intellectually know how they can be improved.

His career goals are to seek an academic job that enables him to research both sides of the fence that opens into a global market. The impact and potential of trade and

environmental policies along the Mexico/US border, the effects and contributions of undocumented migrant labor in the agricultural and industrial sectors; and to utilize this position to mentor underrepresented Hispanic students, and encourage them to seek graduate degrees, and subsequent participation in academia.