AN ABSTRACT OF THE DISSERTATION OF

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Title: Three Essays on Private Landowners' Response to Incentives for Carbon Sequestration through Forest Management and Afforestation

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This dissertation consists of three essays on private landowners' response to incentives for carbon sequestration in forests. The first essay examines private landowner response to incentives for carbon sequestration through various combinations of intermediate management practices. The second essay focuses on agricultural landowners' willingness to participate in an incentive program for carbon sequestration through afforestation, and estimates the potential for carbon sequestration from afforestation, as well as its cost. The third study examines relative performances of incentive targeting strategies for forest carbon sequestration under asymmetric information given spatially heterogeneous land types.

The first essay uses an econometric approach to analyze the factors affecting non-industrial private forest landowners' choice of forest management practices, and

examines how these choices might change in response to the use of incentives for carbon sequestration. I use estimated parameters to simulate the carbon sequestration potential for different combinations of management practices, and compare the effectiveness and costs of performance-based and practice-based incentive payment schemes in the Western U.S. The results suggest that incentive payments can increase the probability that desirable combinations of management practices are adopted, and particularly that incentives targeting increased fertilization yield the highest carbon sequestration potential. I also find that a performance-based payment scheme produces higher carbon sequestration than a practice-based payments scheme. However, the annual sequestration potential of intermediate forest management in response to incentive payment is not as large as the sequestration potential of afforestation.

The second essay uses a survey-based stated preference approach to predict landowners' willingness to participate in a tree planting program for carbon sequestration as a function of various factors affecting landowners' decision making and different levels of incentive payments. The estimation results show that the annual payment for carbon sequestration significantly and positively affects landowners' stated level of enrollment in a tree planting program. I use the estimated parameters to conduct regional level simulations of carbon sequestration in response to incentive payments. These simulations show that the carbon supply function in the Pacific Northwest region is steeper than in the Southeast region because of the lower adoption rate and less available lands. The national level carbon supply functions derived from this study are steeper than those obtained from bottom-up engineering approaches and optimization models, and are in the same range as those from revealed preference approach studies.

The third essay uses both a conceptual analysis and a numerical analysis to examine the relative performances of incentive programs for carbon sequestration using alternative targeting criteria in the presence of asymmetric information and heterogeneity in costs and benefits. The results show that in the presence of asymmetric information, the combination of high cost-high benefit variability and negative correlation, which is the combination that achieves the greatest benefit gains under perfect information, can result in the greatest benefit losses. Additionally, a comparison of two targeting schemes shows that if cost variability is greater than benefit variability with negative correlation, the benefit achieved under benefit-cost ratio targeting can be lower than that under acreage targeting, so that an optimal targeting strategy under perfect information may no longer be optimal under asymmetric information.

Three Essays on Private Landowners’ Response to Incentives for Carbon Sequestration through Forest Management and Afforestation

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I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

Taeyoung Kim, Author

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CONTRIBUTION OF AUTHORS

Christian Langpap contributed to the writing and preparation of all of the essays in this dissertation.

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CHAPTER ONE

INTRODUCTION AND OVERVIEW

It has been widely recognized that forests can play an important role in contributing to greenhouse gas reductions through carbon sequestration. Especially, the potential role of nonindustrial private forests (NIPFs) in carbon sequestration is important since they comprise a significant portion of forests in the U.S. It is often suggested that providing incentives to private landowner is necessary to produce socially desirable environmental outcomes. There is evidence that providing incentives for landowners to sequester carbon in forests is a low-cost option relative to energy-based greenhouse gas mitigation approaches.

However, the potential effect of an incentive program on forest carbon sequestration and its cost depend on various factors such as: i) management types (afforestation, reforestation, timber harvest decisions, and intermediate management activities), ii) incentive payment criteria (performance based scheme, practice based scheme), iii) spatial characteristics of carbon benefits and costs (distributions, variability, correlation), iv) information asymmetry between policy maker and individual landowner, and v) discount rates. Additionally, the literature suggests that the estimated costs of carbon sequestration may vary with the methodological approach underlying the estimation (bottom up engineering approach, optimization, revealed preference, stated preference). The three essays in this dissertation examine private landowners' responses to incentive payments for carbon sequestration in forests and simulate carbon sequestration potential and its cost by taking into account some of these factors which determine the effectiveness of an incentive program.

The first essay (Chapter 2), *Private Forest Landowners' Response to Incentives for Carbon Sequestration in Forest Management*, uses an econometric approach to predict landowners' choices of intermediate forest management practices. There are several important features which distinguish this essay from other studies. First, the use of survey data of each individual landowner allows us to capture various factors affecting intermediate forest management decisions which are rarely taken into account in conventional econometric approaches using historical data. Second, the provided spatial characteristics of each forest site allow us to use the site-specific net returns as a main explanatory variable and to measure the site-specific carbon sequestration potential corresponding to the choice of management practices. This also allows us to use a performance-based scheme as an alternative contract criterion relative to a practice-based scheme. The results show that incentive payments can increase the probability of adopting the desirable combinations of management practices, and that an incentive targeting fertilization yields the highest carbon sequestration potential. The results also indicate that a performance-based payment scheme is more effective in promoting carbon sequestration than a practice-based payments scheme. However, simulation results suggest that the cost of carbon sequestration through intermediate forest management is higher than that through afforestation, because the annual carbon sequestration potential achieved by adopting intermediate management practice in response to incentive payments is not as large as the sequestration potential of afforestation.

The second essay (Chapter 3), *Agricultural Landowners' Response to Incentives for Afforestation*, uses a censored regression model to examine landowners' willingness to participate in a tree planting program for carbon sequestration. The main advantage of this essay is the use of a stated preference approach based on a survey to examine the effects of various owner-specific characteristics affecting landowners' afforestation decisions as an alternative to other approaches, such as a bottom-up engineering approach, an optimization approach, and revealed preference studies. One distinguishing characteristic of this study is that it uses a continuous measure of enrollment as opposed to a simple dichotomous measure of participation to elicit landowners' willingness to enroll in a tree planting program. This allows landowners to choose a level of enrollment based on the different levels of payments offered by considering various heterogeneous factors they face. The estimation results suggest that the landowners' stated level of enrollment in a tree planting program is significantly and positively affected by the annual payment for carbon sequestration. The estimated parameters are used to conduct simulations of carbon sequestration in response to incentive payments to derive a carbon supply function for each region. The carbon supply function in the Pacific Northwest region is steeper than that in the Southeast region because of the lower adoption rate and less available lands despite of the higher carbon sequestration rate per acre. A comparison of carbon supply functions by scaling up from the regional level to the national level shows that the carbon supply functions derived from this study are steeper than those obtained from bottom-up engineering approaches and optimization models, and are within the range of those obtained from a revealed preference approach.

The third essay (Chapter 4), *Targeting Incentives for Carbon Sequestration with Spatially Heterogeneous Land Types under Asymmetric Information*, uses a conceptual and numerical analysis to examine the relative performance of alternative targeting criteria for incentive payments in the presence of asymmetric information and heterogeneity in costs and benefits. The main contribution of this study is that it incorporates asymmetric information into choice of targeting strategies given spatially heterogeneous cost and benefit types. It therefore suggests how policy makers may choose the best targeting tool for a given level of budget in the presence of asymmetric information. The findings from this study show that the combination of high cost-high benefit variability and negative correlation, which achieves the greatest benefits under perfect information, can result in the greatest benefit losses in the presence of asymmetric information. This implies that an optimal targeting strategy under perfect information may no longer be optimal under asymmetric information, and thus may require higher monitoring efforts by the policy maker. However, if cost and benefit variability are low an optimal targeting strategy under perfect information is still optimal under asymmetric information, and thus it does not require highly accurate monitoring by the policy maker.

Taken together, these three essays provide some insight into the potential effectiveness of different incentive programs, as well as a better understanding of other factors affecting landowners' management and participation choices.

CHAPTER TWO

PRIVATE FOREST LANDOWNERS' RESPONSE TO INCENTIVES FOR CARBON SEQUESTRATION IN FOREST MANAGEMENT

2.1. Introduction

There is widespread recognition of the potential role forests can play in contributing to Greenhouse Gas reductions through carbon sequestration (Brand 1998, Metz et al. 2001, Lubowski et al. 2006, Gorte 2009). Nonindustrial private forests (NIPFs) comprise a significant portion of forests in the U.S.[1] Thus, it is crucial to assess the role that NIPF landowners can play in broader carbon sequestration efforts. NIPF ownership characteristics and management information, as well as their spatial characteristics, are essential for understanding NIPF owners' forest management choices.

Management actions by NIPF owners that could increase carbon sequestration on their lands include afforestation of land used for agriculture, reforestation, changing forest management such as increasing rotation length, fire control, fertilization, thinning and pruning, or choosing alternative tree species (Stainback and Alavalapati 2002, Sohngen and Mendelsohn 2003, Shaikh et al. 2007, Gorte 2009). It is generally known that providing incentives for landowners to sequester carbon in forests is a comparatively low-cost option relative to energy-based GHG mitigation approaches (Alig, R. J. 2003, Lubowski et al. 2006, Mason and Plantinga 2011). However, existing studies on

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[1] According to Smith et al. (2009) 423 million acres (56%) out of 751 million acres of forest land in the U.S. is owned by private entities such as private individuals, corporations, and other private groups in 2007.

landowners' response to carbon sequestration incentives have largely focused on afforestation and reforestation (Adams et al. 1993, Alig et al. 1997, Parks and Hardie 1995, Plantinga et al. 1999, Stavins 1999, Newell and Stavins 2000, Lubowski et al. 2006).

Changing management practices (MPs) in existing forests has been often mentioned as a source of carbon sequestration as well. Many studies have shown the potential for forest carbon sequestration by adopting a certain forest management practices. For example, Row (1996) concluded that change in forest management can increase carbon sequestration by 0.6-0.8 metric tons (Mt) of carbon per acre per year in the cases of loblolly pines in Southeast and Douglas Fir in the Pacific Northwest.[2] IPCC (2000) shows that forest management activities such as regeneration, fertilization, choice of species and reduced forest degradation have the potential to sequester around 0.2 Mt per acre per year in developed countries. Intermediate forest MPs which is conducted to increase tree growth rate or enhance resistance from hazard can be a source of carbon sequestration as well.[3] Grayston (2006) concluded that nitrogen fertilization can increase aboveground biomass, and thus increases soil carbon, based on review of various papers published since 1978.[4] Shafii et al. (1989) showed that 200 lb of urea nitrogen application

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[2] Carbon in wood products is also included.
[3] Intermediate management practices are silvicultural treatments which are conducted to improve timber productivity, and enhance resistances from potential hazards such as fire and diseases during the stands are growing. Intermediate management involves the practices that improve the site quality such as fertilization, thinning, and fuel treatment, or manage pests and insects (IPCC 2000, North et al. 2009, McKinley et al. 2011).
[4] Grayston (2006) mentioned that fertilization can be a source of N_2O and CH_4 emissions, however in contrast to agriculture fertilization have limited effects on them. Pang and Cho (1984) showed nitrogen

on stands of Grand fir and Douglas-fir in Idaho results in significant growth of average basal area and height over a 6-year post-treatment period, and increases average tree size by 14% in unthinned stands over a 14-year treatment period, which leads additional carbon sequestration. Miller and Fight (1979) and Miller et al. (1989) mentioned nitrogen fertilization on Douglas-firs in western Washington and Oregon increases growth in diameter and volume. In the case of activities controlling fire hazard, North et al. (2009) concluded that thinning and prescribed burning allow greater long-term storage of carbon since they yield bigger and more fire-resistant trees and decrease the intensity of future wildfires, although they decrease total carbon storage in the short run. On the other hand, McKinley et al. (2011) argued that while thinning is an effective forest management technique used to reduce fire risk, increase tree resistance to insect and disease, and increases the growth of the remaining trees, since overall tree stock is reduced because of thinning, the carbon stock in a thinned stand is generally lower than that in an unthinned stand.[5] Law and Harmon (2011) also argued that large amount (40–50%) of above-ground biomass need to be reduced to achieve a significant level of fire severity reduction. This would lead a net emission of forest carbon if the amount of carbon removed is greater than that saved by reducing fire severity. Although these studies have shown the potential of carbon sequestration by changing forest MPs, the MP changes introduced in these studies are not correspond to landowners' responses with respect to

fertilization can be a negligible source of N_2O emissions from forest soils. Van Miegroet and Jandl (2007) showed the effect of nitrogen fertilization on the aboveground biomass is large enough to offset the possibility of soil carbon loss.

[5] This is because even 100% use of the harvested trees for products or biomass energy may not produce a total carbon benefit greater than that of the higher storage and storage rate in an unthinned stand.

various factors such as annual net returns, and individual characteristics affecting their MP decisions. Thus, it is hard to know what factors affect landowners' MP choices and how much the cost of carbon sequestration is by adopting a certain MP.

There are several studies which examine landowners' forest MP decisions and carbon sequestration potentials in economic perspectives. For example, Plantinga and Birdsey (1993) developed a carbon budget model to examine the effects of forest MPs, harvesting in particular, on carbon sequestration in private forests. Englin and Callaway (1993) showed that the optimal rotation age of Douglas-fir with payment for carbon sequestration is positively correlated with the price of carbon. Van Kooten et al. (1995) examined the implications of carbon subsidies and taxes for economically optimal harvest decisions and found that rotation ages would increase by roughly 20 percent over the level where no carbon costs or benefits are considered. Sohngen and Brown (2008) showed that around 15 million tons of CO_2 could be sequestered at less than $7/ton CO_2 (209 million tons CO_2 at $55/ton CO_2) of carbon price by extending rotation ages in softwood forests in 12 states of the southern and western U.S. Zyrina (2001) estimated the cost of carbon sequestration with different MP regimes, and showed the carbon storage increases from 428 Mt/ha to 589 Mt/ha with a marginal cost of $13.28/Mt, and from 683 Mt/ha to 802.7 Mt/ha with a marginal cost of $32.79/Mt. These studies suggest that incentive programs including taxes or carbon payments or other types of subsidies can impact the management decisions of forest in ways that can lead to increased carbon sequestration. However, most of them have focused on rotation length and harvest decision, and few have focused on other silvicultural management activities such as fertilization and thinning. In addition, one important drawback of these studies is that most of them have analyzed the carbon sequestration effects of the forest management activities independently, while in practice these activities may be conducted jointly rather than independently within certain range of forestland.

One important advantage of this study is the use of survey data which describe the NIPF landowners' management practice choices, and their demographic characteristics, resource characteristics, and other attributes which can affect landowners' decision of management practices.[6] The survey-based approach can capture various factors affecting forest management decisions which are rarely taken into account in conventional econometric approaches using historical data.

The main purpose of this study is to examine private landowner response to incentives for carbon sequestration through combinations of intermediate MPs of existing forests, and to measure the carbon sequestration potential of these forest management combinations given different levels of incentive payments.

The study results show that the factors affecting the probabilities of adopting intermediate MPs of forests differ by the choice of MPs. The own marginal effects and elasticities of the probabilities of choosing the MPs with respect to expected net returns are all positive and significantly different from zero, which is consistent with expectations of economic theory. Landowners' demographic characteristics do not

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[6] There are survey-based studies have shown how landowner attributes and incentives shape forest management decisions for other environment services such as biodiversity and endangered species (e.g. Nagubadi et al. 1996, Conway et al. 2003, Langpap 2004, 2006), but not for carbon sequestration especially through intermediate forest managements.

significantly affect the probability of choosing a certain MP, while the spatial characteristics, objectives of owning forestlands, and concerns they have faced tend to affect these probabilities significantly. The calculated carbon sequestration trends of four different MPs show that the choice of ‘Fertilization’ or ‘No Activity’ can sequester more carbon than the choice including ‘Fuel Treatment’, which suggests that the fact that activities enhancing resistance from fire, quality of remaining trees, and biodiversity, do not always increase the carbon sequestration potentials. The simulation of carbon sequestration potentials in response to incentive payments with different targeting strategies shows that targeting the choice of ‘fertilization’ yields the highest carbon sequestration potential, and a performance-based payment scheme produces higher carbon sequestration than a practice-based payments scheme. However, the comparison of the supply function of carbon sequestration with afforestation studies shows that the annual carbon sequestration potential through changing intermediate MPs of NIPFs in the western U.S. is not as large as that through afforestation.

The remainder of this essay is organized as follows. Section 2 presents the conceptual background and model specification, the data description, and the analysis of the econometric model. Section 3 presents baseline carbon sequestration potentials, the incentive payment design, and the simulation of carbon sequestration potentials with different incentive payments strategies. Section 4 includes a discussion of the main findings and the conclusion.

2.2. Econometric Analysis

2.2.1. Conceptual Background and Model Specification

In this section, I describe the conceptual background of NIPF landowner's forest management decision models and the econometric model. A utility maximization framework is the starting point to evaluate NIPF landowners' forest management activity choices (Pattanayak et al. 2002).

Consider a utility-maximizing NIPF landowner who is faced with various combinations of forest management practices. Since forest management activities can be conducted jointly within the same area of forestland, suppose the NIPF landowner can choose among K different combinations of forest MPs, with $k = 0$ indicating no forest MPs and $k = 1,2,\ldots,K$ indicating the set of mutually exclusive combinations of forest MPs. The NIPF owner maximizes expected utility from managing forestlands by adopting a combination of MPs: combination k $(k=1,2,\ldots,K)$ will be chosen if $U_k > U_j$ for all $k \neq j$, where U_k is the utility of adopting combination k.

Since the landowner' utility can be affected by both observable and unobservable components, the landowner's MPs decision problem can be modeled using a general random utility (RUM) approach (Lubowski et al. 2002; Cooper 2003). Let $U_{ik}(Z_{ik})$ be the expected utility of NIPF landowner i from choosing a combination of MPs k on her forestland. The utility depends on vector of variables $Z_{ik} = [X_{ik}, W_i]$, where X_{ik} is a vector of attributes of forest management choices such as expected net returns, which varies across the forest management choices and across the individual landowners. W_i is a vector of individual landowners' characteristics and their land characteristics which varies only over the landowners (Greene 2008, Lubowski 2002). By considering both observable and unobservable components of NIPF landowners' management decision, $U_{ik}(Z_{ik})$ can be considered a random variable and be written as:

$$U_{ik}(Z_{ik}) = Z_{ik}^{'}\beta_k + \varepsilon_{ik}, \ k = 0,1,2,...,K \ . \tag{1}$$

where β_k are parameters for each variable and ε_{ik} is a random error term. The probability that NIPF owner *i* will choose the forest MPs combination *k* is:

$$\Pr(y_i = k) = \Pr(U_{ik} > U_{ij}) = \Pr(Z_{ik}^{'}\beta_k + \varepsilon_{ik} > Z_{ij}^{'}\beta_j + \varepsilon_{ij}), \ \forall k \neq j \tag{2}$$

If we assume the error term ε_{ik} is independently and identically distributed with the extreme value distribution, then the probability that NIPF owner *i* will adopt intermediate forest MP choice *k* can be specified using a multinomial Logit model (McFadden 1974; Maddala 1993). The MNL model for the choice of intermediate forest MPs can be written as

$$\Pr_{ik} = \frac{e^{Z_{ik}^{'}\beta_k}}{\sum_{j=0}^{K} e^{Z_{ij}^{'}\beta_j}}, \ k = 0,1,2,...,K. \tag{3}$$

Then, the log-likelihood function is:

$$\log L = \sum_{i}^{N}\sum_{k}^{K} d_{ik} \log\left(P_{ik}\right) \tag{4}$$

where $d_{ik} = 1$ if individual *i* chooses alternative *j* and $d_{ik} = 0$ otherwise.

2.2.2. Data description

We rely on data from National Woodland Owner Survey (NWOS),[7] which describes private woodland owners' forest management behaviors, landowners' attributes, and land characteristics conducted by the U.S. Forest Service from 2002 to 2006, to analyze the factors affecting landowners' forest management decision. There are a total of 593 observations which cover the Western United States (AZ, CO, CA, ID, MT, NM, OR, UT, WA, and WY). Of these, 513 observations are defined as NIPFs owners. The spatial location of plots of individual forestlands is also provided,[8] which allows us to incorporate the stand information of each forestland from the Forest Inventory and Analysis (FIA) constructed by the USDA Forest Service.

The forest management activities included in the NWOS data are: i) Partial harvest to improve the growth of remaining trees (Thinning), ii) Fire hazard reduction, and iii) Fertilization. Since most landowners who adopt thinning for remaining trees also conduct fire hazard reduction to improve fire tolerance, and thinning is commonly considered as a type of activity to control fire hazard, we combined thinning and fire hazard control together as one type of intermediate forest MP, fuel treatment. Thus, the

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[7] The National Woodland Owner Survey (NWOS) is the official census of forest owners in the United States. It is aimed at increasing understanding of woodland owners who are the critical link between forests and society (USDA Forest Service 2012).

[8] The NWOS sample locations are corresponding to plot center of the FIA inventory plots (Butler et al. 2005). However, because FIA has a policy of nondisclosure of exact locations of observations due to the confidentiality issues, a certain percentage of plots, which is randomly chosen, is fuzzed within a buffer area of 0.5 to 1 miles around each plot, and swapped with similar plots in the same county to protect landowner privacy (LaPoint 2005). Nevertheless, McRoberts et al. (2005) concluded that if the study area is large enough, the effect of perturbing and swapping on analyses using FIA data is negligible.

choices of intermediate forest MPs are: Fertilization–Fuel Treatment (FFT), Fertilization only (F), Fuel Treatment only (FT), and No activities (NA).

We calculate the owner-specific expected net returns with different choice of intermediate forest MPs as one of key explanatory variables to examine the NIPF owners' responses. As a measure of annual net returns, we use the annualized value of Land and Timber Stands (LTV) (Latta and Montgomery 2004). Because of the lack of identifiable information of each landowner's harvested and replanted trees, we assume all NIPFs landowners plant and harvest their trees. The LTV for each MP choice *k* and landowner *i*, based on the current stand volume is:

$$LTV_{ik} = \frac{\sum_{t=t^0}^{T}(P_{ikt}Q_{ikt} - C_{ikt})(1+r)^{T-t} + SEV_{ik}}{(1+r)^{T-t^0}}, \text{ s.t. } T - t^0 \leq \omega \tag{5}$$

where T is the final harvest year, t^0 is the current year, P_{ikt} is stumpage price for i and k at year t, Q_{ikt} is the per acre harvest volume for i and k at year t, C_{ikt} is the per acre cost of stand treatments applied for i and k at year t, ω is a maximum range of time horizon, r is the annual discount rate, and SEV_{ik} is the value of bare land for i and k, which we assume to be the present value of timber production.[9]

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[9] $$SEV_{ik} = \frac{\sum_{t=0}^{T}(P_{ikt}Q_{ikt} - C_{ikt})(1+r)^{T-t}}{(1+r)^{t} - 1}$$

We then annualized the LTV using a 5% discount rate over a 100-year period.[10] Owner-specific management costs (C_{ikt}) for fuel treatment are calculated by using the fuel reduction cost simulator (FRCS), which estimates the cost of fuel reduction activities by considering stand volumes and each forestland's spatial characteristics, such as distance to the closest main road, average slope, and elevation (Fight et al. 2006). We rely on previous studies to provide a range of fertilization costs (Shumway and Atkinson 1978, Miller and Fight 1979, Zyrina 2001). We then normalize the cost based on application time and amount, and differentiate between parcels based on average slope and distance from main road. The site specific stand volume (Q_{ikt}) with various management combinations is calculated using the Forest Vegetation Simulator (FVS).[11,12] Location information (Longitude and Latitude) of each forestland plot allow us to incorporate forest inventory data (e.g. tree species, stand age, slope, elevation, etc) which is necessary to run FVS.

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[10] We followed the rule of normalization done by Stavins and Richard (2005) to our result be comparable to other study results.

[11] The Forest Vegetation Simulator (FVS) is an individual tree growth model widely used in the U.S. to support decision making on various forest management issues such as silvicultural prescriptions, fuels treatment, insect and disease impacts, and wildlife habitat management. The spatial scale of the FVS can vary from a single stand to thousands of stands. The stand growth simulation models can differ depending on the geographic region by applying regionally specific model variants (Crookston and Dixon 2005). The FVS is a very flexible carbon accounting tool, since it can consider the spatial heterogeneity of each forest parcel and can be applied with various silvicultural forest management activities.

[12] To simulate tree growth with different management options using FVS, we need to define a general silvicultural treatment rule for each management practice. In the case of fuel treatment, we followed the U.S. Forest Service guide to fuel treatment in the western U.S. (Johnson et al. 2007). We apply four silvicultural options (thinning from below to 50 trees per acre (tpa), 100 tpa, 200 tpa, and 300 tpa with 18 bdh limit with surface fuel removal) to calculate trends of stand volume and carbon sequestration potential. In the case of fertilization, we use application of 200 pounds of nitrogen per acre, since the FVS supports only this option.

We categorized the owner-specific variables used in the econometric model as follows: Landowner's demographic characteristics, resource and spatial characteristics, and landowner's attributes. At first, landowner's demographic characteristics which are taken from NWOS include age, level of education, level of household income, and occupation. Several studies have shown that age has a positive correlation with adoption of soil conservation practices (Ervin and Ervin 1982), while it has a negative correlation on harvesting and investment on silvicultural activities (Beach et al. 2005). However, some studies argued that age does not significantly affect timber harvest behavior and the forestry cost share program (Dennis 1989, Nagubadi et al. 1996). It is also argued that income is negatively correlated with timber harvest (Dennis 1989, 1990, Beach et al. 2005), and positively correlated with silvicultural management activities (Beach et al. 2005). But several studies found that both income and education do not significantly affect forest owners' management decision (Dennis 1989, Langpap 2006). The landowners whose occupation is farm or forest related are positively and significantly correlated with timber harvest (Beach et al. 2005).

Regarding the resource characteristics, it is known that site quality and stand volume increase the amount of silvicultural activities (Zhang and Pearse, 1996) and harvests (Dennis 1990), while size of forestland has a positive effect on silvicultural activities in around 40% of the studies cited in Beach et al. (2005). It is also generally recognized that greater stand volume, larger plot size, flatter average slope (below 35-40 degree), higher incidence of mills close to the site, and shorter distance from the site to a main road, all reduce forest management costs, which may induce more intermediate

MPs or harvesting (Cubbage 2004, Latta and Montgomery 2004, Fight et al. 2006, Zhou and Kockelmen 2008). Based on this information, resource characteristics taken from NWOS include size of forestlands owned within a state, forest regions (Pacific Northwest, Pacific Southwest, and Northern Rocky Mountain). Additionally, we create individual land's spatial characteristic variables by overlapping the location information (Longitude and Latitude) of each forestland with other spatial data from Forest Inventory Analysis (FIA) and the U.S. Geological Survey (USGS), which include stand density index (SDI), slope dummy (below 35 degree or not), distance from site to main road, and number of mills within 50 miles from the site.

Finally, landowners' attributes taken from NWOS include: objectives of owning forestland, concerns faced recently (concerns about future development, air quality, insects and disease, and risk of fire), whether a landowner is living within a mile of forestland or not, whether a landowner is a main decision maker of management or not, program enrollment or knowledge (cost-share program, and knowledge about green certification), whether a landowner recently harvested non-timber products or not, and land acquisition method. Landowners who own forests for commercial purposes are more likely to invest in silvicultural MPs such as thinning to improve quality of timber; hence they may be less likely to participate in the program to prevent such activities. On the other hand, we expect that landowners who own forests for privacy or recreational opportunities may be less likely to invest in timber harvest or silvicultural MPs. Some studies mentioned that development pressure can affect land use choice (Mansfield et al. 2000, Kristensen et al. 2001), but it is unclear how landowners who are concerned about future development act for their forests. We expect that landowners who are under pressure of development might invest more to increase their property value, but are less willing to participate in the program to provide environmental services. Many studies mentioned that landowners who are under pressure of fire risk, insect, and disease tend to harvest earlier and invest more for intermediate MPs such as fuel treatment and risk control practice by thinning (Reed 1984, Gregory et al. 2003, Nebeker et al. 2005, Konoshima et al. 2008). We also expect that if landowners who live within a mile of their forests, and if the main decision makers are in forest-related professions such as logging contractor and forester, they are more likely to conduct forest management practices. Program enrollment such as cost sharing and technical assistance has positive effects on encouraging silvicultural treatment (Beach et al. 2005). In this study, the participation dummy of cost sharing program and knowledge about green certification are available to use from NWOS for econometric analysis. Table 2.1 presents the descriptions and summary statistics of all of these variables.

2.2.3. Model Estimates and Interpretation

We specify the component of individual landowner *i*'s utility of MP choice *k* as follows:

$$U_{ik} = \alpha_k + \beta_k AnnLTV_{ik} + \gamma_k^1 OWN_{ik} + \gamma_k^2 LC_{ik} + \gamma_k^3 OA_{ik} + \varepsilon_{ik},\ k = FFT, F, FT, NA. \quad (6)$$

where $AnnLTV_{ik}$ is a vector of annual LTVs, OWN_{ik} is a vector of landowners' demographic characteristics, LC_{ik} is a vector of forestland characteristics, OA_{ik} is a vector of landowners' attributes, and ε_{ik} is a random error term, for landowner *i* and MP choice *k*.

The estimated parameters allow us to analyze the determinants of NIPFs owners' choices of management practice combinations. Since the interpretation of coefficients in a multinomial logit model is difficult, the marginal effects[13] are used to examine what determinants affect NIPFs owners' choices of MPs. Table 2.2 shows the marginal effects of the explanatory variables, calculated using the model coefficients and the sample means of the variables. The main variables of interest are annual LTVs (*AnnLTV1~4*) of forest MPs as proxies of expected net returns. The own marginal effects with respect to LTVs are all positive and significant at least at the 10% significance level, which implies that an increase in the LTV for a forest MP will increase the likelihood that the forest MP will be chosen. The cross marginal effects with respect to annual LTVs have mostly negative signs, although not all are significant. For example, a higher annual LTV for the choice 'FFT (Fertilization-Fuel Treatment)' decreases the probability of choosing choice 'F (Fertilization) and 'FT (Fuel Treatment)'. The cross marginal effects of annual LTV in choice 'F' are negative, but not significant. The higher annual LTV for the choice 'FT' decreases the probability of choosing other MPs significantly.

In cases of marginal effects with respect to landowners' demographic characteristics, age (*Age*) and household income dummy (*Income*) do not significantly affect the probability of choosing MPs. Education dummies (*Education*) do not significantly affect the choice of MPs as well, except that landowners with $50,000 to

[13] Average marginal effects are calculated using the following formula: $\partial \Pr_{ik} / \partial z_{ik}^{j} = \Pr_{ik} \cdot \left[\beta_k^j - \sum_k \left(\Pr_{ik} \cdot \beta_k^j \right) \right]$, where z_{ik}^{j} and β_k^j are the *j*th elements of vectors z_{ik} and β_k, respectively.

$100,000 of household income (*Income2*) are less likely to choose ‘FT’. The landowners whose occupation is related to farm or forests (*Occupation_farm*) are more likely to adopt ‘FT’, which is consistent with other studies showing that it is positively and significantly correlated with timber harvest (Beach et al. 2005). While each of the landowners’ demographic characteristics does not significantly affect the probability of choosing a certain MP, the test for the joint significance of each equation rejects the null hypothesis that all coefficients associated with landowners’ demographic characteristics are zero at the 10% significant level.

In cases of marginal effects on the probability of choosing ‘FFT (Fertilization and Fuel Treatement)’ with respect to resource characteristics and landowners’ attributes, results suggest that the probability of choosing ‘FFT’ increase with higher in-stand density index (*SDI*), which is consistent with previous studies mentioned in Beach et al. (2005).[14] It has positive effects on the probability of choosing ‘FFT’ with landowners who own their forests for recreation (*Obj_recreation*), who have concerns about future development (*Concern_develop*), and who have enrolled in a cost share program (*Costshare*), while it has negative effects for those landowners who have concerns about privacy (*Concern_privacy*).

The marginal effects on probability of choosing ‘F (Fertilization)’ with respect to resource characteristics and landowners’ attributes indicate that landowners who live within a mile of their forests (*Primary_resident*), distance from site to main road

[14] Stand density index (SDI) is a measure of stocking of tree stands based on the number of trees per unit area and diameter at breast height (DBH) of stand trees of average basal area (Avery and Hurkhart 2002).

(*Distance_S2R*), landowners who have concerns about insects and diseases (*Concern_disease*), and who produce non-timber food products recently (*NTFP_recent*) have positive effects on the possibility of choosing ‘F’, while landowners who owns their forests for biodiversity (*Obj_biodiversity*), who have concerns about future development (*Concern_develop*), and who have concerns about fire hazard (*Concern_fire*) are less likely to choose ‘F’.

The marginal effects on probability of choosing between ‘FT (Fuel Treatment)’ and ‘NA (No Activity)’ have opposite signs in most cases. Those landowners with forest lands located in the northern rocky mountain (*NRMT*) region are more likely to adopt ‘FT’, but less likely to choose ‘NA’. The marginal effect of distance from the site to a main road (*Distance_S2R*) shows that the further away from a main road a site is, the less likely a landowner is to ‘FT’, and more likely to choose ‘NA’. The landowners who live within a mile of their forestlands (*Primary_resident*), who are consulted by non-family experts (*Manager*; e.g. logging contractor, forester, and business partner), who own lands for biodiversity (*Obj_biodiversity*) and timber harvest (*Obj_timber*), and are concerned about risk of fire (*Concern_fire*) are more likely to choose ‘FT’, but less likely to choose ‘NA’.[15] On the other hand, those landowners who own forests for recreation (*Obj_recreation*) and privacy (*Obj_privacy*) are less likely to choose ‘FT’, but more likely to choose ‘NA’. In addition, the landowners who have knowledge about green

[15] It is generally known that thinning for fuel treatment can enhance the fire resistance of remaining trees (North et al 2009, McKinley et al. 2010). And Muir et al. (2002) mentioned that thinning on young forests may increase vegetative structure for a variety of plant and wildlife species, and also concluded the total abundance of birds is greater in thinned young- and old-growth stands than in un-thinned stands.

certification, and who produce non-timber food products are less likely to choose ‘NA’. These results are consistent with our expectations and the results of previous studies (Mansfield et al. 2000, Kristensen et al. 2001, Gregory et al. 2005, Nebeker et al. 2005, Beach et al. 2005, Konoshima et al. 2008) mentioned in the previous section. One interesting result is that enrollment into a cost share program affects ‘FFT’ and ‘FT’ in opposite directions, even if both conduct fuel treatment. However, since the purposes and types of cost sharing program that each landowner is enrolled in are unknown, it is difficult to explain why this is.

To get a better idea of the magnitude of these effects, in Table 2.3 we calculate the own- and cross-return semi-elasticities of the probability of choosing the different MP combinations with respect to annual LTVs. The semi-elasticities are calculated as the percentage point change in the probability of adopting a certain combination for a 1% change in the net returns for each choice. For example, the own semi-elasticities of annual LTVs show that a 1% increase in LTV of each MP choice increases the probability of adopting the MP choices ‘FFT’, ‘F’, ‘FT’, and ‘NA’ by 0.20 percentage point (%p), 0.28 %p, 0.7 %p, and 0.41 %p, respectively. The cross-return semi-elasticities show that a 1% increase in annual LTV of choice ‘FFT’ reduces the possibility of choosing ‘F’ by 0.14 %p, and ‘FT’ by 0.22 %p. However, a 1% increase in annual LTV of choice ‘F’ or ‘NA’ does not significantly affect the probability of adopting other MPs, while a 1% increase in annual LTV of choice ‘FT’ reduces the probability of adopting the choice ‘FFT’ by 0.15 %p, and ‘NA’ by 0.52 %p.

We use the predicted probabilities to predict the choice of a landowner's forest MP, so the choice of MP with the highest predicted probability is the predicted choice. This will allow us to calculate the baseline carbon sequestration potentials. Based on the predicted choices, 5.8% of landowners choose 'FFT', 3.7% choose 'F', 38.4% choose 'FT', and 52.0% choose 'NA'. Since each landowner owns forestland of different size, I also calculate predicted probabilities of MP choices weighted by acreage: 14.1% of forest acres are managed with 'FFT', 3.1% with 'F', 49.6% with 'FT', and 33.1% with 'NA'.[16] The model correctly predicts landowners' MPs choice at 70% and 91% of actual choices are predicted as the first or second choice by the models. We also used Theil's Inequality Coefficient to validate the model further by comparing actual choices and predicted choices (Leuthold 1975, Ahn et al. 2000, Langpap and Wu 2008). The coefficient is 0.12 which indicates a good predictive performance.[17]

2.3. Simulation of Carbon Sequestration with Incentives

2.3.1. Calculation of carbon sequestration trend and baseline

We use the estimates from the econometric model and the FVS to simulate carbon accumulation trends for the different management options. Specifically, for each management option (NA, F, FT, and FFT) we assume that all landowners choose only

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[16] Actual probabilities of MP choices weighted by acreage were 12.1% with 'FFT', 3.9% with 'F', 48.2% with 'FT', and 35.8% with 'NA'.

[17] Theil's Inequality Coefficient is a measure of forecasting accuracy, which ranges between 0 and 1 with a value of 0 indicating a perfect prediction (Leuthold, 1975). The coefficients in Langpap and Wu (2008) range between 0.007 and 0.17 in projection of different land use categories.

that option[18], and that trees are allowed to grow without harvest for 100 years[19]. The results, shown in Figure 2.1, indicate the carbon sequestration potential, over a hundred year period, of each individual management option. The carbon accumulation trends show that fertilization ('F') has the highest carbon sequestration potential, followed by no management activities ('NA'). Note that the carbon sequestration potential of 'NA' is always greater than that of fuel treatment ('FT') and of fertilization and fuel treatment combined ('FFT'). This implies that removing some portion of trees by thinning to enhance the quality of remaining trees and fire resistance does not provide higher total carbon benefits than the choice of no thinning. This result is consistent with McKinley et al. (2011) and Law and Harmon (2011).[20]

Given the carbon sequestration trend of each management choice, we calculate the baseline carbon sequestration trend per acre, which is the average of annual carbon accumulation of the different management practices weighted by the corresponding predicted probabilities of management choices (i.e. 14.1% of forest acres are managed

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[18] The carbon accumulation trend for 'FFT' is calculated by combining management rules from 'FT' and 'F'.

[19] We only considered NIPF lands that are stocked with more than 50 trees per acre. Harvested or un-stocked lands were excluded. Since the data on landowners' management choices correspond to the years 2002 - 2006, our simulation is calibrated to begin in 2006. We use the *Carbon Report in the Fire and Fuel Extension of Forest Vegetation Simulator (FFE–FVS)* (Hoover and Rebain, 2011), which accounts for carbon in above ground live trees, below ground live trees, below ground dead trees, standing dead trees, down dead wood, the forest floor, the understory, wood products in use, products in landfills, and carbon emitted from combustion. Carbon accumulation trends of each MP choice are calculated by assuming 100% of landowners choose one specific MP.

[20] We expect that the cost of carbon sequestration with consideration of fire risk can be higher than that we estimated, because the difference in carbon sequestration between thinned ('FFT' and 'FT') and unthinned ('F' and 'NA') stands may be lower, and hence the carbon sequestration potential of converting practices may be smaller. Law and Harmon (2011) mentioned even if the risk of fire is considered, the carbon sequestration potential with fuel treatment is lower than with the no activity option. This implies that the amount of carbon loss caused by fuel treatment is larger than carbon sequestration induced by reducing the possibility of fire.

with ‘FFT’, 3.1% with ‘F’, 49.6% with ‘FT’, and 33.1% with ‘NA’).[21] We assume that the predicted proportion of MPs will not change over time, if other conditions facing landowners remain the same over time.

2.3.2. Incentive payments design

The goal of the incentive payments program is to increase carbon sequestration by encouraging the NIPF owners to switch their current intermediate MP to alternative MPs. The simulation of carbon sequestration examines how the adoption rate of each MPs will change with incentive payments and measures how much carbon can be additionally sequestered with this change in adoption rate. I assume incentives are paid to NIPF owners to encourage implementation of forest MPs which can increase carbon sequestration. The effects of incentive payments to encourage a certain forest MP for carbon sequestration are simulated by changing the level of annual LTV of that particular MP choice given different level of payments. An incentive payment to adopt forest MP choice *k* increases the annual LTV of that MP, and therefore modifies the estimated adoption probabilities P_k as follows (Lubowski et al. 2006):

$$P_{ik} = f(\hat{\beta}_k, AnnLTV_{ik} + AnnPAY_{ik}, AnnLTV_{ij}, OWN_i, LC_i, OA_i) \tag{7}$$

where $AnnLTV_{ik}$ is the annual payment per acre for carbon sequestration. We then calculate the impact of the incentive on carbon sequestration based on the net increment

[21] Baseline Carbon Sequestration (Mt/acre) = $\sum_{i=1}^{N}\left(\bar{C}_{ik} \times Acreage_i \Big/ \sum_{i=1}^{N} Acreage_i\right)$, where $\bar{C}_{ik}$ is the amount of carbon stored per acre for the MP *k* with the highest predicted probability, and $Acreage_i$ is acreage of forestlands owned by each individual landowner *i*.

in the adoption rate of a given management practice relative to the baseline.

We assume that the landowner and an agency providing the incentive enter into a contract specifying the agreed-upon activity and the amount of the payment.[22] The duration of the contract is ten years (we check the robustness of our results to alternative contract lengths in section 2.3.6).[23] The incentive payments we use in the simulations range from $0 to $150 per acre for the duration of contract, rising in $10 increments.[24] When measuring the additional sequestration induced by the incentive payment, we only consider the amount of carbon sequestered within the duration of the contract.[25] We annualize the amount of carbon sequestration over a hundred year time horizon using a 5% rate.

An important aspect of an incentive contract is the payment criterion. We consider two criteria: i) a practice-based contract in which the goal of incentive payments is to change the management practice itself, and ii) a performance-based contract in which the goal is to change the environmental benefits, i.e. the amount of carbon

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[22] We assume that no harvesting is allowed during the length of the contract to ensure there is enough time for sequestration to take place. This is necessary because there is a time lag between switching management practices and achieving a given level of sequestration.

[23] The contract length of federal conservation payment programs is 10-15 years for the Conservation Reserve Program (CRP), 5-10 years for the Wildlife Habitat Incentives Program (WHIP), and 6 years for the Environmental Quality Incentives Program (EQIP) (USDA Natural Resources Conservation Service 2008).

[24] It is difficult to choose the appropriate range of incentive payment since there are no comparable examples from previous studies of intermediate forest management choices. Therefore, we chose the range of incentive payments based on the average range of maximum carbon price from U.S. EPA (2005) and the U.S. Agricultural Sector Model (Lewandrowski et al. 2004).

[25] The amount of carbon sequestration achieved in the long-run is uncertain since it is unknown when each plot will be harvested. If we knew the distribution of final harvest schedules of these forestlands, we could calculate the expected amount of carbon sequestered in the long-run. However, since the distribution of the harvest schedule is unknown, we only account the amount of carbon sequestered within the duration of a contract.

sequestration, through the change of management practice. Antle et al. (2003) find that performance-based contracts achieved greater benefits in soil carbon sequestration than practice-based contracts.[26] However, existing environmental programs such as the Conservation Reserve Program (CRP), the Environmental Quality Incentive Program (EQIP), and the Wetland Reserve Program (WRP) have offered payments to support voluntary changes in management practices rather than to directly support the production of environmental benefits by taking into account the spatial variability of ecosystems (Antle et al. 2002). We use our simulation framework to compare the additional carbon sequestration achieved by these two payment criteria.

The carbon sequestration trends shown in Figure 2.1 suggest that (without considering the risk of fire) an increase in the adoption of 'FT' does not increase, and may even reduce, the annual carbon sequestration rate, while an increase in the adoption of 'F' or 'NA' can increase the carbon sequestration rate. Since the goal of the incentive payments is to produce additional carbon sequestration, we focus on incentive payments targeted to increase the likelihood that 'F' and 'NA' are chosen.[27] Hence, the possible combinations of the incentive payment targets can be classified as follows: i) Provide incentives for fertilization only, so only landowners who adopt the choice 'F' (Fertilization) receive payments and those who implement other activities are not eligible; ii) Pay for fertilization no matter what other combined activities are, so

[26] Antle et al. (2003) also showed that estimated measurement costs to implement the performance based contract is less than the efficiency losses under practice based contract.

[27] Note that this is comparable to removing incentives for the 'Fuel Treatment' choice.

landowners who choose ‘FFT’ (Fertilization and Fuel Treatment) or ‘F’ receive payment (hereafter referred as ‘FFT-T’); iii) Pay only for ‘NA’ (No activity) so only landowners who make this choice receive payment; and iv) Provide incentives for both ‘F’ and ‘NA, so the landowners who adopt fuel treatment are not eligible (hereafter referred as ‘F-NA’).

Finally, we use the simulation results to derive a supply function for carbon sequestration based on the annualized carbon price (the incentive payment in $/Mt) and the corresponding annualized amount of carbon sequestration. Since this study focuses on NIPF landowners in the western U.S., we derive the supply function for this region by defining 42 million acres (62%) out of 68 million acres of total private forest lands in the region as NIPFs.[28]

2.3.3. Carbon Sequestration Potential under Practice-Based Payments

Under a practice-based payment criterion, we assume that NIPF landowners are offered incentive payments to change their current management to practices that might lead to increased carbon sequestration. Hence, each landowner receives incentive payments based on the acreage of lands enrolled in the program. We carry out simulations for each of the four possible incentive payment targets: ‘F’ only, ‘F’ or ‘FFT’ (FFT-F), ‘NA’ only, and ‘F’ or ‘NA’ (F-NA).

[28] We define NIPF lands as family and individual-owned forests based on NWOS, which include forest land owned by individuals, couples, estates, trusts, or other groups of unincorporated individuals. These represent 62 % of the private forest land, and 35 % of all forest land in the U.S. (Smith et al. 2009).

Table 2.4-a shows the corresponding carbon sequestration potential in the region within the duration of contract. The incentive payment of targeting ‘F’, ‘NA’, and ‘F-NA’, respectively increases the annual carbon sequestration potential, ranging from 1.3 MMt to 6.8 MMt for target ‘F’, from 1.1 MMt to 3.7 MMt for target ‘NA’, and from 1.5 MMt to 4.2 MMt for the combination ‘F-NA’. It is also noticed that as the payment level for these targets increases, the amount of carbon sequestration increases at a diminishing rate, because of a declining increment of adoption rate, as shown in Figure 2.A.1-a, 2.A.1-c and 2.A.1-d in appendix.[29] However, for the combination ‘FFT-F’ the sequestration potential initially increases, but then decreases if the incentive payment exceeds a certain level. Thus, the carbon sequestration potential for the combination ‘FFT-F’ ranges from 1.1 MMt to 1.5 MMt and then to 0.1 MMt. This is because as the incentive payment goes up a higher proportion of landowners choose ‘FFT’, crowding out those choosing ‘NA’, which has a larger carbon sequestration potential than ‘FFT’. Additionally, the adoption rate of the choice ‘F’ starts decreasing at payments above $50/acre because the own marginal effect of the annual LTV of ‘FFT’ is higher than that of ‘F’ (Figure 2.A.1-b in Appendix). This suggests that a payment for fertilization without restricting the choice of fuel treatment may reduce the carbon sequestration potential as the payment level increases.

Figure 2.2-a shows the corresponding carbon supply function (marginal cost curve) for the western U.S. with respect to the annualized carbon prices ($/Mt) under

[29] Figure 2.A.1 and Figure 2.A.2 in appendix describe adoption rates of each management practices with respect to the annualized payments per acre for each incentive payment targets.

practice-based payment. The payment targeting ‘F’ yields the highest annual carbon sequestration potential for the prices higher than \$105/Mt relative to other payment targets, and achieves maximum annual carbon sequestration of 6.8 million metric tons (MMt) at a price of \$186/Mt, while targeting the ‘F-NA’ option produces the highest carbon sequestration potential for prices less than \$105/Mt. The payment to not carry out any management activities on their property (i.e. payment for ‘NA’) produce 1.7 MMt of annual carbon sequestration at 100/Mt, while the payment targeting ‘FFT-F’ achieves the lowest carbon sequestration potential with 1.2 MMt at price of \$100/Mt, which indicate that allowing partial harvests for fuel treatment (FFT) costs higher in carbon sequestration than do nothing.

2.3.4. Carbon Sequestration Potential under Performance-Based Payments

Under a performance-based criterion, NIPF landowners are offered incentive payments based on the amount of carbon stored on their forestlands by adopting a certain MP over the duration of the contract, so that each individual is offered different amount of payments.

Table 2.4-b shows the corresponding simulation results for each of the four incentive payment targets. As the incentive payment increases, the annual carbon sequestration potential increases, which ranges from 2 MMt to 6.3 MMt for target ‘F’, from 1 MMt to 4.1 MMt for target ‘FFT-F’, from 1.5 MMt to 3.6 MMt for target ‘NA’, and from 2.2 MMt to 6.3 MMt for target ‘F-NA’.

Figure 2.2-b shows the corresponding carbon supply function for the western U.S. Targeting the management options ‘F’ yields the highest annual carbon sequestration

achieving 3.1 MMt, 5.4 MMt, and 5.8 MMt at the price of $50/Mt, $100/Mt, and $150/Mt, respectively. However, note that the trend of annual carbon sequestration along the payment levels for targeting of targeting ‘F-NA’ is similar to the case of targeting only for the choice ‘F’. This is because, in case of targeting ‘F-NA’, even if the choice ‘NA’ is eligible to get paid as well as the choice ‘F’, since the carbon sequestration rate of choice ‘F’ is greater than that of choice ‘NA’, landowners switch from the choice ‘NA’ to the choice ‘F’ to get paid more as the payment level increases (Figure 2.A.2-d in appendix). For the combination of ‘F’ and ‘FFT’, the supply of carbon stops increasing and begins to decline slightly as the carbon price increases beyond roughly $160/Mt. This is because at higher payment levels landowners begin switching from choice ‘NA’ to ‘FFT’, which reduces the amount of carbon sequestration (Figure 2.A.2-b in appendix). At the same time, the amount of carbon gained from increased adoption of ‘F’ is very close to the amount of carbon lost from increased adoption of ‘FFT’. Another finding is that carbon sequestration potential of targeting ‘FFT-F’ becomes greater than that of targeting ‘NA’ as the carbon price increases beyond roughly $130, which is because targeting ‘FFT-F’ increases the adoption of the choice ‘F’ as the payment level increases (Figure 2.A.2-b in appendix), while targeting ‘NA’ doesn’t (Figure 2.A.2-c in appendix).

2.3.5. Practice-Based Payments vs. Performance-Based Payments

In this section, we compare the carbon sequestration potentials in the western U.S. between practice-based payment schemes and performance-based payment schemes with a 10-year contract. Figure 2.3 shows the annual carbon sequestration potentials in the western U.S. with four different MP targets under a two payment scheme. Under the practice-based payment scheme, at the price of $50/Mt, the potential of carbon sequestration in the western U.S. ranges from 0.7 MMt to 1.2 MMt depending on the different payment targets. Under the performance-based payment scheme, at the price of $50/Mt, the carbon sequestration potential ranges from 0.7 MMt to 3.9 MMt. Overall, payment only for the choice ‘F’ yields the highest carbon sequestration relative to other MPs under both schemes. The performance-based payment scheme yields higher levels of carbon sequestration than the practice-based payment scheme in almost every instance, particularly at lower annual payment levels.[30,31] This is because the lands with higher carbon sequestration potentials are paid more under the performance-based payment scheme. This implies that paying incentives directly to support carbon sequestration by taking into account spatial variability performs better than that supporting acreage enrollment of a certain management practice.

2.3.6. Sensitivity analysis

1) *Discount Rates*

In the econometric and simulation analysis, we use a 5% discount rate to calculate annualized net returns (annual LTV) and incentive payments. We examined the

[30] We do not consider measurement and monitoring costs when comparing the cost of carbon between a practice-based scheme and a performance-based scheme. If they were taken into account, the carbon sequestration potential under a performance-based approach could be more costly than our estimate because generally measurement and monitoring costs are greater under a performance-based scheme than under a practice-based scheme (Antle et al. 2003, Richards and Stokes 2004, Stavins and Richards 2005).

[31] The exception is no activity (NA) at higher payment levels. This is because as the payment increases relatively more high cost-high benefit landowners choose this option under a performance-based payment, while more low cost-low benefit landowners enroll under a practice-based payment. The difference in benefits is small, and the adoption rate increases faster with the payment under a practice-based payment scheme. Hence, for high enough payment levels the practice-based scheme outperforms the performance-based scheme for NA.

sensitivity of the predicted probability of MP choices and carbon sequestration with alternative discount rates of 3% and 7 %. In calculation of annual LTVs (*AnnLTV*), as the discount rate rises from 3% to 5% and 7%, the annual LTV of each MP becomes lower. Table 2.5 shows the own semi-elasticities of annual LTVs with alternative discount rates through econometric analysis. This indicates that as the discount rate becomes higher, the relative magnitude of semi-elasticities of ‘FFT’ and ‘FT’ increases, which implies the probability of choosing MPs which allow partial harvest become more responsive.

An increase in the discount rate changes also the predicted probability of adopting the MPs. In particular, as the discount rate increases, the predicted probability of adopting the choices including fuel treatment (FFT and FT) increases by 0.2%. This implies that a higher discount rate increases partial harvest (i.e. thinning as a type of fuel treatment). As a result, the baseline carbon accumulation declines by 0.2 Mt/acre as well.

The effect of an increasing discount rate on the carbon sequestration potential is ambiguous. As the discount rate increases, the level of annualized payments increases as well. However, the responsiveness to annual returns also changes with the discount rate, so the net effect is ambiguous. Table 2.6 shows the annual carbon sequestration potentials at a carbon price of $100/Mt when the discount rate increases from 3% to 5% and 7%. When the payment targets only the choice ‘F’, as the discount rate increases from 3% to 5% and 7%, the annual carbon sequestration increases from 1 MMt to 2.5 MMt, and 2.5 MMt under practice-based payments, and from 4.4 MMt to 5.4 MMt and 5.7 MMt under performance-based payments. The payments targeting the choice ‘FFT’ or ‘F’ (FFT-F) and the choice ‘F’ or ‘NA’ (F-NA) showed the same trends with targeting only for the choice ‘F’ as well. That is as the discount rate increases the annual carbon sequestration potential increases at the same level of payment. However, in the case of payment targeting for the choice ‘NA’, annual carbon sequestration decreases from 1.9 MMt to 1.7 MMt and 1.5 MMt under practice-based payments and from 2 MMt to 2 MMt and 1.9 MMt under performance-based payments at discount rates of 3%, 5%, and 7%. This is because of the relatively large decrease in own-return elasticities of the choice ‘NA’ as the discount rate increases, which leads to a lower adoption rate of the choice ‘NA’ at a discount rate of 7% relative to 3% and 5% even if the payment level at 7% is relatively high. However, the result that management practices ‘F’ and ‘F-NA’ yield higher sequestration, and that carbon performance-based payments yield higher carbon sequestration potential than a practice-based scheme are robust to changes in the discount rate, which is the same across the carbon prices.

2) *Contract Duration*

We also conducted simulations with alternative contract durations of 5 and 15 years to examine how carbon sequestration potentials and prices of carbon differ with contract duration. As the duration of the contract increases, the annual payment level per acre increases. This induces an increase in the adoption rate of choosing alternative MPs for carbon sequestration, and thus increases annual carbon sequestration potential. However since the annual carbon sequestration rate is decreasing over time, it is ambiguous the impact of an increase in the duration of a contract on the cost per unit of carbon under different incentive payment targets and criteria. In particular, note that if incentive payments rise faster than annual carbon sequestration as the duration of the contract increases, the marginal cost of carbon sequestration will go up. Our simulation results suggest that that as the duration of the contract increases from 5 to 10 years, the average carbon sequestration potential increases for a given level of carbon price, and hence the marginal cost decreases. When contract duration increases from 10 to 15 years, average carbon sequestration for a given price tends to decrease, and hence the marginal cost goes up.[32]

An example is illustrated in Table 2.7, which shows annual carbon sequestration for the various management practices and the two payment schemes at different contract lengths at a carbon price of $100/Mt. In general, a ten-year contract yields higher levels of carbon sequestration. This is because there is a time lag to achieve a given level of carbon sequestration particularly with the choices ‘F’ and ‘FFT’, and thus a 5-year contract cannot produce as much carbon as a 10-year contract for a given a level of annual payment. With a 15-year contract, because of the rate decreasing yield of annual carbon sequestration, the marginal cost to produce an additional carbon is higher than with a 10-year contract. The exception to this pattern is the case of payments targeting ‘NA’, for which annual carbon sequestration potential decreases as the duration of the contract increases. This is because a large portion of additional carbon sequestration is lost by converting from other practices to ‘NA’ as soon as the decision to convert is made. For example, the amount of carbon stored by preventing anticipated thinning for fuel treatment accounts for additional carbon sequestration as soon as the decision is

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[32] We only consider the carbon sequestration potential within the duration of the contract. These results might change if carbon flows after the termination of the contract are considered.

made. Nevertheless, the results in Table 2.7 suggest that our results are robust to the choice of contract duration.

2.4. Comparison the results with other studies

It is difficult to compare the results of the carbon sequestration potentials under incentive payments in this study with other study results. The main reason is that there are no comparable previous studies which examine the carbon sequestration potential by managing intermediate practices of forests in response to incentive payments. The created carbon supply functions with four different targeting options are comparable with studies estimating the cost of carbon sequestration through afforestation. However, to compare with the results from other studies, we need to normalize the results by adjusting for discount rates, geographic region, and constant-year dollars.

Stavins and Richards (2005) summarized and compared the 11 studies on carbon sequestration potentials through afforestation using the normalized carbon supply function. They show that the cost of carbon after normalization to 2006 dollars ranges from \$35/Mt to \$104/Mt for 272 MMt of annual carbon sequestration, and between \$41/Mt and \$124/Mt for 454 MMt of annual carbon sequestration in the U.S.[33] Since our study covers only the western U.S. region, we scaled up a regional level supply function to the national level by applying our results to 721 million acres of the forestlands in the

[33] Stavins and Richards (2005) concludes that after normalization to 1997 dollars, the cost of carbon for afforestation ranges from \$28/Mt to \$83/Mt for 272 MMt of national scale annual carbon sequestration, and from \$33/Mt to \$99/Mt for 454 MMt of national scale annual carbon sequestration.

U.S. This allows us to compare our results with those of other studies. In our results, the cost of carbon by targeting the option ‘F’, ‘NA’, or ‘F-NA’ ranges from $92/Mt to $210/Mt for 50 MMt of annual carbon sequestration. Only payments targeting option ‘F’ can achieve 100 MMt of annual carbon sequestration at a carbon price of $155/Mt. Since we take into account only the NIPFs in the western U.S., it is difficult to directly compare the carbon sequestration potential with an absolute amount; nevertheless, the result suggests that incentive payments for intermediate forest management yield less carbon at a relatively higher cost than incentives for afforestation, and hence that the carbon supply function for intermediate forest management is steeper than that for afforestation. This is shown in Figure 2.4, which compares the carbon supply functions for targeting the option ‘F’ with those from previous afforestation studies (normalized following the same rule applied by Stavins and Richards (2005) and Lubowski et al. (2006)). An important implication of this is that changing only intermediate forest management practices without extending the rotation period cannot produce as much sequestration as afforestation, because the physical carbon sequestration potential per acre is lower than that with afforestation.

2.5. Summary and Conclusion

It is generally agreed that the cost of carbon sequestration through afforestation is comparable to or lower than the cost of energy-based mitigation approaches. However, we know much less about the cost effectiveness of using incentives to elicit additional carbon sequestration in existing forests through intermediate forest management practices

(MPs). This study takes a first step towards filling this void by analyzing the factors affecting NIPF landowners' choice of intermediate forest MPs and examining how these choices might change in response to the use of incentives for carbon sequestration. Additionally, we simulate the carbon sequestration potential for each MP given different incentive payment schemes.

Our results suggest that that the factors affecting the probabilities of adopting intermediate MPs of forests differ by the choice of MPs. The own marginal effects of the probabilities of choosing an MP with respect to expected net returns are all positive and significant, and indicate that an increase in expected net returns of a certain MP increases the probabilities of adopting that MPs. Landowners' demographic characteristics do not significantly affect the probability of choosing a certain MP, while spatial characteristics, objectives of forestland ownership, and landowners' concerns all have significant impacts on the choice probabilities.

The calculated carbon sequestration trends of four different MPs show that the choice of 'Fertilization' or 'No Activity' can sequester more carbon than practices which include 'Fuel Treatment'. This result highlights potential tradeoffs between management objectives, as activities such as fuel treatment which are designed to enhance resistance to fire, the quality of remaining trees, and biodiversity, do not always increase carbon sequestration potential.

Our simulations of changes in carbon sequestration potential in response to incentive payments with different targeting strategies show that targeting the choice of 'Fertilization' yields the highest carbon sequestration potential. Additionally, our results suggest that a performance-based payment scheme can produce more carbon sequestration than a practice-based payment. However, a comparison of carbon sequestration supply with other studies shows that the annual carbon sequestration potential through changing management practices is not as large as that created through afforestation. This implies that the cost of carbon sequestration using intermediate forest management is relatively high compared to carbon sequestered using afforestation.

Finally, we want to highlight that the incentive payment strategies considered in this study only focus on carbon sequestration as an environmental benefit provided through alternative management practices. If the incentive policy targets one or more environmental benefits such as biodiversity, soil erosion, and water quality, the net effects of an incentives program will depend on the correlation among the environmental benefits considered.

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2.7. Tables

Table 2.1. Variable description and summary statistics

Variable	Variable description	Mean	Std.Dev.
Annual Net Returns			
AnnLTV1	Annual LTV of Fuel Treatment-Fertilization ($/acre)	41.374	53.538
AnnLTV2	Annual LTV of Fertilization only ($/acre)	45.699	59.207
AnnLTV3	Annual LTV of Fuel treatment only ($/acre)	43.297	56.565
AnnLTV4	Annual LTV of No activity ($/acre)	42.628	54.604
Demographic Characteristics			
AGE	Age of landowners	62.814	11.461
Income1-4	Dummies: Household income, less than $50,000 (1) to $200,000 or more (4). Income4 is used as a reference group in the econometric model.	-	-
Education1-5	Dummies: Education level of landowner, less than high school (1) to graduate or professional school (5). Education1 used as reference group.	-	-
Occupation_farm	Dummy: Occupation related to farming, logging, and timber industry	0.162	0.369
Manager	Dummy: Consulted by forest experts (e.g. logging contractor, forester) rather than by family	0.125	0.331
Resource Characteristics and Spatial Characteristics			
Forest_acre	Acres of forestland owned inside of the state (1,000 ac)	1.366	2.617
SDI	Stand Density Index	274.871	219.218
PNW	Dummy: Pacific Northwest	0.216	0.412
PSW	Dummy: Pacific Southwest	0.281	0.450
NRMT	Dummy: Northern Rocky Mountain	0.138	0.346
Slope_low	Dummy: Average slope lower than 35 degree	0.634	0.482
Distance_S2R	Dummy: Distance from the site to main road	4.814	5.168
Num_Mills50	Number of mills within 50 miles	8.733	12.182
Landowner attributes			
Primary_Resident	Dummy: Owners living within a mile of forestland	0.439	0.497
Obj_biodiversity	Dummy: Objective of owning for biodiversity	0.635	0.482
Obj_timber	Dummy: Objective of owning for timber harvest	0.265	0.442
Obj_recreation	Dummy: Objective of owning for recreation	0.483	0.500
Obj_privacy	Dummy: Objective of owning for privacy	0.655	0.476
Concern_develop	Dummy: Concern about development	0.425	0.495
Concern_disease	Dummy: Concern about insects and diseases	0.577	0.495
Concern_air	Dummy: Concern about air quality	0.298	0.458
Concern_fire	Dummy: Concern about risk of fire	0.622	0.485
Costshare	Dummy: Participated in a cost-share program	0.175	0.381
Green_certified	Dummy: Knowledge about green certification	0.230	0.421
NTFP_recent	Dummy: Recently harvested non-timber food products	0.125	0.331
Acquire_bought	Dummy: Land acquisition method: bought	0.620	0.486

Table 2.2. Marginal Effects of probabilities of choosing alternative MPs

Variables	Choice 1: Fuel treatment & Fertilization	Choice 2: Fertilization only	Choice 3: Fuel treatment only	Choice 4: No activity
AnnLTV1	0.0043 (0.0014)***	-0.0039 (0.0021)*	-0.0057 (0.0029)**	0.0054 (0.0035)
AnnLTV2	-0.0001 (0.0011)	0.0068 (0.0025)***	-0.0065 (0.0042)	-0.0003 (0.0055)
AnnLTV3	-0.0030 (0.0013)**	-0.0007 (0.0021)	0.0204 (0.0034)***	-0.0167 (0.0037)***
AnnLTV4	-0.0013 (0.0017)	-0.0030 (0.0027)	-0.0079 (0.0052)	0.0122 (0.0071)*
Age	0.0006 (0.0009)	0.0008 (0.0012)	-0.0011 (0.0016)	-0.0003 (0.0016)
Income1	-0.0209 (0.0322)	-0.0122 (0.046)	-0.0245 (0.0582)	0.0577 (0.0613)
Income2	-0.0156 (0.0301)	0.0521 (0.0397)	-0.1092 (0.0551)**	0.0727 (0.0558)
Income3	-0.0238 (0.0329)	0.0157 (0.0439)	-0.0059 (0.0588)	0.0141 (0.0609)
Education3	0.0155 (0.0289)	0.0478 (0.0411)	0.0249 (0.0541)	-0.0882 (0.055)
Education4	0.0267 (0.0298)	0.0257 (0.0444)	0.0126 (0.0582)	-0.0650 (0.0595)
Education5	-0.0228 (0.0348)	0.0065 (0.0477)	-0.0437 (0.0621)	0.0599 (0.0626)
Occupation_farm	-0.0141 (0.0283)	-0.0658 (0.0439)	0.0994 (0.0505)**	-0.0195 (0.0533)
Manager	-0.0100 (0.0276)	0.0101 (0.0444)	0.1206 (0.0564)**	-0.1207 (0.0614)**
Forest_acre	0.0022 (0.003)	0.0027 (0.0053)	0.0030 (0.0069)	-0.0079 (0.0078)
SDI	0.0001 (0.0001)*	0.0000 (0.0001)	0.0000 (0.0001)	0.0000 (0.0001)
PNW	0.0182 (0.0347)	-0.0091 (0.0527)	-0.0071 (0.0717)	-0.0021 (0.0717)
PSW	0.0159 (0.0269)	-0.0276 (0.0369)	0.0447 (0.0482)	-0.0329 (0.0486)
NRMT	0.0153 (0.0368)	-0.0051 (0.0467)	0.1222 (0.0619)**	-0.1324 (0.0661)**
Slope_low	0.0344 (0.0236)	-0.0218 (0.0283)	0.0994 (0.0399)**	-0.1120 (0.0385)***
Distance_S2R	0.0006 (0.0019)	0.0039 (0.0023)*	-0.0108 (0.004)***	0.0063 (0.0038)*
Num_Mills50	0.0010 (0.001)	-0.0005 (0.0018)	0.0006 (0.0023)	-0.0011 (0.0024)
Primary_resident	0.0018 (0.0204)	0.0907 (0.0286)***	0.0998 (0.0377)***	-0.1923 (0.0375)***
Obj_biodiversity	-0.0286 (0.0211)	-0.0509 (0.0296)*	0.1149 (0.04)***	-0.0354 (0.0405)
Obj_timber	0.0029 (0.0252)	-0.0520 (0.0369)	0.1382 (0.0471)***	-0.0892 (0.051)*
Obj_recreation	0.0392 (0.0207)*	0.0420 (0.0284)	-0.0645 (0.0374)*	-0.0168 (0.0381)
Obj_privacy	-0.0601 (0.0226)***	-0.0419 (0.0303)	-0.1210 (0.0406)***	0.2229 (0.0422)***
Concern_develop	0.0567 (0.0222)**	-0.0719 (0.0308)**	0.0445 (0.0405)	-0.0292 (0.0416)
Concern_deasese	0.0097 (0.0256)	0.0947 (0.0391)**	-0.0579 (0.049)	-0.0465 (0.049)
Concern_air	-0.0299 (0.0228)	0.0459 (0.0329)	-0.0174 (0.0433)	0.0014 (0.0455)
Concern_fire	-0.0050 (0.026)	-0.1100 (0.035)***	0.2374 (0.0527)***	-0.1224 (0.0526)**
Costshare	0.0892 (0.0214)***	0.0369 (0.0341)	-0.2073 (0.0528)***	0.0812 (0.0542)
Green_certified	0.0074 (0.0231)	0.0206 (0.0326)	0.0718 (0.0456)	-0.0998 (0.0471)**
NTFP_recent	0.0074 (0.024)	0.0666 (0.0348)*	0.0558 (0.054)	-0.1298 (0.0585)**
Acquire_bought	0.0341 (0.0273)	0.0385 (0.0334)	-0.0048 (0.0455)	-0.0678 (0.0438)
Log-likelihood	-387.657			
χ^2	411.070			
pr $\geq \chi^2$	0.000			
Pseudo-R^2	0.347			

AIC [i)]	985.315
BIC [i)]	1430.54
Observation	513

Note: *, **, *** Statistical significance at α = 10, 5, and 1 %. Parentheses are standard errors.

i) The AIC (Akaike's Information Criteria) and BIC (Bayesian Information Criteria) are known as popular measures for comparing maximum likelihood models. AIC is defined as $\mathrm{AIC} = -2(\text{Log-likelihood}) + 2K$, and BIC is defined as $\mathrm{BIC} = -2(\text{Log-likelihood}) + K \log N$, where K is number of parameters estimated, and N is number of observations (Burnham and Anderson 2004).

Table 2.3. Semi-elasiticities of probabilities of choosing alternative MPs

Variables	FFT (Fertilization & Fuel treatment)	F (Fertilization only)	FT (Fuel treatment only)	NA (No activity)
AnnLTV1	0.204 (0.063)***	-0.139 (0.071)*	-0.218 (0.09)**	0.154 (0.109)
AnnLTV2	-0.002 (0.049)	0.282 (0.101)***	-0.249 (0.14)	-0.032 (0.19)
AnnLTV3	-0.147 (0.051)*	-0.035 (0.069)	0.699 (0.096)***	-0.517 (0.105)***
AnnLTV4	-0.056 (0.071)	-0.111 (0.096)	-0.238 (0.163)	0.405 (0.229)*

Note: *, **, *** Statistical significance at α = 10, 5, and 1 %. Parentheses are standard errors.

Table 2.4. Annual carbon sequestration potential with respect to incentive payments

Payment ($/acre)	a. Practice-based payment				b. Performance-based payment			
	F	FFT-F	NA	F-NA	F	FFT-F	NA	F-NA
	C Sequestration (MMt)							
10	1.26	1.06	1.09	1.45	2.02	0.97	1.54	2.15
50	3.72	1.53	2.50	3.17	4.80	2.93	2.70	4.66
100	5.48	0.84	3.16	3.91	5.79	4.03	3.21	5.82
150	6.77	0.09	3.67	4.19	6.30	4.06	3.75	6.28

Table 2.5. Own semi-elasticities of annual LTVs with different discount rates

Discount rate	FFT (Fertilization & Fuel treatment)	F (Fertilization only)	FT (Fuel treatment only)	NA (No activity)
3%	0.199(0.069)	0.339(0.114)	0.667(0.094)	0.671(0.303)
5%	0.204(0.063)	0.282(0.101)	0.699(0.096)	0.405(0.229)
7%	0.236(0.065)	0.262(0.100)	0.592(0.087)	0.253(0.149)

Table 2.6. Annual carbon sequestration potential at $100/Mt with alternative discount rates

Payment Targets	a. Practice-based payment			b. Performance-based payment		
	3%	5%	7%	3%	5%	7%
	C Sequestration (MMt)					
F	1.0	2.5	2.5	4.4	5.4	5.7
FFT-F	0.0	1.2	1.2	0.7	1.6	2.0
NA	1.9	1.7	1.5	2.0	2.0	1.9
F-NA	1.8	2.8	3.5	3.6	4.8	6.1

Table 2.7. Annual carbon sequestration potential at $100/Mt with alternative contract durations

Payment Targets	a. Practice-based payment			b. Performance-based payment		
	5-year	10-year	15-year	5-year	10-year	15-year
	C Sequestration (MMt)					
F	1.98	2.96	2.54	3.18	4.77	4.77
FFT-F	0.87	1.07	1.06	1.14	1.79	1.37
NA	1.49	1.61	1.41	2.16	2.06	2.02
F-NA	2.11	2.52	2.47	3.30	4.42	4.12
Average	1.61	2.04	1.87	2.44	3.26	3.07

2.8. Figures

Figure 2.1. Carbon accumulation with different management practices and baseline carbon accumulation (Mt/acre)

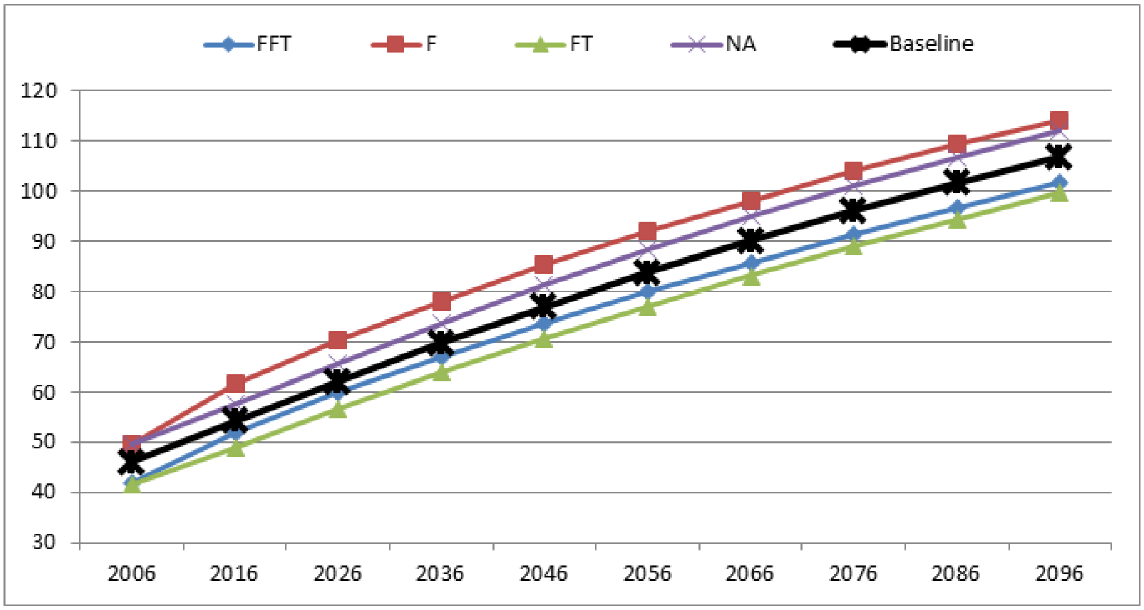


Figure 2.2. Carbon supply function for each management option for the western U.S.

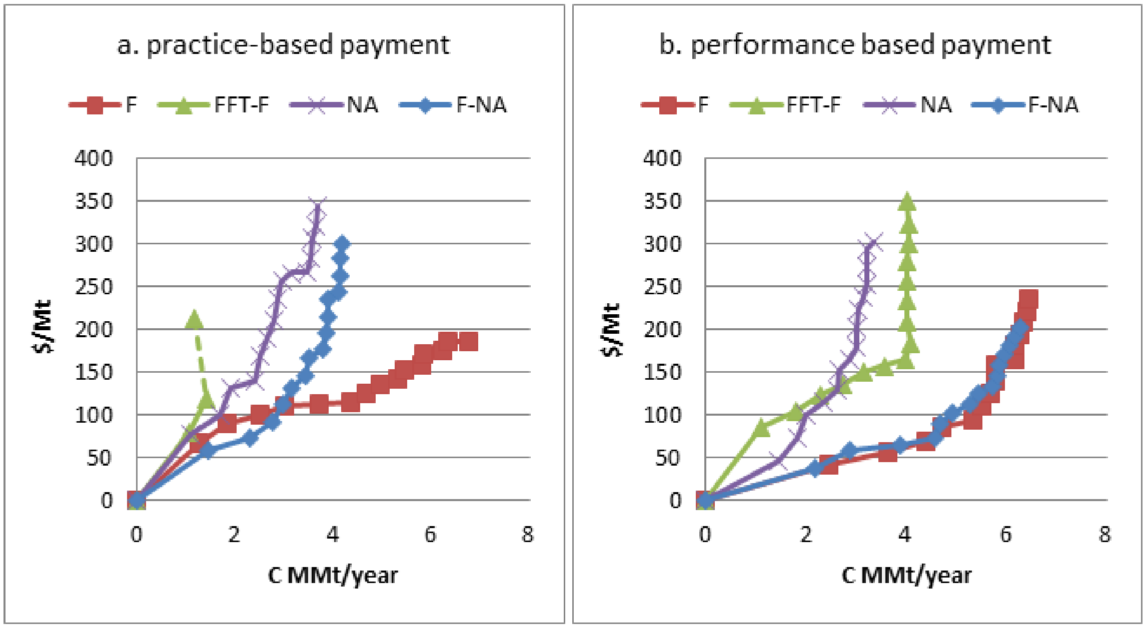


Figure 2.3. Carbon supply function under different payment schemes for the western U.S.

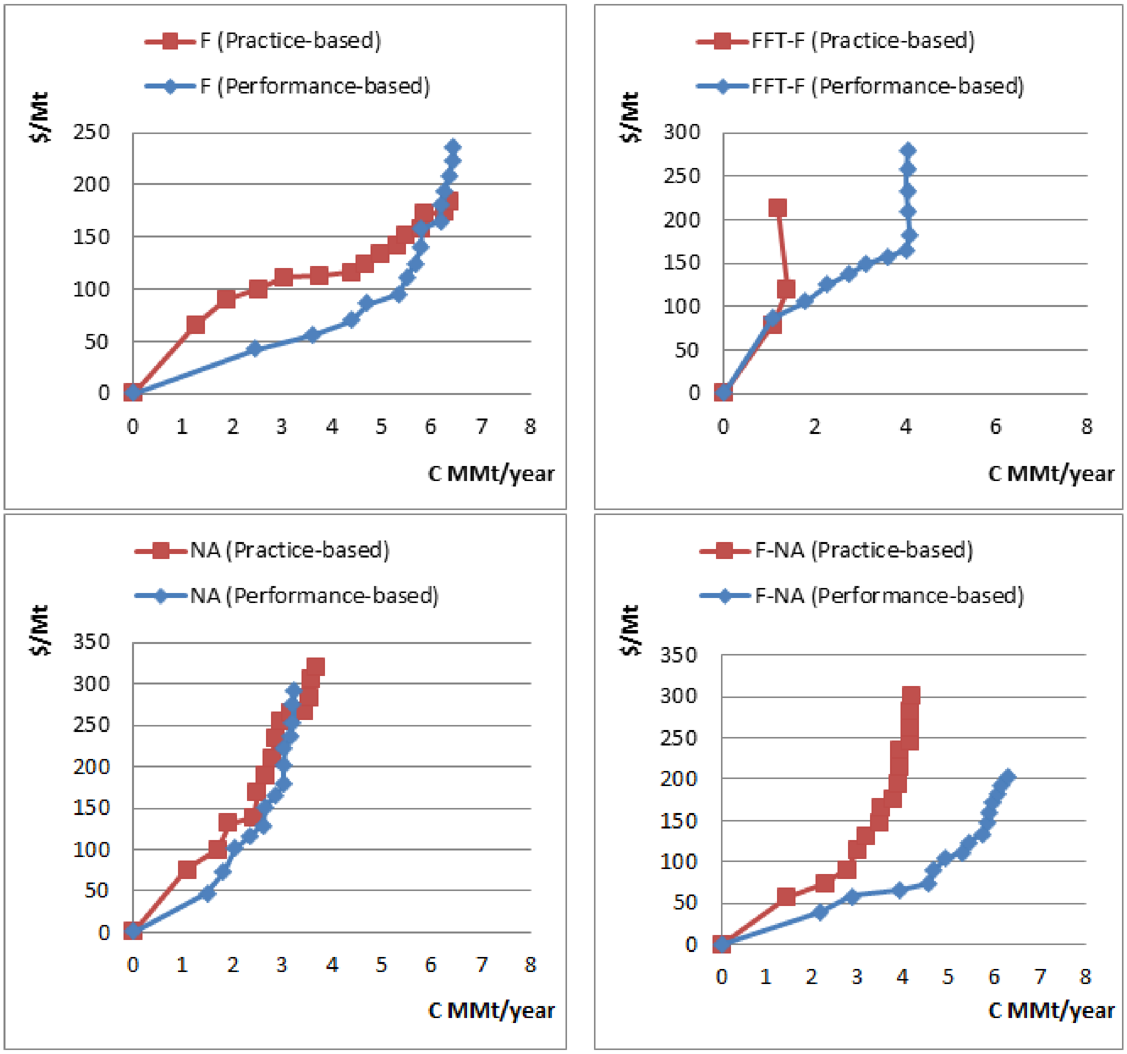
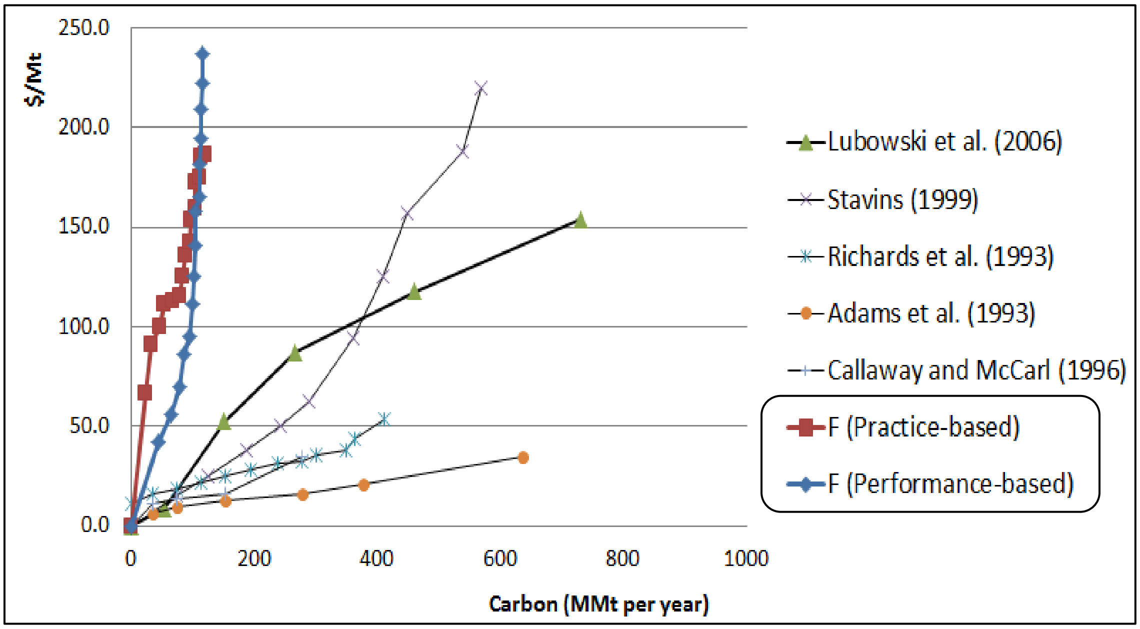


Figure 2.4. Comparison of normalized carbon supply functions for intermediate management practices and afforestation



Note: All carbon supply functions except the two from this study are from Lubowski et al (2006).

2.9. Appendix

Figure 2.A.1. Adoption rate under practice-based incentive payment with different MPs strategies

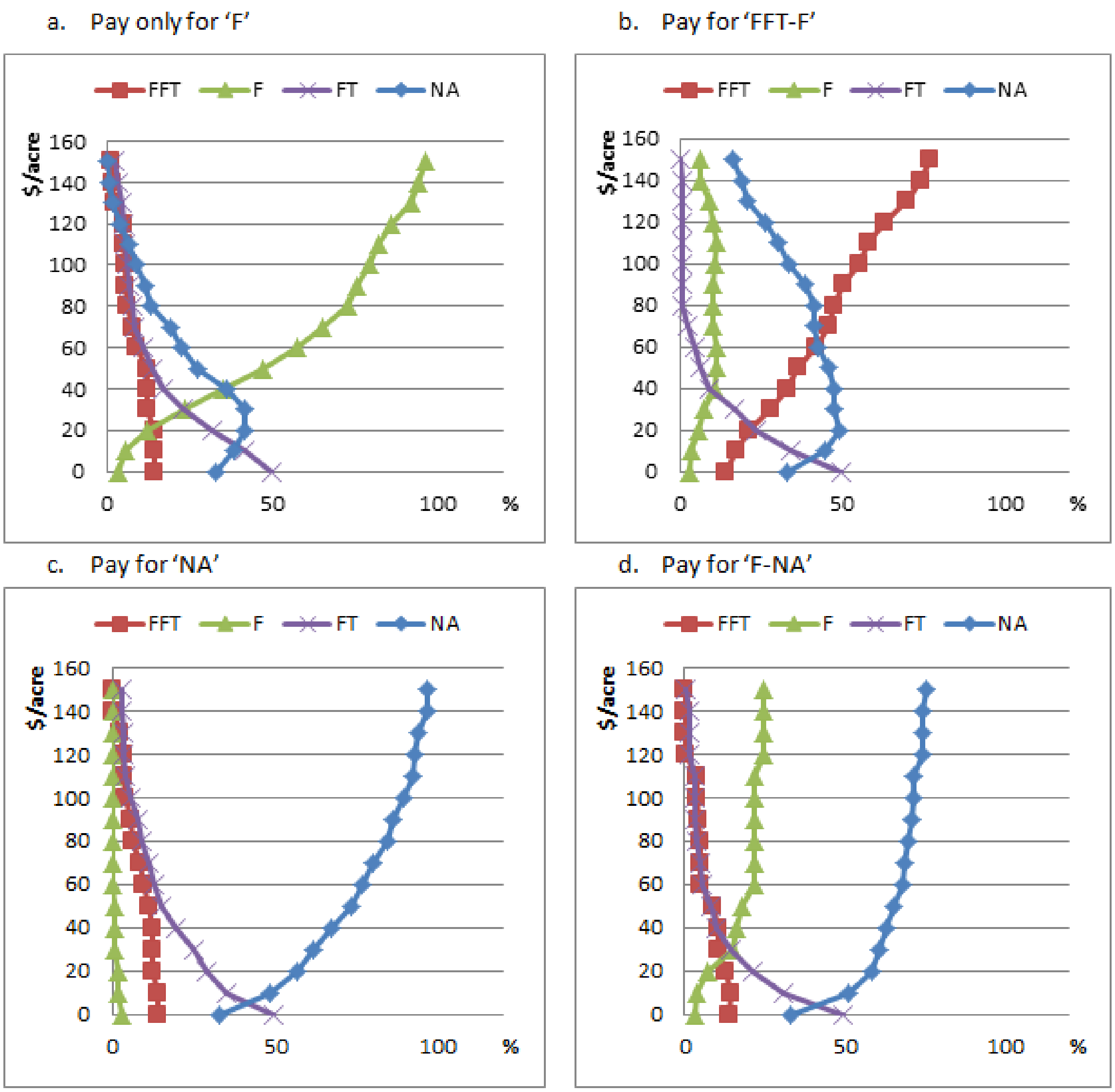
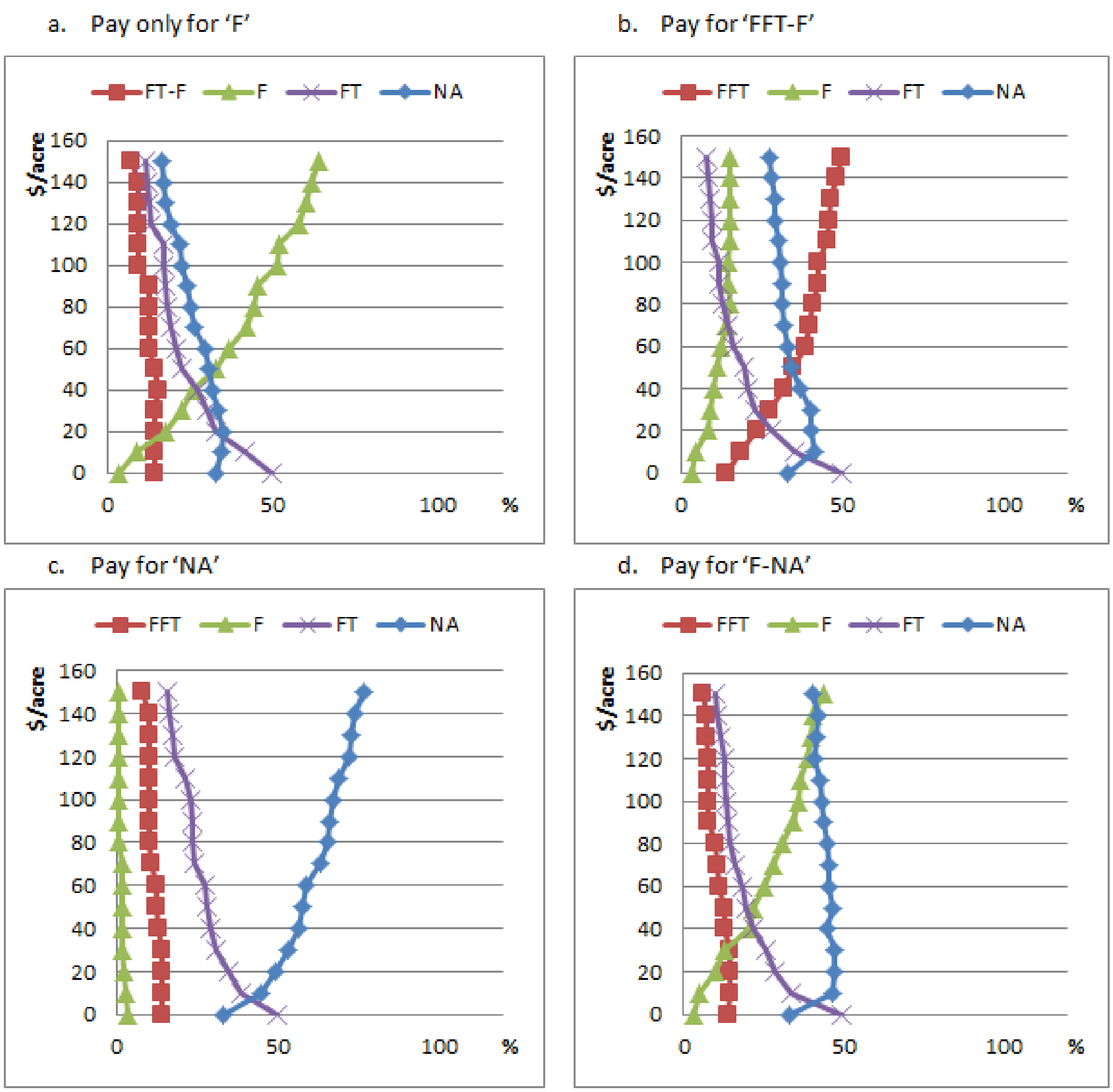


Figure 2.A.2. Adoption rate under performance-based incentive payment with different MPs strategies



CHAPTER THREE

AGRICULTRUAL LANDOWNERS' RESPONSE TO INCENTIVES FOR AFFORESTATION

3.1. Introduction

Global warming and global climate change due to the accumulation of greenhouse gas (GHG) emissions in the atmosphere for decades is one of the major issues in the global economy. Various efforts to mitigate climate change are ongoing at national, regional, and individual levels in the U.S. The forest sector plays an important role in mitigating greenhouse gas emissions by transferring carbon from the atmosphere through the process of photosynthesis of standing live trees and in other forest ecosystem components such as the understory and soil (Alig 2010). Forests offset approximately 13 percent of U.S. GHG emissions in 2008 (USDA 2011). Afforestation, tree planting on lands previously not in forestry, has been often suggested as one of the strategies for carbon sequestration (Adams et al. 1999, Moulton and Richards 1990), and has relatively larger potential for carbon sequestration than other land use choices (Gorte 2009). Afforestation of crop or pasture land can respectively sequester 2.2~9.5 Mt CO_2 eq./acre/year (US EPA 2005) and 2.7~7.7 Mt CO_2 eq./acre/year (Lewandrowski et al. 2004).

Much of the literature that examines afforestation of agricultural land has focused on estimating the costs of carbon sequestration, and has shown that afforestation is a relatively low-cost measure for mitigating CO_2 emissions. Sectoral model approaches, such as the USMP and FASOM models, have explicitly modeled the links between agricultural land, forest land, and timber markets, and examined the potential for offsetting changes in land use (from forest to agriculture) resulting from price feedbacks (Adams et al. 1993, Alig et al. 1997, Lewandrowski, 2004). These studies rely on financial incentives, mostly tax/subsidy combinations, to measure the costs of afforestation programs. They strongly suggest that financial incentives and changes in relative returns to land use affect landowner behavior and can be used to increase carbon sequestration in private forests. Parks and Hardie (1995) simulated the impacts of subsidies for sequestering carbon in new forests established on agricultural land, and derived a carbon supply function through afforestation of marginal agricultural land to develop criteria for enrolling lands in a national carbon sequestration program. However, Plantinga et al. (1999) argued that these studies tend to underestimate the marginal costs of carbon sequestration by simply assuming that landowners will participate in afforestation program if the specified agricultural returns are compensated, which ignores various factors affecting landowners' decisions. As an alternative approach to increase the accuracy of estimating marginal costs of carbon sequestration through afforestation, Plantinga (1997), Plantinga et al. (1999), Stavins (1999), Newell and Stavins (2000), and Lubowski et al. (2006) used econometric models to calculate the opportunity costs of afforestation, which account for additional factors affecting land enrollment decisions such as the cost of acquiring skills, non-market benefits, and so on. The estimated costs of carbon are not comparable across studies due to an inconsistent use of assumptions, definitions, and methods (Richard and Stokes 2004). Stavins and Richard (2005) showed that the cost of carbon sequestration ranged from \$25 to \$75 per short ton of carbon (\$7.5 - \$22.5/Mt CO_2 eq.) at 300 million tons of annual carbon sequestration with normalization to 1997 dollars, based on reviews of eleven previous analyses of carbon sequestration costs in the U.S.

An alternative approach, which has been used less frequently, is to examine the carbon sequestration potential of afforestation, as well as its cost, using stated preferences based on survey. Although econometric models account for additional factors affecting land enrollment decisions such as the cost of acquiring skills, and non-market benefits, since most studies are not based on surveys of individual landowners, a lack of information about individual landowners' characteristics and land characteristics is the main obstacle to elicit the key factors affecting individual landowners' land use decisions and to improve the accuracy of examining the cost of carbon through afforestation. A stated preference approach allows us to examine the various factors affecting landowners' afforestation decisions as a complement to revealed preference studies. Van Kooten et al. (2002) and Shaikh et al. (2007) both examined the effects of incentives to encourage landowners to plant trees on their agricultural lands in Western Canada based on a survey conducted in 2000. The estimated costs of carbon uptake by afforestation in western Canada range from \$5.7/Mt CO_2 eq. to \$180.3/Mt CO_2 eq. The important difference of our study from these studies is that a continuous measure of acreage or proportion of enrollment as opposed to a simple dichotomous measure of participation is used to elicit landowners' willingness to enroll in a tree planting program assuming that each landowner owns at least one parcel of agricultural land. A continuous measure of enrollment allows landowners to choose their amount of enrollment based on the different level of incentives offered by considering various heterogeneous factors they face. Siikamaki and Layton (2007) used a continuous form questionnaire to examine landowners' willingness to enroll their forestlands in incentive payment programs for the protection of non-industrial private forest in response to different level of incentives.

The objectives of this study are to elicit agricultural landowners' willingness to participate in an incentive program for carbon sequestration through afforestation, to examine the key factors affecting landowners' program participation, to measure the potential extent of participation in a tree planting program, and to estimate the corresponding potential for carbon sequestration and its cost based on a stated preference approach as a complement to other approaches such as revealed preference approach, optimization approach, and bottom-up engineering approach. A mail survey supports empirical analysis of landowner responses to a hypothetical afforestation incentives program. The survey was conducted in two different regions, the Pacific Northwest (PNW) and the Southeast (SE). We use the censored regression model (Tobit model) to predict the proportion of land enrolled in a tree planting program as a function of the various factors affecting landowners decision making and different level of incentive payments.

The proportion of agricultural land willing to plant trees in the PNW region and SE region are estimated as a function of incentive payments for carbon sequestration and various factors such as landowners' characteristics and spatial characteristics of agricultural lands. The estimation results show that the annual payment for carbon sequestration significantly and positively affects to landowners' level of enrollment in a tree planting program, while the PNW region is less responsive than SE region associated with the increase in annual payment. We also found that the variables which represent productivity of lands, spatial characteristics (e.g. distance from fire hazard), and reasons for owning agricultural lands affect landowners' level of enrollment in the program in both regions. In the PNW region, landowners' demographic characteristics do not significantly affect landowners' level of program participation, while they affect significantly in the SE region.

The regional level simulations of carbon sequestration in response to incentive payments show that the carbon supply function in the PNW region is steeper than the SE region because of the lower adoption rate and less available lands, but the range of carbon price is lower than in the SE region because of the higher annual carbon sequestration rate. The national level carbon supply function indicates that the cost of carbon ranges from $72/Mt to $111/Mt for 300 MMt of annual carbon sequestration, and from $109/Mt to $158/Mt for 500 MMt of annual carbon sequestration. This results place higher than those obtained from bottom-up engineering approaches and optimization models, and include the range of econometric approach done by Lubowski et al (2006) at lower than 500 MMt of annual carbon sequestration.

The rest of this paper is organized as follows: Section 2 presents analytical framework including econometric model specifications, Section 3 presents the survey procedure and variable description, Section 4 examine the landowners' responses to incentives for carbon sequestration and the factors affecting their decisions based on the estimation results from econometric model, Section 5 presents the simulation results of carbon sequestration associated with the change in annual payments, and derives regional level carbon supply functions including sensitivity analysis, and Section 6 compares the national level carbon supply functions from this study with those from other studies. Finally, section 7 discusses the conclusion and implications.

3.2. Analytical Framework

We assume an agricultural landowner is facing the choice of whether to enroll in a tree planting program given incentives for carbon sequestration. The landowner maximizes her utility, which is a function of agricultural commodities and amenities such as carbon sequestration. The landowner will plant trees on her agricultural land if the expected annual net return through afforestation with an incentive payment for carbon sequestration minus conversion cost is at least as much as the expected annual net returns in agriculture.

The primary goal of the econometric analysis is to predict the amount of land enrolled in a tree planting program as a function of the various factors affecting landowner decision making and different level of incentive payments.

Because we elicited landowners' willingness to participate in a tree planting program using an open-ended question, we need to carefully consider the possibility of a large number of zero or non-responses which can impede estimation of landowner's true willingness to enroll in the tree planting program. In this study, the censored regression model (Tobit model), which assumed to observe the dependent variable only if it is above or below some cut off level,[34] is the first option to run the econometric analysis by observing zero enrollment or continuous proportion of agricultural lands actually stated by each landowner (Moeltner and Layton 2002, Cho et al. 2005). Especially, since we use the proportion of agricultural land that each landowner, *i*, is willing to allocate for tree planting program, a two-sided censored regression model (Tobit model) is specified by the following rule:

$$
\begin{aligned}
& y_i^* = X_i^{'}\beta + \varepsilon_i, \\
& y_i = 0 \quad \text{if } y_i^* \le 0 \\
& y_i = y^* \quad \text{if } 0 < y_i^* < 100 \\
& y_i = 100 \quad \text{if } y_i^* \ge 100
\end{aligned}
\tag{1}
$$

where y_i^* denotes the latent variable for landowner *i*, y_i is the stated proportion of agricultural land enrolled by owner *i*, X_i is a vector of explanatory variables, β is a parameter vector which is common to all landowners, and ε_{it} is distributed $N(0, \sigma_\varepsilon^2)$.

The log-likelihood function is:

$$\log L = \sum_{y=0} \log \Phi\left(\frac{0 - x_i\beta}{\sigma}\right) + \sum_{0<y<100} \log \frac{1}{\sigma}\phi\left(\frac{y_i - x_i\beta}{\sigma}\right) + \sum_{y=100} \log \Phi\left(\frac{x_i\beta - 100}{\sigma}\right) \tag{2}$$

where Φ represents the normal distribution function, ϕ represents the normal density function, and σ represents the standard deviation. The log-likelihood is made up of three parts. The first and third parts correspond to relevant probabilities that an observation is censored, and the second part indicates the classical regression for the uncensored observations. The expected value of y for an observation is:

---

[34] In this study, the true distribution of wiliness to participate in the incentive program is assumed to be censored at zero (Halstead et al., 1991).

$$E(y|x) = 0 \cdot \Pr(y=0|x) + E(y|x, 0<y<100) \cdot \Pr(0<y<100|x) + 100 \cdot \Pr(y=100|x)$$
$$= x\beta \cdot \left\{ \Phi\left(\frac{100-x\beta}{\sigma}\right) - \Phi\left(\frac{0-x\beta}{\sigma}\right) \right\} + \sigma \left\{ \phi\left(\frac{0-x\beta}{\sigma}\right) - \phi\left(\frac{100-x\beta}{\sigma}\right) \right\} \quad (3)$$
$$+100 \cdot \Phi\left(\frac{100-x\beta}{\sigma}\right)$$

And the marginal effect of expected value of y (censored and uncensored) is

$$\frac{\partial E(y|x)}{\partial x_j} = \left\{ \Phi\left(\frac{100-x_i\beta}{\sigma}\right) - \Phi\left(\frac{0-x_i\beta}{\sigma}\right) \right\} \beta_j \quad (4)$$

3.3. Survey and Data

3.3.1. Survey

The main purpose of this survey is to generate data to conduct an empirical analysis of landowners' responses to an afforestation incentives program. The survey gathered data on factors affecting landowners' decisions regarding use of their land, including program participation. Survey respondents were asked a series of questions about their demographic characteristics, the types and areas of lands they own, annual net returns and level productivity of their lands, the spatial characteristics of agricultural lands they own, reasons for owning their agricultural lands, and their understanding and attitudes about the importance of environmental services provided by their lands.

Two comparative regions, the Pacific Northwest (PNW) and the Southeast (SE) [35],

[35] The specific counties selected for the survey are: i) Pacific Northwest region (PNW): Benton, Jefferson, Columbia, Lane, Polk, Coos, Crook, Deschutes, Douglas, Josephine, Lake, Marion, Linn, and Clatsop in western Oregon, and Grays Harbor, Pierce, Whatcom, San Juan, Clallam, Jefferson, Skamania, and

were selected to conduct the survey, because it has been shown that the Pacific Northwest is relatively less responsive to incentive payment for afforestation than the Southeast (Lewandrowski et al. 2004, Alig et al. 2010).[36]

Agricultural landowners' mailing lists for both regions were provided by county tax assessor's offices, except for six counties in Georgia, for which data was purchased from qPublic.net, which manages counties' GIS, parcel, and tax data. 1,000 landowners in each region, 2,000 landowners in total, were randomly chosen to participate in the survey. A draft of the survey was reviewed by a group of experts (in USDA Forest Service, Department of Statistics, Department of Agricultural and Resource Economics, and College of Forestry in Oregon State University). An in-person pretest was conducted with a group of agricultural landowners to design the questionnaires and to establish an appropriate bid range of carbon prices. Based on the in-person discussions and expert reviews, a total of 42 questions were written, including an open-ended question asking recipients' willingness to participate in an incentives program. We provided a flyer to help respondents understand the detailed incentive scheme.

The mailing procedure and survey design was followed Dillman's (1978, 2007) survey design method. The final sets of survey questionnaires were mailed out on January

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Kitsap in western Washington, ii) Southeast (SE): Alleghany, Ashe, Buncombe, Swain, and Wilkes in western North Carolina, and Bartow, Gillmer, Harbersham, Stephens, Catoosa, Walker, Banks, Fannin, Lumpkin, Murray, Rabun, and Union in Northern Georgia.

[36] Alig et al. (2010) mentioned that around 80% of U.S. tree planting has been conducted in the South region (13 states). This is because i) the South has a large suitable area (marginal agricultural land) for planting tree, ii) has relatively shorter harvest rotation because of abundant precipitation and long growing season (a favorable climate condition), and iii) has relatively large timber markets because of high concentration of wood-processing facilities and highly populated surrounding region (close to the Eastern states).

14, 2011, with a personalized cover letter, university letterhead, a flyer explaining the incentive program, and a $2 bill as a token of appreciation for survey participation.[37] A follow-up postcard reminder was mailed out a week after the first mailing, and a third reminder with a replacement survey questionnaire was mailed out a month after the first mailing. The final response rates of mail survey are 47% for the PNW region and 27% for the SE region.

Finally, a follow-up phone survey of a sample of non-respondents for the PNW region and mail survey for both the PNW and SE region was conducted to assess and control for selection bias induced by non-responses. Out of 100 non-respondents (around 20% of non-respondents) contacted in the PNW region, 27 non-respondents answered the follow-up phone survey. Additionally, 26 out of 100 returned a follow-up mail survey in PNW region and 38 out of 150 returned a follow-up mail survey in SE region.

We designed an incentive scheme that is consistent with components of USDA Conservation Reserve Programs (CRP), including a 50% cost-share subsidy for establishing trees and annual rental payment for the 15-year duration of contract.[38] Based on the in-person pretest and expert review, the range of annual rental payment per acre offered to agricultural landowners was calculated by multiplying annual carbon sequestration rates of proposed species by price of carbon ranging from $1 to $150 per

[37] Many studies have shown that prepaid monetary incentives can achieve higher response rates (e.g. Salant and Dillman 1994, James and Bollstein 1990, Brennan 1992, Hubbard and Little 1988).

[38] The duration of contract of CRP between USDA and agricultural landowners is for 10 to 15 years with the longer agreements for land planted to trees (USDA Farm Service Agency 2012). A 15-year contract also accounts for the time lag due to tree growth between enrollment and generation of meaningful amounts of sequestration (Lewandrowski et al. 2004, Smith et al. 2006).

metric ton of carbon with 12 breaks. The carbon price range assumed to be consistent with the average of the maximum carbon price of U.S. EPA (2005) and U.S. Agricultural Sector Model (Lewandrowski et al. 2004). Each respondent was asked to reveal the amount or proportion of acreage he/she would enroll in a tree planting program, given three different levels of per acre annual payments out of 12 breaks offered to each survey respondents. We proposed to plant Douglas-Fir for the PNW region and Southern Pine (e.g. Loblolly and Shortleaf pine) for the SE region.[39] Thus, annual carbon accumulation rates within the duration of contract were calculated by using the carbon accumulation table created by Smith et al. 2006. Lewandrowski et al. (2004) mentioned that it is reasonable to have a 15-year duration of contract by taking into account time lag to achieve a certain amount of carbon sequestration, and Smith et al. (2006) also estimated that carbon sequestration rate tend to increase at increasing rate over a 15-year period while it depends upon what the tree species are.

3.3.2. Data

The dependent variable used in the econometric model is the stated proportion of agricultural lands that landowner *i* would be willing to enroll in a tree planting program.

The independent variables that might affect the landowners' level of enrollment in a tree planting program can be categorized as follows: annual rental payments, average annual net returns of agricultural lands, lands' characteristics, landowners' management

[39] The proposed tree species, Douglas fir and Southern Pine, are most commonly used tree species with the highest carbon accumulation rate over time in each region (Lewandrowski et al. 2004, Smith et al. 2006, Lubowski et al. 2006).

attributes, and demographic characteristics. The annual rental payment per acre (*AnnPay*) offered to each landowner with a 15-year contract, which is a main variable to examine the landowners' response to annual payment for tree planting program, ranged from $15 to $192.[40] The average annual net returns of agricultural lands (*Agri_Return*) are included to take into account an opportunity cost of converting from agricultural lands to forests. Shaikh et al. (2007) used agricultural net returns from adopting a tree planting program as an opportunity cost, which is the weighted average of annual net returns based on the land use categories. We expect that an increase in annual net return from agriculture may decrease the adoption rate of afforestation, although Shaikh et al. (2007) did not find a significant effect of annual net returns on the decision of accepting a tree planting program.

Variables describing land characteristics include dummies for high- and low-productivity land (*D_Highprod, D_Lowprod*) to consider the quality of lands of each individual. We expect that high productivity lands are less likely to be enrolled in a tree planting program, and low productivity lands are more likely to be enrolled in a tree planting program. The size of agricultural land (*Agland_size*) is included to examine the effect of the size of land holdings on level of enrollment. The spatial characteristics of lands associated with where they are located can also affect the decision of enrollment in a tree planting program, although their effect is not well examined in the existing

[40] IRB (2003) mentioned that Landowners who enroll in CRP enter into cost share contract and annual rental payment for the 10 to 15-year contract duration. Annual rental payments range from $30 to $160 per acre, depending upon local market rates and types of soil.

afforestation studies so far because of lack of information on spatial configuration of each land parcel. Zhou and Kockelmen (2008) recognized that variables such as CBD access, and distance to the nearest highway, as well as each parcel's neighborhood attributes can affect landowner's land use and management decision. Development pressure, such as distance from major city, contiguity with urban growth boundary, and so on, can affect land use choice (Mansfield et al. 2000, Kristensen et al. 2001, Langpap and Wu 2008). Potential risk of fire can affect land use and management decision (Amacher et al. 2005, Konoshima et al. 2008). To identify the spatial characteristics of each land based on survey, we directly asked landowners whether their agricultural lands are close to home (*Resident_owner*), and are adjacent to highway, forest, agricultural lands, or fire hazard (*Location*).

Landowners' management attributes variables include the landowners' opinions on providing environmental services (*Envi_*) for the public such as preventing soil erosion, improving water quality, preserving wildlife habitat, and sequestering carbon. In the survey, landowners are asked to rank the importance of providing these environmental services for the public with a 5-point scale ranging from 'not important' to 'very important'. We then included these as dummy variables, so that for each environmental service if the importance level is greater than equal to 4, landowners consider it is important to provide environmental services. The reasons for owning agricultural lands (*Reason_*) can be important factors affecting level of enrollment in a tree planting program as well. Dummy variables are created for each reason, so that landowners who gave a ranking of at least 4 for each reason are defined as landowners who consider that reason important. We expect that landowners who own their agricultural lands to produce and sell farm products may be less likely to allocate their agricultural lands for forests than landowners who own land for amenity or to protect nature. Additionally, we include dummy variables that identify landowners who adopt conservation farming practices (*Conserv_Farm*), who have been paid incentives (*D_payment*), who own forest (*Own_forest*), who have experience with afforestation (*Past_aff*), who have a plan for future afforestation (*Future_aff*), who have family ownership (*Ownership*), and who are members of NGO (*Member_NGO*) to control for possible factors affecting landowners' adoption rate of afforestation.

Finally, a number of landowners' demographic characteristics such as age, gender, education, income, and occupation are included as independent variables that may have an effect on enrollment in a tree planting program.

Summary statistics and a description of all these variables are presented in Table 3.1.

3.4. Estimation Results

The empirical model setup for Tobit analysis will be:

$$y_i = \beta_0 + \beta_1 \mathrm{AnnPAY}_i + \beta_2 \mathrm{LCH}_i + \beta_3 \mathrm{OCH}_i + \beta_4 OA_i + \varepsilon_i ,\ i = 1,..., N, \qquad (5)$$

where y_i is the stated proportion of lands of landowner *i* would be willing to enroll in a tree planting program, PAY_i is the per acre payment offered to each agricultural landowner, LCH_i is a vector of land characteristics, OCH_i is a vector of landowner's demographic characteristics, OA_i is a vector of landowners' attributes, β are parameter vectors, and ε_i is a random disturbance term.

3.4.1. Consideration of Sample Selection Bias

Controlling selection bias is necessary because if there is a relatively large number of non-responses of willingness to enrollment, and/or if the response rate is a relatively low, then the standard Tobit model, with no consideration of non-responses, cannot examine landowners' true willingness to participate in the tree planting program. Langpap (2006) mentioned that if there are a large number of non-responses, the factors affecting a landowner's decision to participate in the program and the factors affecting response of survey may be correlated, and thus the parameter estimates may be biased. The information about non-respondents is collected through a follow-up phone and mail survey to conduct a test for sample selection bias. An additional possibility of selection bias is considered as well, because those survey respondents who denied participating in a tree planting program regardless of the condition of incentives offered were excluded from the sample. A two-step Heckman test for sample selection bias has been commonly used to correct the biases associated with sample selection (Heckman 1979, Desvousges et al. 1987, Whitehead et al.1993, Messonnier et al. 2000, Cho et al. 2005, Langpap 2006). A probit model of participation in tree planting program is estimated as a first step. This participation model is based on demographic characteristics (age, gender, education, income), property characteristics (size of land, land use type), and landowners' opinions on providing environmental services (soil erosion, water quality, wildlife, carbon) of both participants and non-participants (including non-respondents) of a tree planting program. The parameter estimates are used to calculate the inverse Mills ratio, which indicates the probability of a landowner having participated in the program. Then, the inverse Mills ratio is included as an additional regressor in a censored Tobit model, and if the test for sample selection bias shows that it is not significantly different from zero, the null hypothesis of no bias cannot be rejected.

3.4.2. Estimation Results

The estimated parameters show us the factors affecting landowners' willingness to participate in the tree planting program for carbon sequestration. However, the coefficients estimated from the Tobit model are not easy to interpret because they represent the change in unobservable y^* with respect to the change in independent variables. The marginal effects associated with the change in explanatory variables are the better measure to interpret the results. Table 3.2 shows the analysis of marginal effects at mean on the expected willingness to plant trees with a 15-year contract in the PNW and SE regions, respectively.

1) *Pacific Northwest region*

In case of the PNW region, in Table 3.2, the marginal effect on proportion of agricultural lands landowners are willing to enroll in the tree planting program with respect to annual payment (*AnnPay*) is positive and significant at 1% significance level indicating that $1 increase in annual payment increases the proportion of land enrollment by 0.209 percentage point. This implies that if a representative landowner enrolls 10% of agricultural land in the tree planting program at $100/acre payment, then 1% increase in annual rental payment ($101/acre) achieves 10.21% of agricultural land enrollment.

The marginal effect with respect to lands characteristics shows that the stated average annual returns of agricultural lands (*Agri_return*) has not significant effect on the amount of willingness for participation, while the negative sign indicating that increase in agricultural returns decrease the proportion of land enrollment in the tree planting program. The landowners who own high productivity land (*D_Highprod*) allocate less land for afforestation, and the landowners who own low productivity land (*D_Lowprod*) allocate more lands for afforestation than who do not own it. The marginal effect, with respect to size of agricultural land (*Agland_size*), implies that the larger the size of agricultural land, the lower the proportion of agricultural land allocated to afforestation.

In case of the marginal effects with respect to the variables representing spatial characteristics of agricultural lands, lands adjacent to fire hazard (*Loc_firehazard*) are less likely to be allocated to a tree planting program, but the rest of spatial characteristic variables do not significantly affect the willingness to participate in a tree planting program.

The marginal effects with respect to landowners' attitudes about environmental services which they may provide for the public show that landowners who believe carbon sequestration (*Envi_carbon*) is very important are more likely to allocate their lands for afforestation. However, landowners' attitudes about other environmental services such as preventing soil erosion (*Envi_soil*), preserving water quality (*Envi_water*), and providing wildlife habitat (*Envi_wild*) do not significantly affect the level of participation in afforestation. In addition, landowners who own their agricultural lands to protect nature (*Reason_nature*), and have experienced afforestation in the past (*Past_aff*), and who are a member of NGO (*Member_NGO*) allocate more agricultural lands for a tree planting program, while the landowners who are conducting conservation farming methods (*Conserv_Farm*) are less willing to allocate their lands for a tree planting program.

In case of marginal effects with respect to the landowners' demographic characteristics, the male landowners (*Gender*) are more willing to allocate their agricultural land for afforestation, while the landowners with graduate school degree (*Education5*) are less willing to allocate their lands for afforestation than with at most high school degree. However, other demographic characteristics of landowners do not significantly affect the landowners' willingness to participate in a tree planting program independently. Additionally the null hypothesis that the coefficients of education dummies and household income dummies together are zero is failed to reject even at 10% of significant level.

Finally, the coefficient of inverse mills ratio of program non-participants (*IMR_participant*) is not significantly different from zero indicating that there is no sample selection bias associated with excluding out the non-participants in the analysis.

2) *Southeast Region*

In the case of the SE region, in Table 3.2, the marginal effect on proportion of agricultural lands willing to participate in the tree planting program with respect to annual payment (*AnnPay*), which is positive and significant at 1% significance level indicating that $1 increase in annual payment increases the proportion of land enrollment by 0.341 percentage point. Compared to the marginal effect of annual payment in the PNW region, the SE region is more responsive to annual payment, which is consistent with the results done by previous studies.

The marginal effects on proportion of agricultural land enrollment for afforestation with respect to lands characteristics show that the landowners who own low productivity land (*D_Lowprod*), and whose land is adjacent to forest (*Location_forest*) allocate more lands for afforestation than who do not own it. However, if the land is adjacent to fire hazard (*Location_firehzd*), less land is likely to be allocated in a tree planting program. In contrast to the PNW region, high productivity dummy (*D_Highprod*), and size of agricultural land (*Agland_size*) owned do not significantly affect the level of program enrollment.

Landowners' attitudes about environmental services for soil, water, wildlife, and carbon sequestration show that landowners who landowners who believe carbon sequestration (*Envi_Carbon*) to be very important are more likely to enroll the tree planting program. The marginal effects with respect to the reasons for owning land indicate that the landowners who own their lands to protect nature (*Reason_nature*) allocate more lands for afforestation. Finally, the landowners who have received any payment in the past (*D_payment*) are more likely to participate in the program.

Marginal effects with respect to the landowners' demographic characteristics suggest that as age (*Age*) increases more lands are allocated for afforestation, but male landowners (*Gender*) allocate fewer lands for afforestation than female landowners. Landowners who have a college school degree (*Education3*), have a graduate school degree (*Education5*) are less willing to allocate their agricultural land for afforestation, while landowners whose annual household income level is more than $100,000 (*HH_income5*) are more willing to allocate their agricultural land for afforestation. Overall, the null hypothesis that the coefficients of demographic characteristic variables together are zero is rejected at 5% of significant level, which implies that the demographic characteristics of landowners significantly affect the landowners' willingness to participate in a tree planting program.

Finally, the coefficient of inverse mills ratio of program non-participants (*IMR_participant*) is not significantly different from zero at 10% significance level indicating that there is no sample selection bias associated with excluding out the non-participants in the analysis.

3.4.3. Robustness

This section conducts the estimation using alternative model specification to check the robustness with consideration of unobservable characteristics. Since the landowner *i* is offered three different levels of incentive payments, we suspect the group-wise heteroskedasticity facing different levels of rental payments, thus we specified a panel Tobit model with random effect with the following rule to correct potential heteroscedasticity:

$$\begin{aligned} y_{it} &= \max(0, X_{it}^{'}\beta + v_i + \varepsilon_{it}, 100), \\ \varepsilon_{it} \mid X_i, v_i &\sim N(0, \sigma_{\varepsilon}^2) \end{aligned} \tag{5}$$

for different incentive payment sets $t=1,2,3$, where the unobserved effect v_i is distributed $N(0,\ \sigma_v^2)$, and ε_{it} is distributed $N(0, \sigma_{\varepsilon}^2)$. We assume that $E(v_i v_j) = 0$, $E(v_i \varepsilon_{it}) = 0$, and

$E(\varepsilon_{it}\varepsilon_{ij}) = 0$, for all $i \neq j$.

A disadvantage of the random effect panel Tobit model is that it assumes v_i and X_i are uncorrelated, thus if this assumption is not satisfied, the estimator will be inconsistent. However, since the number of payment set is small, the fixed effect estimator will be inconsistent because of incidental parameter problem. The fixed effects estimator is inconsistent when t is not large. Thus, both estimators have problems. A Chamberlain's Random Effect (CRE) Tobit model, rather than a general random effects panel Tobit model, can be another alternative which allows v_i and X_i to be correlated (Woodridge 2001). Chamberlain's conditional estimator provides a way to estimate the fixed effects model consistently. The approach is based on conditioning on the group means of selected (theoretically relevant) independent variables by including these means in the model as additional regressors. Specifically, assume $v_i \mid X_i \sim N(\psi + \bar{X}_i \xi, \sigma_a^2)$, where σ_a^2 is the variance of a_i in the equation $v_i = \psi + \bar{X}_i \xi + a_i$. Then the CRE Tobit can be specified as follows:

$$\begin{aligned} & y_{it} = \max(0, \psi + X_{it}^{'}\beta + \bar{X}_i \xi + a_i + \varepsilon_{it}, 100) \\ & \varepsilon_{it} \mid X_i, a_i \sim N(0, \sigma_\varepsilon^2), \quad t = 1,2,3 \\ & a_i \mid X_i \sim N(0, a_a^2) \end{aligned} \tag{6}$$

where $\bar{X}_i$ is an additional set of explanatory variables which is constant in each incentive payment set, and ψ is a constant. We also assume that $E(a_i a_j) = 0$, $E(a_i \varepsilon_{it}) = 0$, and $E(\varepsilon_{it}\varepsilon_{ij}) = 0$, for all $i \neq j$.

Table 3.3 shows marginal effects on proportion of enrollment in tree planting program with respect to independent variables with two alternative model specifications for two separate regions. The marginal effect on proportion of agricultural land enrollment in the tree planting program with respect to annual payment (*AnnPay*) ranged from 0.208 to 0.210 in the PNW region, and from 0.340 to 0.350 in the SE region, which are not significantly different from the marginal effect with respect to annual payment under the standard Tobit model in Table 3.2. The LR test failed to reject the null hypothesis that $v_i=0$ in the random effect panel Tobit model, and $a_i=0$ in the Chamberlain panel Tobit model, and the coefficient of group mean of annual payment (*Avg_AnnPay*) is not significantly different from zero under the Chamberlain panel Tobit model, which implies the estimates from standard Tobit model are robust.

We also conduct estimations using pooled data of two survey regions to check how robust the estimation results conducted in previous section using three different model specifications: Standard Tobit, Random effect panel Tobit, and Chamberlain panel Tobit model. The marginal effects on level of enrollment with respect to annual payment are between that in PNW region and in SE region, but more close to that in PNW region. Overall, the sign and magnitude of marginal effects and significances of independent variables have similar patterns with PNW region.

3.5. Simulation of Carbon Sequestration

3.5.1. Carbon supply function

To estimate a carbon sequestration supply function, we conduct a simulation of landowner’s response to different levels of annual payment ranging from $0/acre to $300/acre with a 15-year contract. The annual carbon sequestration rate is estimated by using carbon yield tables from Smith et al. (2006) assuming that the stand is periodically harvested with a 50-year rotation. As mentioned before, the tree species used for simulation of carbon sequestration are Douglas-fir for the PNW and Southern-Pine for the SE region, which are the fastest growing species for each region. We account for the amount of carbon accumulated in the live tree, standing dead, understory, down dead wood, forest floor, soil, wood products, and landfills, but we don't consider the potential emission reductions from fossil fuels when wood products substitute more energy-intensive materials, or when wood waste is used to generate energy. The areas of agricultural lands used in the simulation are 31.2 million acres for the PNW region and 41.1 million acres for the SE region based on the year 2010, assuming that adoption rates from samples apply to entire region.[41] We derive the carbon supply function based on the same procedure used by Stavins and Richards (2005), who expressed total cost and carbon in response to different rates of annual payments as annualized equivalents with a 5% discount rate.[42]

Figure 3.1 shows adoption rate and carbon supply function of each region with respect to different level of payments, which are the simulation results based on standard Tobit model. The results show that as the rates of annual payment increase, the adoption rates of a tree planting program increase, and thus carbon sequestration rates increase as

[41] We apply the available agricultural land area for each region based on *Farms, Land in Farms, and Livestock Operations 2010 Summary* released in 2011 by the National Agricultural Statistics Service (NASS), Agricultural Statistics Board, United States Department of Agriculture (USDA). PNW region includes Oregon and Washington, and SE region includes Florida, Georgia, North Carolina, South Carolina, and Virginia.

[42] Stavins and Richards (2005) compute the marginal costs of carbon sequestration as the ration of increment in annualized costs to the increment in annualized amount of carbon.

well. As shown in Figure 3.1-a, however, since the increment of adoption rate turns to decline as the rate of annual payment increases, carbon sequestration also increases at a diminishing rate. As we expected based on the marginal effect of each region with respect to the rates of annual payment, the adoption rate in the SE region is higher than in the PNW region. The carbon supply function of each region in Figure 3.1-b indicates that, at $50/Mt and $100/Mt of carbon prices, respectively, the PNW region sequesters 14.7 MMt and 39.9 MMt of carbon, while the SE region sequesters 28.3 MMt and 57.8 MMt of carbon.

3.5.2. Sensitivity Analysis

Since we derive the carbon supply function with fast growing tree species, Douglas fir for the PNW and Southern Pine for the SE region, associated with the change in the annual payment for carbon sequestration, it can be overly estimated if the landowners plant other species rather than fast growing tree species. Thus we derive the carbon supply function by supposing landowners plant mixed tree species and compare with the results from planting fast growing tree species. We calculate annual carbon sequestration rate of mixed tree species based on the average of annual growth rate of carbon presented in Smith et al. (2006) weighted by the proportion of tree species in each region. As shown in Figure 3.2, planting mixed tree species makes the supply function steeper since the annual carbon sequestration rate with mixed tree species is lower than that with the fast growing tree species.

In Figure 3.2, we also derive the carbon supply function assuming no harvest takes place in contrast to periodic harvesting. The figure indicates that the carbon sequestration rate with no harvest is greater than that with harvest, hence the carbon supply function with no harvest is flatter than that with harvest, which is consistent with the result from Lubowski et al. (2006).

It is also important to assess the sensitivity of our results to alternative discount rates. The higher the discount rate lowers the present value of both annualized carbon sequestration and annualized rental payment (Lubowski et al. 2006). However, this makes it unclear that how the ratio between annualized payment and annualized carbon sequestration would change with different discount rates. Figure 3.3 shows that as discount rates change from low to high, the decrease in the rate of present value of carbon sequestration is greater than that of present value of annual payment, thus the carbon supply functions become steeper.[43]

3.6. Comparison of Carbon Supply Function with Other Studies

In this section, we compare the carbon supply functions estimated in this study with those from other studies. Comparison of the carbon supply function with other studies is difficult because of the differences in cost estimation methods used in other studies, as well as the differences in assumptions applied such as geographic regions, tree species, discount rates, rotation lengths, and constant-year dollars. Fortunately, there are several review papers which have compared the cost of carbon through afforestation from groups

[43] Because relatively higher growth rate of carbon accumulation in the first three decades, decreasing rate of annualized carbon sequestration is greater than that of annualized payment, as discount rates become higher. Thus the ratio of annualized payment to annualized amount of carbon sequestration decreases when discount rates change from low to high.

of studies by normalizing the different assumptions. For example, Richards and Stokes (2004) compared cost of carbon sequestration using 36 studies. Although not all of them are directly comparable with a common criterion, the comparison of national scale studies based on three different cost estimation methods concludes that the marginal cost curve under the econometric approach is much steeper than that under the bottom-up approach. Stavins and Richards (2005) summarized and compared the 11 studies on carbon sequestration potential through afforestation using the normalized carbon supply function by adjusting discount rates, constant dollars, geographic scope, and methods of estimating annual costs. They show that the cost of carbon after normalization to 2010 dollars ranges from $38/Mt to $113/Mt for 272 MMt (300 million ton) of annual carbon sequestration, and from $45/Mt and $135/Mt for 454 MMt (500 million ton) of annual carbon sequestration in the U.S.[44] Lubowski et al. (2006) also compared their results with the results from other previous studies with the same criteria applied in Stavins and Richards (2005).

As we mentioned in the previous section, since we followed the same procedure applied by Stavins and Richards (2005), our results are comparable with the results from Stavins and Richards (2005) and Lubowski et al (2006) by scaling up the regional level to the national level. We scaled up the regional level carbon supply function for the PNW and the SE regions to the national level by applying 920 million acres of the agricultural

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[44] Stavins and Richards (2005) concludes that after normalization to 1997 dollars, the cost of carbon for afforestation ranges from $28/Mt to $83/Mt for 272 MMt of national scale annual carbon sequestration, and from $33/Mt to $99/Mt for 454 MMt of national scale annual carbon sequestration.

lands in the U.S. A simple scaling-up can be problematic, because landowners' responses to incentives and carbon sequestration rates can be different across the regions. To reduce shortcomings of scaling-up, we used different annual carbon sequestration rates for different forest regions, so that the annual carbon sequestration rate for the entire U.S. is the weighted average of carbon sequestration rates with representative tree species for each forest region using carbon yield tables from Smith et al. (2006). As results, the cost of carbon estimated in this study ranges from $72/Mt to $111/Mt for 300 MMt ($66/Mt~$104/Mt for 272 MMt) of annual carbon sequestration in the U.S., and ranges from $109/Mt to $158/Mt for 500 MMt ($101/Mt~$147/Mt for 454 MMt) of annual carbon sequestration. Figure 3.4 shows the result of comparison of carbon sequestration costs found by this study with that found by Stavins and Richards (2005), and indicates that our study results are within the range of cost from Stavins and Rechards (2005) for 272 MMt and slightly higher than that for 454 MMt of annual carbon sequestration.

In Figure 3.5, we compare the carbon supply functions derived from this study with those from other afforestation studies derived under different approaches. The marginal costs of carbon estimated from our study are higher than those obtained from bottom-up engineering approaches (Richards et al. 1993) and optimization models (Adams et al. 1993, Callaway and McCarl 1996). Compare to other econometric models, the marginal costs estimated from Lubowski et al (2006) place within range of our results at lower than 500 MMt of annual carbon sequestration, while the marginal cost curves from our study become steeper than Lubowski et al (2006) as total amount of carbon sequestered per year increases. The comparison with the marginal cost from Stavins

(1999) found that the cost from our study is higher than his finding at lower than 400 MMt of annual carbon sequestration, but lower than his finding at more than 400 MMt of annual carbon sequestration.

We also compare our results with the result from the stated preference approach conducted by Shaikh et al. (2007). Although it is hard to normalize based on above mentioned criteria, our study results place at lower range than those from Shaikh et al. (2007) which estimated costs of carbon uptake by afforestation in western Canada range from \$20.9/Mt of carbon (\$5.7/Mt CO_2 eq) to \$661.1/Mt of carbon (\$180.3/Mt CO_2 eq). Our study results indicate that consideration of various owner-specific factors affecting land use decision can make carbon supply functions steeper than those from optimization approach and bottom-up engineering approach.

3.7. Conclusion

This study analyzes agricultural landowners' willingness to participate in a tree planting program, and examines the key factors affecting landowners' level of enrollment in the program based on a survey.

Using the data collected from a mail survey in the Pacific Northwest (PNW) and the Southeast (SE) regions, we estimate the proportion of agricultural lands landowners are willing to enroll in both regions as a function of incentives payments for carbon sequestration and various factors such as spatial characteristics of lands and landowners' characteristics. The estimation results show that the annual payment for carbon sequestration significantly and positively affects to landowners' level of enrollment in a tree planting program, while the PNW region is less responsive than the SE region associated with the increase in annual payment. We also found that the variables which represent productivity of land, spatial characteristics, and reasons for owning agricultural lands affect to landowners' level of enrollment in the program in both regions. The marginal effects with respect to landowners' demographic characteristics shows that the landowners with graduate school degree (*Education5*) are less willing to allocate their lands for afforestation compare to at most high school degree in both region, however, in the PNW region, overall effects of demographic characteristics on landowners' level of program participation are not significant, while they are significant in the SE region.

The regional level simulations of carbon sequestration in response to incentive payments show that the carbon supply function in the PNW region is steeper than the SE region because of the lower adoption rate and less available lands. A sensitivity analysis shows that planting fast growing tree species with no harvest has the highest carbon sequestration potential, and that carbon supply function shifts up as the discount rate increases. The national level carbon supply function suggests that the cost of carbon from this study (Stated preference approach) is higher than that obtained from bottom-up engineering approaches and optimization models. However, the carbon supply functions derived from our study shares a common range of marginal cost of carbon sequestration with the revealed preference approach done by Lubowski et al (2006) at lower than $170/Mt, while they become steeper than that from Lubowski et al (2006) as the price of carbon increases. Thus the results from this study can be a complement of the revealed preference approach. Moreover, this study can provide us better understanding of landowners' willingness to plant trees on their agricultural lands than the studies based on other approaches by considering various factors affecting landowners' afforestation decisions, and will give the policy maker better sense to identify target groups who are more likely to participate in a tree planting program.

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3.9. Tables

Table 3.1. Summary statistics and description of independent variables

Variable name	Variable description	PNW		SE	
		Mean	Std.Dev.	Mean	Std. Dev.
AnnPay	Annual payment per acre	103.50	55.40	99.51	50.96
Agri_type	Dummy: 1 if Cropland, 0 if Grassland	0.44	0.50	0.29	0.46
Agri_Return	Stated agricultural net returns ($/acre/year)	196.41	255.46	180.60	261.22
D_Highprod	Dummy: 1 if own high productive lands	0.514	0.50	0.382	0.487
D_Lowprod	Dummy: 1 if own low productive lands	0.63	0.48	0.44	0.50
Agland_size	Size of agricultural land (acres)	70.74	272.61	48.30	59.65
Resident_owner	Dummy: 1 if lands close to home	0.90	0.30	0.61	0.49
Location_hwy	Dummy: 1 if lands close to highway	0.54	0.50	0.71	0.46
Location_forest	Dummy: 1 if lands close to forests	0.33	0.47	0.67	0.47
Location_agland	Dummy: 1 if lands close to forests	0.86	0.35	0.78	0.42
Location_firehzd	Dummy: 1 if lands close to fire hazard	0.18	0.39	0.45	0.50
Envi_soil	Dummy: 1 if preventing soil erosion is important	0.75	0.43	0.88	0.32
Envi_water	Dummy: 1 if water quality is important	0.79	0.41	0.88	0.33
Envi_Wildlife	Dummy: 1 if preserving wildlife habitat is important	0.76	0.43	0.78	0.41
Envi_Carbon	Dummy: 1 if carbon sequestration is important	0.47	0.50	0.54	0.50
Reason_Sellfood	Dummy: 1 if owning lands to sell agri-products	0.39	0.49	0.54	0.50
Reason_Invest	Dummy: 1 if owning lands for investment	0.31	0.46	0.34	0.47
Reason_amenity	Dummy: 1 if owning lands to enjoy amenity	0.90	0.31	0.89	0.32
Reason_nature	Dummy: 1 if owning lands to protect nature	0.48	0.50	0.80	0.40
Conserv_Farm	Dummy: 1 if currently adopt conservation farming practice	0.32	0.47	0.22	0.42
D_payment	Dummy: 1 if ever received conservation payment	0.11	0.31	0.13	0.34
Own_forest	Dummy: 1 if own forests	0.49	0.50	0.79	0.41
Past_aff	Dummy: 1 if afforested in the past	0.41	0.49	0.39	0.49
Future aff	Dummy: 1 if have future afforestation plan	0.51	0.50	0.37	0.48
Ownership	Dummy: 1 if individual family ownership	0.71	0.45	0.66	0.47
Member_NGO	Dummy: 1 if member of NGO	0.19	0.40	0.24	0.43
Age	Age of landowner or main operator	59.59	11.64	60.55	10.61
Gender	Dummy: 1 if male	0.68	0.47	0.82	0.38
Education	Dummies: Education level, elementary school (1) to graduate school (5)				
HH_income	Dummies: Household income; (1) below $40K, (2) $40K-$60K, (3) $60K-$80K, (4) $80K-$100K, and (5) at least $100K				
Occup_Farm	Dummy: Occupation of landowner: 1 if related to ranching, farming, forests	0.19	0.39	0.18	0.38
Retired	Dummy: 1 if retired	0.39	0.49	0.42	0.49

Table 3.2. Marginal effects with respect to independent variables across the regions

Variables	Pacific Northwest	Southeastern
AnnPay	0.209 (0.023)***	0.341 (0.048)***
Agri_type	-2.286 (3.055)	-10.332 (6.851)
Agri_Return	-0.009 (0.007)	-0.012 (0.01)
D_Highprod	-10.804 (3.265)***	-5.890 (7.209)
D_Lowprod	6.633 (2.985)**	10.927 (6.681)*
Agland_size	-0.029 (0.017)*	0.052 (0.047)
Resident_owner	-1.279 (4.924)	-11.492 (7.456)
Location_hwy	2.705 (3.228)	-4.531 (6.715)
Location_forest	2.013 (5.05)	13.064 (7.629)*
Location_agland	-2.684 (5.231)	-9.474 (8.465)
Location_firehzd	-9.379 (3.768)**	-36.571 (9.268)***
Envi_Soil	4.988 (3.882)	-12.829 (13.75)
Envi_Water	-7.584 (4.658)	-22.458 (14.821)
Envi_Wildlife	4.113 (3.741)	1.306 (8.59)
Envi_Carbon	5.701 (3.227)*	11.441 (6.277)*
Reason_Sellfood	-0.527 (4.725)	-7.564 (6.715)
Reason_Invest	3.402 (3.767)	-4.049 (7.459)
Reason_Amenity	8.555 (5.801)	16.008 (10.776)
Reason_Nature	9.622 (4.677)**	25.618 (9.214)***
Conserv_Farm	-5.868 (3.147)*	11.440 (11.791)
D_payment	1.976 (5.8)	37.500 (10.207)***
Own_forest	0.989 (5.745)	-6.917 (8.779)
Past_aff	5.226 (3.046)*	-3.307 (7.79)
Future aff	7.489 (7.287)	4.165 (9.104)
Ownership	-3.915 (3.257)	21.106 (7.003)***
Member_NGO	9.240 (3.61)***	11.852 (9.643)
Age	-0.103 (0.148)	0.829 (0.385)**
Gender	6.502 (3.021)**	-23.531 (9.103)***
Education3	-3.490 (6.808)	-28.195 (10.591)***
Education4	-7.159 (5.849)	-5.781 (9.661)
Education5	-8.959 (4.423)**	-20.068 (10.414)*
HH_income2	4.138 (4.315)	-10.044 (12.354)
HH_income3	-3.456 (5.591)	4.497 (9.494)

HH_income4	1.456 (5.221)	19.674 (13.933)
HH_income5	-0.174 (4.668)	22.525 (8.281)***
Occup_Farm	-4.059 (4.979)	14.506 (11.728)
Retired	-2.319 (3.429)	8.596 (7.523)
IMR_participants	-3.580 (15.29)	13.504 (8.389)
Log-likelihood	-1250.633	-523.765
χ^2	206.060	213.470
pr ≥ χ^2	0.000	0.000
Pseudo-R^2	0.076	0.169
AIC [i)]	2581.267	1127.531
BIC [i)]	2758.520	1271.021
Observations	621	267

Note: *, **, *** Statistical significance at α = 10, 5, and 1 %. Parentheses are standard errors.

i) The AIC (Akaike's Information Criteria) and BIC (Bayesian Information Criteria) are known as popular measures for comparing maximum likelihood models. AIC is defined as $\text{AIC} = -2(\text{Log-likelihood}) + 2K$, and BIC is defined as $\text{BIC} = -2(\text{Log-likelihood}) + K \log N$, where K is number of parameters estimated, and N is number of observations (Burnham and Anderson 2004).

Table 3.3. Marginal effects with alternative model specifications

Ind. Var.	Pacific Northwest Random effect Panel Tobit	Pacific Northwest Chamberlain Panel Tobit	Southeast Random effect Panel Tobit	Southeast Chamberlain Panel Tobit
AnnPay	0.208 (0.024)***	0.210 (0.037)***	0.340 (0.051)***	0.350 (0.051)***
Agri_type	-2.276 (3.051)	-2.176 (3.053)	-10.449 (6.85)	-10.207 (6.827)
Agri_Return	-0.009 (0.007)	-0.008 (0.007)	-0.012 (0.01)	-0.013 (0.01)
D_Highprod	-10.644 (3.324)***	-10.067 (3.37)***	-5.999 (7.211)	-7.451 (7.395)
D_Lowprod	6.669 (2.987)**	6.850 (3.011)**	11.141 (6.714)*	11.761 (6.737)*
Agland_size	-0.029 (0.017)*	-0.031 (0.018)*	0.051 (0.047)	0.049 (0.047)
Resident_owner	-1.123 (4.961)	-0.902 (4.923)	-11.805 (7.538)	-12.090 (7.528)
Location_hwy	2.671 (3.228)	2.708 (3.222)	-4.368 (6.741)	-4.266 (6.731)
Location_forest	1.992 (5.043)	2.197 (5.031)	12.941 (7.648)*	11.802 (7.718)
Location_agland	-2.624 (5.232)	-2.333 (5.241)	-8.966 (8.688)	-7.935 (8.725)
Location_firehzd	-9.398 (3.768)**	-9.425 (3.79)**	-36.297 (9.33)***	-36.480 (9.355)***
Envi_Soil	4.946 (3.878)	4.813 (3.886)	-12.611 (13.729)	-11.105 (13.783)
Envi_Water	-7.565 (4.654)	-7.765 (4.676)*	-22.182 (14.865)	-23.846 (14.913)
Envi_Wildlife	4.075 (3.74)	3.729 (3.752)	1.153 (8.601)	1.595 (8.619)
Envi_Carbon	5.824 (3.262)*	6.192 (3.265)*	11.548 (6.285)*	12.120 (6.315)*
Reason_Sellfood	-0.546 (4.721)	-0.312 (4.711)	-7.747 (6.771)	-8.243 (6.75)
Reason_Invest	3.373 (3.764)	3.132 (3.775)	-4.671 (7.812)	-5.047 (7.786)
Reason_Amenity	8.693 (5.82)	9.467 (5.864)	15.773 (10.789)	15.960 (10.796)
Reason_Nature	9.623 (4.674)**	9.341 (4.694)**	25.598 (9.213)***	25.602 (9.156)***
Conserv_Farm	-5.811 (3.152)*	-5.491 (3.171)*	11.346 (11.814)	10.495 (11.839)
D_Payment	2.020 (5.795)	2.550 (5.828)	37.426 (10.256)***	37.021 (10.238)***
Own_forest	1.062 (5.744)	1.052 (5.729)	-7.213 (8.834)	-6.279 (8.916)
Past_aff	5.194 (3.044)*	5.131 (3.049)*	-3.358 (7.781)	-2.616 (7.8)
Future_aff	7.545 (7.284)	7.098 (7.287)	4.727 (9.36)	6.510 (9.524)
Ownership	-3.917 (3.253)	-4.155 (3.26)	21.273 (7.041)***	22.488 (7.15)***
Member_NGO	9.230 (3.607)**	9.032 (3.637)**	12.064 (9.684)	12.603 (9.66)
Age	-0.101 (0.148)	-0.099 (0.148)	0.822 (0.387)**	0.734 (0.398)*
Gender	6.517 (3.018)**	6.429 (3.037)**	-23.645 (9.104)***	-22.855 (9.126)**
Education3	-3.348 (6.825)	-3.364 (6.792)	-28.247 (10.585)***	-28.954 (10.578)***
Education4	-6.953 (5.898)	-6.475 (5.883)	-5.898 (9.66)	-8.041 (9.97)
Education5	-8.847 (4.441)**	-8.499 (4.449)*	-20.358 (10.488)*	-22.291 (10.681)**
HH_income2	4.190 (4.315)	4.392 (4.318)	-9.744 (12.418)	-6.907 (12.743)
HH_income3	-3.352 (5.603)	-3.329 (5.587)	4.863 (9.592)	6.915 (9.848)

HH_income4	1.583 (5.239)	1.856 (5.219)	19.835 (13.961)	21.834 (14.151)
HH_income5	-0.127 (4.665)	0.072 (4.657)	22.801 (8.352)***	24.228 (8.494)***
Occup_Farm	-4.040 (4.97)	-4.240 (4.966)	14.577 (11.74)	16.869 (11.969)
Retired	-2.295 (3.426)	-2.276 (3.421)	8.785 (7.562)	10.614 (7.808)
IMR_participants	-3.364 (15.297)	-3.706 (15.238)	13.579 (8.389)	13.065 (8.407)
Avg_AnnPay	-	-0.072 (0.082)	-	-0.190 (0.216)
Log-likelihood	-1250.599	-1249.479	-523.730	-523.355
χ^2	128.120	114.970	113.580	115.620
pr $\geq \chi^2$	0.000	0.000	0.000	0.000
AIC [i)]	2583.198	2582.958	1129.460	1130.710
BIC [i)]	2764.882	2769.074	1276.538	1281.375
LR test (H_0: v=0):				
$\bar{\chi}^2$	0.07	1.41	0.07	0.01
pr $\geq \bar{\chi}^2$	0.397	0.118	0.395	0.459
Observations	621	621	267	267

Note: *, **, *** Statistical significance at α = 10, 5, and 1 %. Parentheses are standard errors.

i) The AIC (Akaike's Information Criteria) and BIC (Bayesian Information Criteria) are known as popular measures for comparing maximum likelihood models. AIC is defined as $\text{AIC} = -2\ln(\text{likelihood}) + 2K$, and BIC is defined as $\text{BIC} = -2\ln(\text{likelihood}) + K\ln(N)$, where K is number of parameters estimated, and N is number of observations (Burnham and Anderson 2004).

3.10. Figures

Figure 3.1. Adoption rate and carbon supply function of each region

a. Adoption rate b. Carbon supply function

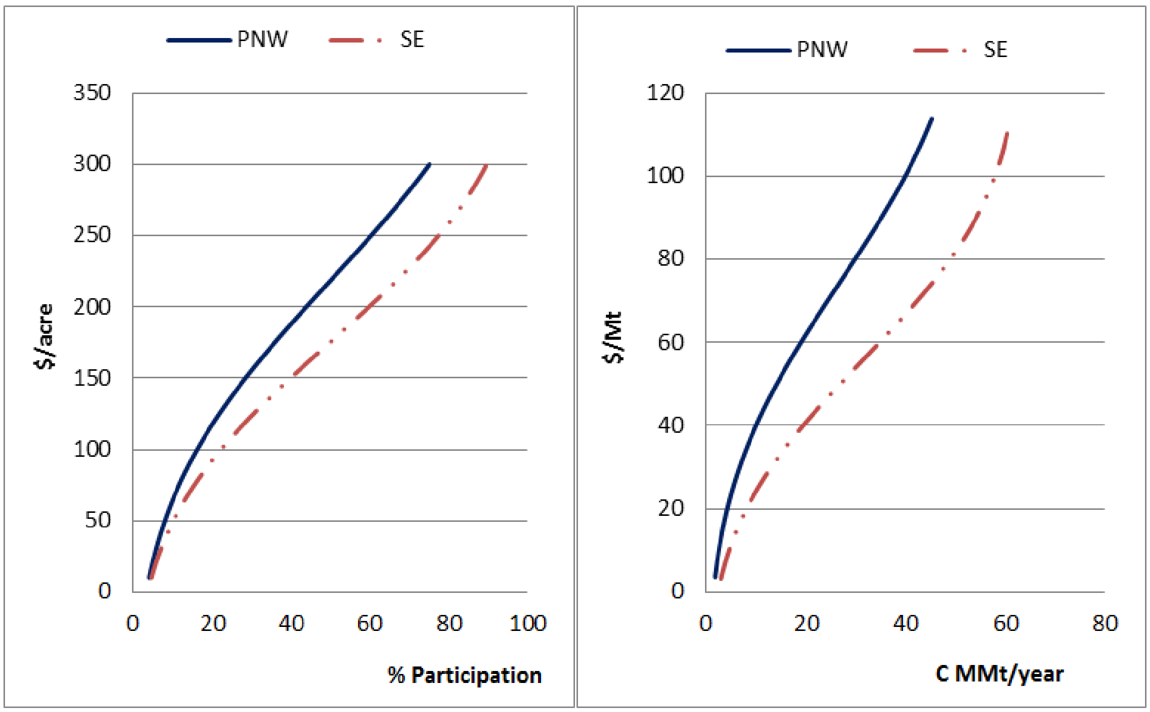


Figure 3.2. Carbon supply functions with different assumptions of harvest and tree species

a. Pacific Northwest

b. Southeast

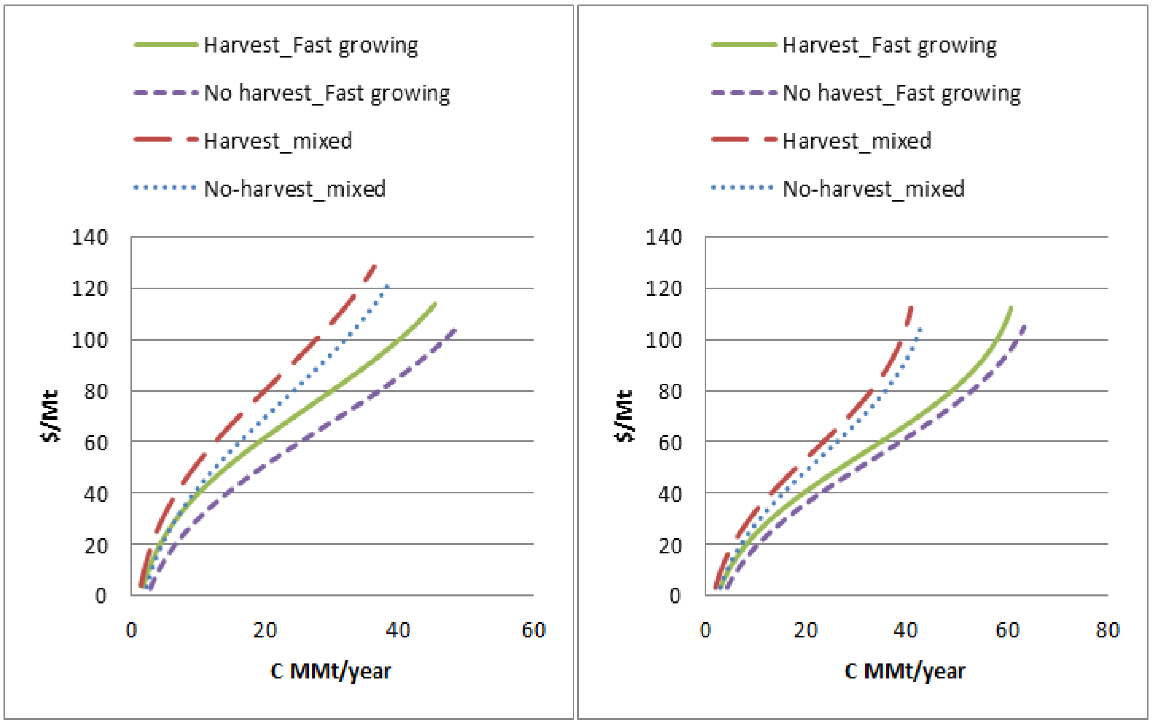


Figure 3.3. Carbon supply functions with alternative discount rates

a. Pacific Northwest b. Southeast

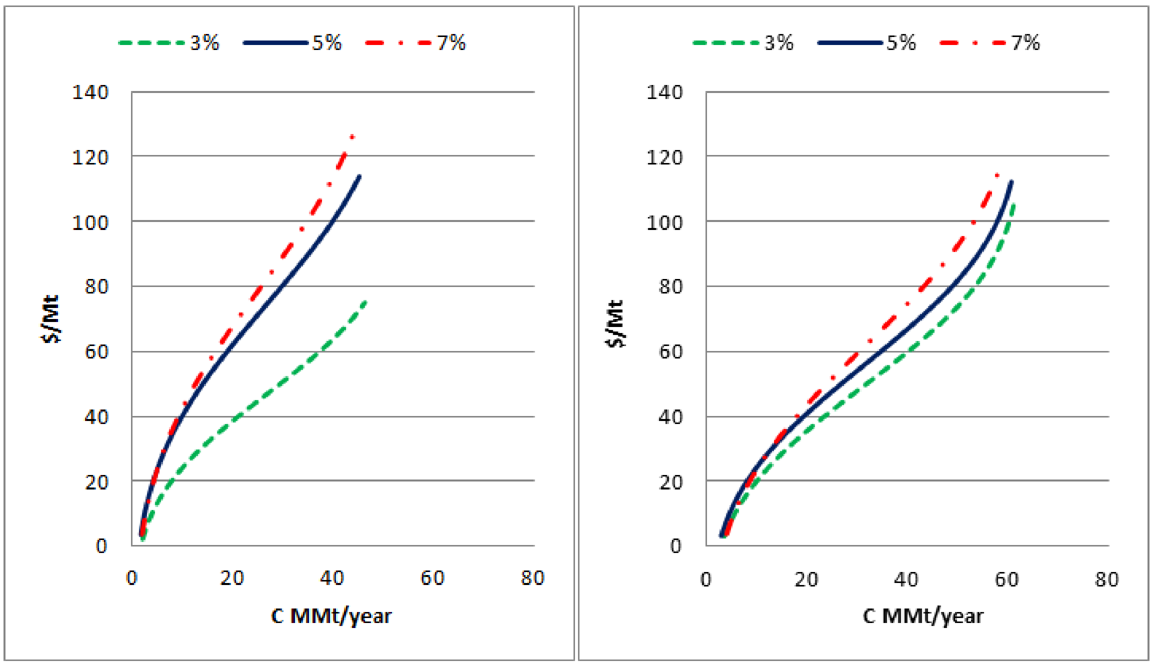


Figure 3.4. Comparison of marginal cost of carbon with other studies

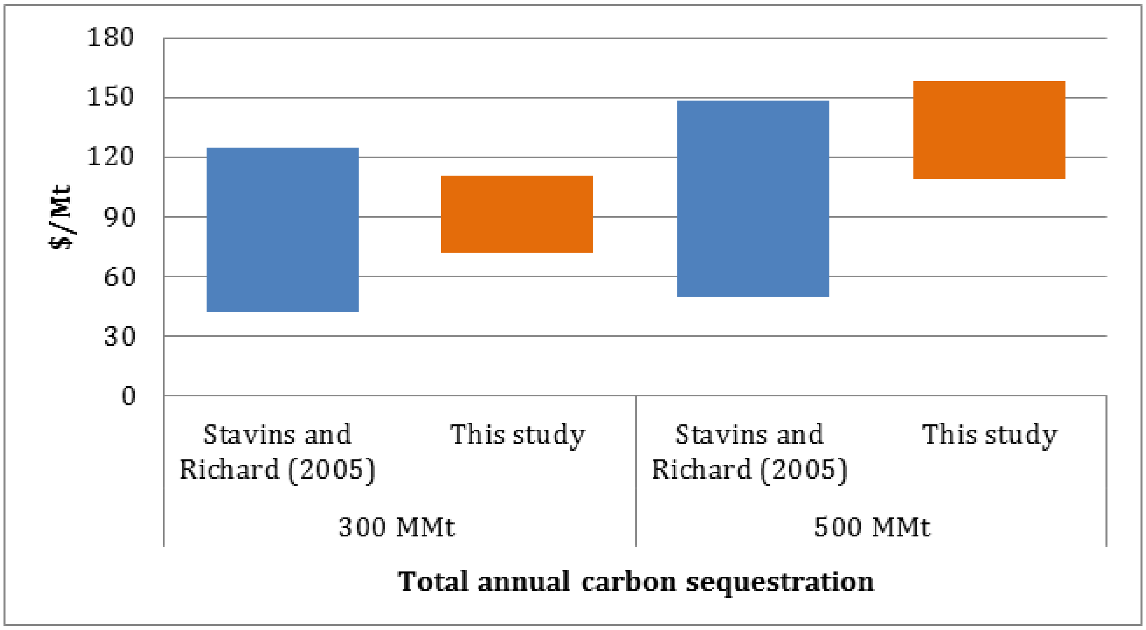
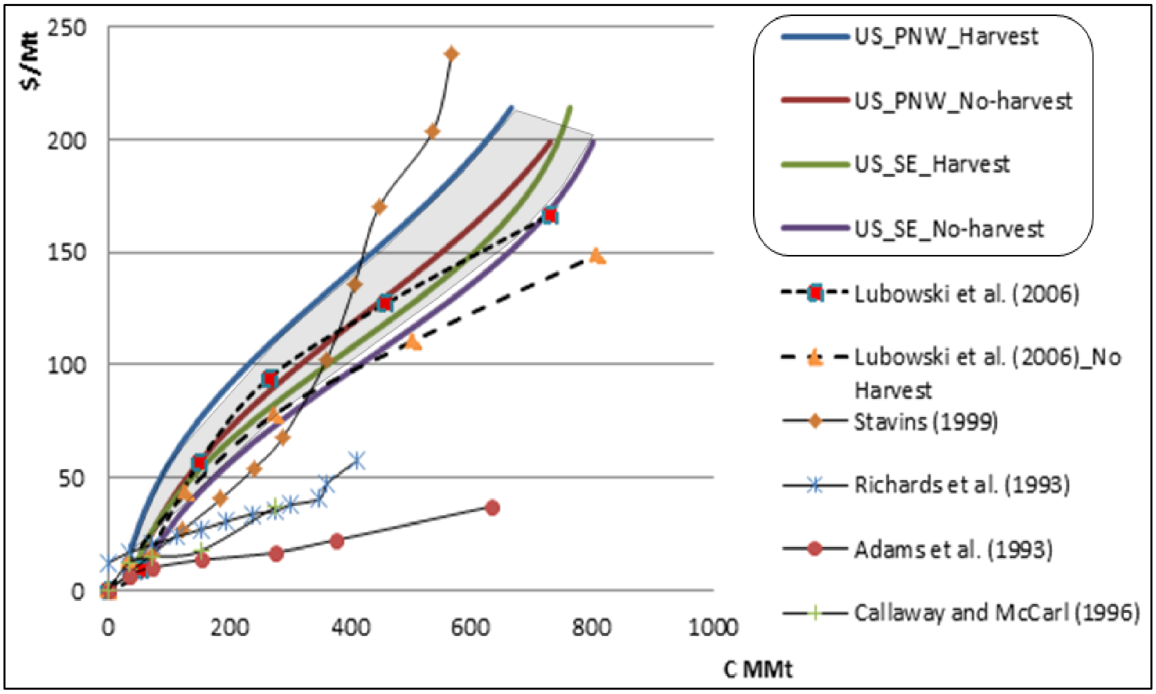


Figure 3.5. Comparison of carbon supply functions with other studies



Note: All carbon supply functions except the four from this study are from Lubowski et al (2006), and normalized at 2010 dollar.

CHAPTER FOUR

TARGETING INCENTIVES FOR CARBON SEQUESTRATION WITH SPATIALLY HETEROGENEOUS LAND TYPES UNDER ASYMMETRIC INFORAMTION

4.1 Introduction

Several studies have shown that forest-based mitigation activities can offset a large portion of carbon emissions with similar or lower cost than energy-based mitigation approaches (Richards and Stokes 2004, van Kooten et al. 2004, Stavins and Richards 2005, Mason and Plantinga 2011). Incentive programs have been suggested to encourage adoption of afforestation, reforestation, and certain silvicultural treatments to produce additional carbon sequestration, and several studies have analyzed and compared their efficacy and cost effectiveness (Lewandrowski et al. 2004, Lubowski et al. 2006, Gorte 2009, Johnson 2009). However, Murray et al. (2007) argued that carbon sequestration under an incentive program may not be entirely additional compared to what would be achieved without incentives, and that other factors could lead to lower amounts of carbon sequestration compared to what an incentive policy intends to achieve. For example, inefficient policy targeting strategies and asymmetric information can prevent optimal allocation of funds for boosting forest carbon sequestration given a budget constraint, and thus the amount of carbon sequestration actually achieved by the incentive policy might be lower than what the policy makers expected to achieve.

There are several studies which address the issue of losses of environmental benefits induced by suboptimal contract targeting[45] and asymmetric information. Some authors have compared the relative environmental performances of an incentive program under alternative targeting criteria and examined the potential benefit losses caused by suboptimal targeting. For example, Babcock et al. (1996) compared the environmental benefits of the Conservation Reserve Program (CRP) in terms of water erosion, wind erosion, surface water quality, and wildlife habitat under three alternative targeting criteria (benefit-to-cost ratio targeting, benefit targeting, and cost targeting) by considering cost and benefit heterogeneity. Babcock et al. (1997) argue that the wrong targeting tools to acquire environmental benefits can increase public expenditures, and that the difference in total benefits among alternative targeting criteria depend on the correlation between benefits and costs and their relative spatial variability. Zhao et al. (2003) compared the environmental impact of a subsidy directly targeting conservation tillage relative to targeting environmental benefits achieved through adoption of conservation tillage under heterogeneous costs and benefits. Antle et al. (2003) shows that a performance-based contract (per ton based payment) that takes into account spatial variability performs better than a practice-based contract (per acre based payment), even if additional costs to implement a performance-based contract are accounted.

Although an optimal targeting tool is applied, in the presence of asymmetric information an efficient outcome cannot be achieved because the marginal costs of

[45] Babcock et al. (1997) introduced three different targeting rules which are based on cost (acreage), benefit, and benefit to cost ratio. They defined the defined benefit-to-cost ratio targeting as optimal targeting tool, and benefit targeting and cost (acreage) targeting as suboptimal targeting tool, and compared environmental performances of suboptimal targeting relative to optimal targeting given spatially heterogeneous land types in terms of costs and benefits.

environmental benefits (carbon sequestration in this paper) faced by the policy maker are higher than the true level of marginal cost. The reason is that low cost types have an incentive (i.e. information rent) to pretend to be high cost types. Wu and Babcock (1996) show that the socially optimal level of benefits cannot be achieved when there is information asymmetry between the government and farmers. They recognized farmers' potential moral hazard by misrepresenting their cost types, because the government has less information than farmers to identify each individual farmer's cost types. Ferraro (2008) argues that reducing informational rents is important to maximize the amount of services obtained from limited budgets in the context of payments for environmental services. He adds that reducing informational rents also mitigates concerns about loss of benefits. Crépin (2005) examines the use of incentives to create wetlands in an asymmetric information context. She uses a theoretical principal-agent model to show that contract choice can create welfare gains, and that the choice of contract depends on the distribution of the unobserved landowner type, the elasticity of costs and benefits to wetland size changes, and on the costs of acquiring information. Sheriff (2009) discusses the possibility of inefficient allocations in a conservation payment program because of hidden information, and evaluates the relative costs of alternative land conservation mechanisms based on an empirical methodology by using commonly accessible data from government to identify the technology and distribution of types. Recently, Mason and Plantinga (2011) examine a contract scheme to mitigate the asymmetric information problem for forest carbon sequestration, and find that the optimal contract scheme is less costly than the uniform subsidy.

In previous studies the issues of inefficient outcomes induced by suboptimal contract targeting and asymmetric information have only been considered separately. In this paper, as a different feature from previous studies, I combine alternative contract targeting criteria and asymmetric information to analyze the relative performance, in terms of environmental benefits, of an incentive program aimed at forest carbon sequestration. Additionally, I consider spatial heterogeneity in costs and benefits to examine the relative performances of alternative incentive programs. There are several studies which mention that inherent heterogeneity in farm production and environmental outcomes must be taken into account for conservation programs because farm production and environmental benefits may vary across space due to different climate conditions and land qualities (Wu and Babcock 1996, Babcock et al. 1997, Zhao et al. 2003, Antle et al. 2003). Specifically, Babcock et al. (1997) showed that highly variable, negatively correlated benefits and costs perform better in producing environmental benefits, and that if cost variability is greater than benefit variability, particularly with negative correlation, acreage targeting becomes more consistent with optimal targeting (BC ratio targeting). However, this study has not been examined in the context of asymmetric information. In this essay, I incorporate asymmetric information into choice of targeting strategies given spatially heterogeneous cost and benefit types to examine how the presence of asymmetric information affects these findings. This is important because if their findings fail to hold under asymmetric information, then the conditions which yield an optimal outcome under perfect information are no longer optimal conditions under asymmetric information.

Thus, the main objective of this essay is to assess the benefits achieved by an incentive program using alternative targeting criteria in the presence of asymmetric information and heterogeneity in costs and benefits. More specifically, this essay will examine i) the relative environmental performances in terms of carbon sequestration and potential carbon benefit losses caused by asymmetric information under alternative targeting criteria, and how they may differ for different combinations of spatial variability between benefits and costs and the correlation between them, ii) under what conditions of spatial characteristics of benefits and costs, the findings under asymmetric information are consistent or inconsistent with those under perfect information, and iii) how asymmetric information, variability of benefits and costs, and their correlation, may affect the carbon supply function of afforestation in the PNW.

The results show that in the presence of asymmetric information, the combination of high cost-high benefit variability and negative correlation, which is the combination that achieves the greatest benefit gains under perfect information, can result in the greatest benefit losses. This implies that the greater the benefit gains under perfect information the greater the possibility of a loss of benefit under asymmetric information, and thus that for certain conditions the findings from this study are not consistent with those from Babcock et al. (1997). Specifically, a comparison of two targeting schemes shows that if cost variability is greater than benefit variability with negative correlation, the benefit achieved under benefit-cost ratio targeting can be lower than that under acreage targeting because of asymmetric information, so that an optimal targeting strategy under perfect information may no longer be optimal under asymmetric information.

A numerical analysis of carbon benefits through an afforestation program in the Pacific Northwest (PNW) region shows that the magnitude of carbon benefit losses associated with asymmetric information under benefit-cost ratio targeting is greater than that under acreage targeting. The carbon supply functions for the PNW region derived from this study show that as the degree of asymmetric information becomes greater, the carbon supply functions become steeper, and thus carbon sequestration becomes more expensive, while the price of carbon depends upon the spatial variability of carbon sequestration rates per acre and correlations between costs and carbon sequestration rates.

The remainder of this study is organized as follows. Section 2 presents the conceptual background and analytical framework, section 3 conducts numerical analyses under asymmetric information with various combinations of spatial variability and correlations, section 4 describes the results of numerical analyses of carbon sequestration through afforestation program in the PNW region, and derives carbon supply functions with respect to different level of variability, correlation, and degree of asymmetric problem, section 5 shows the key findings and the conclusion.

4.2. Analytical Framework

Suppose there are spatially heterogeneous types of forests in terms of costs and benefits of enrolling in an incentive program to increase carbon sequestration. For example, in Figure 4.1, forest land types can be classified into one of four regions in the cost-benefit plane (Babcock et al. 1997). Type I corresponds to low transition cost[46] and high level of carbon sequestration, Type II to high transition cost and high level of carbon sequestration, Type III corresponds to low transition cost and low level of carbon sequestration, and Type IV to high transition cost and low level of carbon sequestration.

I set up a conceptual model which considers two different targeting criteria and scenarios with and without asymmetric information.

4.2.1. Targeting strategies under perfect information

Suppose the policy maker propose an incentive program with per acre payments to individual landowners to produce additional carbon sequestration by changing land use or management practices. Individual landowners are assumed to participate in this program as long as their opportunity costs per acre by giving up their current land use or management practices are fully compensated. The policy maker has a budget of M to implement this incentive program. The area of land that can be conserved for carbon sequestration is denoted by x_i, for individual land types $i=1,2,\ldots I$. For simplicity, the costs of producing x are assumed to be linear, expressed by $C(x_i) = c_i x_i$, where c_i are marginal costs per acre of each land type i. The environmental benefit of carbon sequestration in x is assumed to be linear as well, expressed by $B(x_i) = b_i x_i$ for $i=1,2,\ldots,I$.

Suppose we consider two different targeting strategies following Babcock et al. (1997): Acreage maximization targeting (hereafter referred to as "Acreage targeting"),

[46] The transition cost implies the cost generated by adoption of a certain forest management practices or by land use conversion from other uses to forests.

and benefit-cost ratio maximization targeting (hereafter referred to as "BC ratio targeting"). Under acreage targeting, the policy maker's optimization problem with perfect information is specified as follows:

$$\max \sum_{i=1}^{I} x_i, \text{ s.t. } \sum_{i=1}^{I} c_i x_i \leq \text{M}.$$

The Lagrange function for the problem is $L = \sum_{i=1}^{I} x_i + \lambda\left(M - \sum_{i=1}^{I} c_i x_i\right)$, where λ is the shadow price of the budget constraint (*M*). Then the optimal solutions are given by x_i^* and λ^*. Thus, $x_i^* = \begin{Bmatrix} 0 \text{ if } 1/c_i < \lambda^* \\ x_i \text{ if } 1/c_i \geq \lambda^* \end{Bmatrix}$, so that the critical level of marginal cost c^* is given by $c_i = 1/\lambda^*$. Hence land with $c_i > 1/\lambda^*$ will not be enrolled in the carbon sequestration program, while land with $c_i \leq 1/\lambda^*$ will be enrolled in the program. As the budget level (*M*) increases, the critical level of marginal cost (c^*) increases, because $\partial\lambda^*/\partial M < 0$.

Under BC ratio targeting, the policy maker's optimization problem with perfect information is specified as follows:

$$\max \sum_{i=1}^{I} b_i x_i, \text{ s.t. } \sum_{i=1}^{I} c_i x_i \leq \text{M}.$$

The Lagrange function for the problem is $L = \sum_{i=1}^{I} b_i x_i + \lambda\left(M - \sum_{i=1}^{I} c_i x_i\right)$. The optimal solution of x for individual *i* is given by $x_i^* = \begin{Bmatrix} 0 \text{ if } b_i/c_i < \lambda^* \\ x_i \text{ if } b_i/c_i \geq \lambda^* \end{Bmatrix}$, so that land with $b_i/c_i \geq \lambda^*$ will be enrolled in the carbon sequestration program, while land with

$b_i / c_i < \lambda^*$ will not be enrolled in the program. Additionally, $\partial\lambda^* / \partial M < 0$, which implies that as the total budget (*M*) increases, the critical benefit-cost ratio (*b/c*) decreases.

<u>4.2.2. Targeting strategies under asymmetric information</u>

I consider the type of asymmetric information problem induced by unknown cost type, because it is difficult for policy makers to observe the true marginal cost of additional land enrollment of each individual forestland when the landowner overstates its cost. Suppose there is asymmetric information and the policy maker does not know the landowners' cost c_i. In this case a low cost type has incentive to pretend he is a high cost type to get a higher payment for producing x_i. For simplicity, suppose first that there are only two different land types in terms of marginal cost per acre, and suppose the marginal cost of type 1 is greater than that of type 2, i.e. $c_1 > c_2$. In the perfect information scenario, they are offered per acre payment c_1 and c_2 respectively. Since $c_1 > c_2$, with asymmetric information type 2 has incentive to pretend he is a high cost type to get higher payment c_1 from producing x_2. By doing so, type 2 can be offered the compensation c_1x_2, but its actual costs will be c_2x_2, and thus type 2 gets additional profit of $c_1x_2 - c_2x_2 > 0$, which can be interpreted as information rents of type 2.

If there are many different types of lands, then the landowners whose marginal costs are lower than the critical level (c^*) have an incentive to overstate their true marginal cost to get higher payments. I assume that landowners can observe the critical level of marginal cost that determines eligibility to enroll in the program from historical records of enrollment.[47] Low cost landowners therefore will have an incentive to overstate their cost up to this critical level c^*. Specifically, under acreage maximization targeting, I assume a low cost type uses the highest cost (c^*) as a reference to choose the stated costs because stated costs higher than the critical level would not be enrolled in the program. Then, the stated marginal cost under asymmetric information of the low cost type will be $\hat{c}_i = c_i + \delta(c^* - c_i)$, where $c^* \geq c_i$ and $\delta \in (0,1]$ represents the degree of asymmetric information determined by the level of regulator's ability to monitor or discriminate an actual cost type of land[48], thus $c^* \geq \hat{c}_i \geq c_i$. Figure 4.2 shows how costs change under asymmetric information with different targeting schemes graphically. As shown in Figure 4.2-a, a landowner with cost c_i gives a stated cost $\hat{c}_i$ somewhere between c_i and c^*, depending on δ. Then, the policy maker's budget constraint will be $\sum_{i=1}^{I} \hat{c}_i x_i \leq \mathrm{M}$, and the optimal solution $\hat{x}_i^*$ in the presence of asymmetric information when $0 < \delta < 1$ will be $\hat{x}_i^* = \begin{Bmatrix} 0 \text{ if } 1/\hat{c}_i < \hat{\lambda}^* \\ x_i \text{ if } 1/\hat{c}_i \geq \hat{\lambda}^* \end{Bmatrix}$, so that the critical level of marginal cost $\hat{c}^*$ is given by $\hat{c}^* = 1/\hat{\lambda}^* < c^*$. Note that if $\delta = 1$ this is equivalent to the case of a uniform payment per acre in terms of marginal cost. It is clear that since the low cost types

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[47] For example, landowners can access through internet or request the historical records of the annual rental payment of federally funded conservation program such as Conservation Reserve Program, Wetland Reserve Program, and Environmental Quality Incentives Program.

[48] $\delta = 0$ implies policy maker has perfect knowledge about the marginal cost of each type, while $\delta = 1$ implies policy maker has no ability to observe the marginal cost of each type.

overstate their costs, given level of budget, more lands will be ruled out from the incentive program.

Under BC ratio targeting, the land where $b_i/c_i \geq \lambda^*$ is enrolled in the program, thus the landowners for whom $b_i/c_i > \lambda^*$ have an incentive to pretend to be the high cost type by increasing their stated marginal cost to be where $b_i/c_i^* = \lambda^*$ given b_i remains the same. Thus, as shown in Figure 4.2-b, a landowner with cost c_i has an incentive to state a cost $\hat{c}_i$ between c_i and c_i^* given b_i. The marginal cost of a low cost type under asymmetric information will be $\hat{c}_i = c_i + \delta(c_i^* - c_i)$, where $\delta \in (0,1]$ and $c_i^* = \frac{1}{\lambda^*} b_i$ which represents critical level of marginal cost given b_i and $c_i^* \geq c_i$. Then, the budget constraint will be $\sum_{i=1}^{I} \hat{c}_i x_i \leq \mathrm{M}$, and the optimal solution $\hat{x}_i^*$ in the presence of asymmetric information when $0 < \delta < 1$ is $\hat{x}_i^* = \begin{Bmatrix} 0 \text{ if } b_i/\hat{c}_i < \hat{\lambda}^* \\ x_i \text{ if } b_i/\hat{c}_i \geq \hat{\lambda}^* \end{Bmatrix}$, thus, the lands with $b_i/\hat{c}_i \geq \hat{\lambda}^*$ will be enrolled in the incentive program. Since $\hat{c}_i < c_i^*$, the critical level of benefit-cost ratio under asymmetric information ($\hat{\lambda}^*$) is greater than that under perfect information (λ^*), which implies that fewer parcels will enroll for a given budget.

Suppose costs and benefits are continuously distributed, and suppose *f (b)* and *f(c)* are the marginal density functions of benefits (*b*) and costs (*c*) respectively, where c represents cost types of land determined by per acre annual cost of candidate land, $\underline{c} \leq c \leq \overline{c}$, and *b* represents benefit types of lands determined by per acre annual carbon sequestration rates, $\underline{b} \le b \le \bar{b}$. Then the joint density function is $f(c,b)$ and the total share of acreage will be defined as $\int_{b}^{\bar{b}} \int_{\underline{c}}^{c} f(c,b)dcdb$. The distribution of land types is assumed to be known to policy maker, but the cost type of particular individual is assumed to be unknown under asymmetric information.

Under acreage targeting, given budget constraints, the highest bid (c^*) under perfect information will be given by $1/\lambda^*$, which is the marginal cost of one unit of land. Then, acreage enrolled under perfect information is $X_1^* = X(c^*, \underline{b}) = X_0 \int_{\underline{c}}^{c^*} \int_{\underline{b}}^{\bar{b}} f(c,b)dcdb$, where X_0 is total candidate land. However in the presence of asymmetric information associated with unknown cost type, the total acreage enrolled will be determined by the critical marginal cost $\hat{c}^* = 1/\hat{\lambda}^*$, which is less than the critical level under perfect information (c^*) as long as $\delta > 0$. This leads to some of the lands being bid out of the program (ΔTA_1), which leads loss of benefit (ΔTB_1) as well. Thus, total acreage enrolled with unknown cost type is $\hat{X}_1^* = X(\hat{c}, \underline{b}) = X_0 \int_{\underline{c}}^{\hat{c}^*} \int_{\underline{b}}^{\bar{b}} f(\hat{c},b)d\hat{c}db$, total acreage loss is $\Delta TA_1 = X_1^* - \hat{X}_1^* \ge 0$, and total benefit loss is

$$\Delta TB_1 = X_0 \int_{\underline{c}}^{c^*} \int_{\underline{b}}^{\bar{b}} b \cdot f(c,b)dcdb - X_0 \int_{\underline{c}}^{\hat{c}^*} \int_{\underline{b}}^{\bar{b}} b \cdot f(\hat{c},b)d\hat{c}db \ge 0.$$

Under BC ratio targeting, since the land for which the benefit-cost ratio (*b/c*) is greater than or equal to λ^* is enrolled under perfect information, total acreage enrolled is $X_2^* = X(\bar{c}, c\lambda^*) = X_0 \int_{\underline{c}}^{\bar{c}} \int_{c\lambda^*}^{\bar{b}} f(c,b)dcdb$. However, in the presence of asymmetric information, the total acreage enrolled with unknown cost type will be determined by the cost for which the critical ratio of benefit and cost is $\hat{\lambda}^*$ which is greater than λ^* given fixed level of budget since $\hat{c}^* \leq c^*$. Thus, total acreage enrolled with unknown cost is $\hat{X}_2^* = X\left(\hat{c}, \underline{b}\right) = X_0 \int_{\underline{c}}^{b/\hat{\lambda}^*} \int_{\underline{b}}^{\bar{b}} f(\hat{c}, b) d\hat{c} db$, total acreage loss is $\Delta TA_2 = X_2^* - \hat{X}_2^* \geq 0$, and total benefit loss is $\Delta TB_2 = X_0 \int_{\underline{c}}^{\bar{c}} \int_{c\lambda^*}^{\bar{b}} b \cdot f(c,b) dc db - X_0 \int_{\underline{c}}^{b/\hat{\lambda}^*} \int_{\underline{b}}^{\bar{b}} b \cdot f(\hat{c}, b) d\hat{c} db \geq 0$.

The amount of benefit loss associated with asymmetric information also depends on the size of the budget (*M*). It is clear that as the size of the budget increases the critical level of marginal cost of land enrollment under acreage targeting and the critical ratio of benefits and costs under BC ratio targeting increase. I can also expect that as the distance from the marginal costs of low cost types to the critical level of marginal cost ($|c_i^* - c_i|$) become greater, the low cost type's information rent become larger, and thus the magnitude of benefit loss becomes larger as the size of the budget increases.

4.2.3. Effect of spatial characteristics under asymmetric information

Given the assumption that benefits and costs are jointly distributed, it is reasonable to expect that the characteristics of the joint distribution of benefits and costs, $f(c,b)$, affect the magnitude of benefit loss in the presence of asymmetric information. Babcock et al. (1997) have shown how the characteristics of the joint distribution of benefits and costs, such as a spatial variability[49] of costs and benefits and the correlation between them, affect the environmental outcomes of different targeting schemes. They showed that the benefits from benefit targeting are larger when the variability of benefits is greater, and similarly that the benefits from cost targeting are larger when the variability of costs is greater. In addition, for a given budget constraint, desired levels of environmental outcomes can be better achieved when benefits and costs are negatively correlated, regardless of targeting schemes. However, if we assume there is asymmetric information in terms of marginal costs, it is unclear that the findings of Babcock et al. (1997) still hold. Thus in this section I examine how the change in cost-benefit variability and correlation would affect the amount of benefits achieved by an incentive program under asymmetric information with two different contract targeting criteria: BC ratio targeting and acreage targeting.

1) *Effect of spatial variability*

Figure 4.3 shows how increases in spatial variability of costs and benefits affect the degree of loss of benefits. The dark shaded area represents relatively low variability, and as variability becomes greater, cost or benefit types disperse more widely to the light shaded area. I assume 50% of land enrollment in the program given targeting strategies under perfect information, so that the lands in area *P*, *Q*, and R in Figure 4.3 are enrolled in the incentive program. Area *P* represents relatively low cost type in terms of costs

[49] Spatial variability is the degree of spatial inequality. Given the same mean value of benefit or cost, greater spatial inequality of cost or benefit implies a greater spatial variability of costs or benefits (Babcock et al. 1997).

variability, and relatively high benefit type in terms of benefit variability compared to area *Q* and *R*. It is clear that the greater variability achieves the greater benefits under perfect information, since more lands in area *P* are enrolled first. Suppose there is asymmetric information in costs, and thus the type of lands whose marginal costs are lower than the critical level move toward the critical level by overstating their costs.

The key expected results with respect to increases in spatial variability under asymmetric information are as follows:

First, under acreage targeting, in Figure 4.3-a-i, as spatial variability of costs increases holding benefit variability constant, more land in area *P* (relatively lower cost type than area *Q*) will be enrolled. This results in an increase of information rent for low cost types since the expected distances in costs between low cost types and the critical level ($E(|c^* - c_i|)$) increases. As a result, the magnitude of benefit loss induced by asymmetric information become greater as cost variability becomes greater. In Figure 4.3-a-ii, the change in benefit variability does not affect the degree of asymmetric information, since land enrollment under acreage targeting depends only on costs, so that the degree of asymmetric information would not change in response to the change in benefit variability.

Second, under BC ratio targeting, on the other hand, in Figure 4.3-b-i, an increase in cost variability holding benefit variability constant leads to some land enrollment from area *P*, which represents relatively lower cost area than area *Q*. This increases the information rent of low cost types as well because the expected distance in costs between low cost types and the critical level ($E(|c_i^* - c_i|)$) increases. Therefore, as cost variability changes from low to high, the magnitude of benefit loss associated with asymmetric information becomes larger. In Figure 4.3-b-ii, an increase in benefit variability holding cost variability constant results in some enrollment from area *P*, which represents relatively higher benefit area than area *Q* and *R*. As the benefit variability increases, the critical level of cost per acre (c_i^*) increases, which results in an increase of the expected distances in costs between low cost types and the critical level ($E(|c_i^* - c_i|)$), and thus information rent increases. Thus greater benefit variability might lead to a greater amount of benefit loss under asymmetric information.

2) *Effect of correlations*

Figure 4.4 shows how spatial correlation between costs and benefits affects the degree of loss of benefits. The shaded area and the dotted area, respectively, represent negative and positive correlation between costs and benefits. Again, I assume 50% of land enrollment in the program given targeting strategies under perfect information. Area *P* represents relatively low cost and high benefit types, and area R represents relatively low cost and low benefit types.

Under perfect information, higher benefits can be achieved with negative correlation because the lands in area *P* are enrolled, whereas they are not enrolled with positive correlation. However, if the landowners with costs below the critical level overstate their costs under asymmetric information, then the key expected results are as follows:

First, under acreage targeting in Figure 4.4-a, the level of enrollment would not be affected by the correlation between costs and benefits. However, the benefit losses caused by asymmetric information are greater with negative correlation than with positive correlation, because relatively high benefit types (area *P*) would be bid out from the incentive program with negative correlation. Nevertheless, total expected benefit with negative correlation under asymmetric information is still greater than that with positive correlation, because relatively higher benefit types (given the same cost level) are enrolled first with negative correlation.

Second, under BC ratio targeting in Figure 4.4-b, the benefit losses caused by asymmetric information with negative correlation are greater than that with positive correlation, because lands in area P have greater information rent than lands in area *R* and *S*. In this case, the total benefit achieved is greater with negative correlation than with positive correlation under perfect information. However, this result may be reversed under asymmetric for a large enough budget and high enough degree of asymmetric information, because information rent of relatively low cost and high benefit types (area *P*) given negative correlation is greater than that of area *S* and *R*, which results in greater benefit losses with negative correlation than positive correlation.

Third, in comparing the two targeting criteria, it is clear that under perfect information BC ratio targeting is the optimal targeting relative to acreage targeting. However, under asymmetric information, if costs and benefits are negatively correlated, the information rent in area *P* under BC ratio targeting is greater than that under acreage targeting. This implies that larger benefit losses may occur with BC ratio targeting than with acreage targeting because of asymmetric information. This problem becomes more severe as the budget and the degree of asymmetric information increase, and thus if they are large enough BC ratio targeting may no longer be the optimal targeting strategy.

However, this graphical analysis does not allow us to see how much the loss of benefits in the presence of asymmetric problem would be, and it is also intractable to analytically examine the effects of spatial variability and correlation (Babcock et al. 1997). Thus, in the next section I conduct a numerical analysis to examine how large the benefit losses associated with asymmetric information would be under different targeting strategies and different level of spatial variability of costs and benefits and correlation between them.

4.3. Numerical Analysis of Carbon Benefit Losses under Asymmetric Information

In this section, I conduct a numerical analysis to show how much the variability of costs and benefits and their correlation affect the magnitude of benefit loss under asymmetric information with different targeting strategies.

The procedure to conduct the numerical analysis is as follows: i) specify marginal density functions for benefit and cost with different degrees of spatial variability, ii) randomly draw 50,000 combinations of benefits and costs normalized[50] between 0 and 1 using a Copula function[51] with three different sets of Spearman's rank correlations[52] ρ,

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[50] Costs and benefits are normalized between 0 and 1, because it is convenient to interpret them as proportions (Babcock et al. 1996, 1997).

[51] The Copula is a kind of distribution function which describes dependence structures among random variables. It allows us to specify a joint distribution with given marginal distributions (Trivedi and

where ρ = –0.5, 0, and 0.5, iii) rank the benefit and cost combinations according to costs (c) for acreage targeting and according to the ratio of benefits and cost (λ) for BC ratio targeting, iv) calculate total benefits under perfect information given different budget levels and obtain the critical level of costs (c^*) and the ratio of benefit and costs (λ^*) for each targeting strategy, and v) calculate total benefits achieved and benefit losses under asymmetric information given different budget levels and different degrees of asymmetric information (δ = 0.5 and δ =1).

I use the beta distribution as a marginal distribution for benefits and costs because it provides flexibility to assume different degrees of spatial variability according to combinations of the parameters α and β, which is expressed as $B(\alpha,\beta)$.[53] According to Babcock et al. (1997), $B(0.5,0.5)$, $B(2,2)$, and $B(50,50)$ represent a high, medium, and low degree of spatial variability, respectively. Given three different degrees of spatial

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Zimmer, 2005). Among several different kinds of Copula function, we use the Gaussian Copula, which is the most commonly used copula function, to construct a bivariate distribution of benefits and costs. The Gaussian Copula with bivariate normal structure can be written as follow:

$$C^{Ga}(u_1,u_2,\rho)=\Phi_2(\Phi^{-1}(u_1),\Phi^{-1}(u_2))=\int_{-\infty}^{\Phi^{-1}(u_1)}\int_{-\infty}^{\Phi^{-1}(u_2)}\frac{1}{2\pi\sqrt{(1-\rho^2)}}\exp\{-\frac{v_1^2-2\rho\, v_1v_2+v_2^2}{2(1-\rho^2)}\}dv_2dv_1 .$$

where Φ denotes the standard univariate normal distribution, Φ^{-1} denotes the inverse of a univariate normal distribution, Φ_2 denotes bivariate normal distribution, and ρ denotes the correlation of u_1 and u_2.

[52] Spearman's rank correlation is the linear correlation between two continuous distribution functions F_1(X) and F_2(Y), defined as $\rho(X,Y)=\rho(F_1(X),F_2(Y))$, which represents a measure of monotonic dependence between two random variables X and Y (Trivedi and Zimmer, 2005).

[53] Given randomly drawn combinations of benefits and costs from the copula function, I then obtain the value x, which is the inverse beta CDF for a given probability p and a given pair of parameters α and β. This can be written as follows:

$$x=F^{-1}(p\mid\alpha,\beta)=\{x:F(x\mid a,b)=p\}, \text{ where } p=F(x\mid\alpha,\beta)=\frac{1}{B(\alpha,\beta)}\int_0^x t^{\alpha-1}(1-t)^{\beta-1}dt, \text{ and}$$

B(α,β) is the Beta function. Each element of the output x is the value whose cumulative probability under the beta CDF defined by the corresponding parameters in a and b is specified by the corresponding value in p (Mathworks 2012).

variability, I calculate the benefits achieved and benefit losses because of asymmetric information with respect to three different sets of correlations (ρ) and two different degrees of asymmetric information (δ), under two different targeting strategies. Tables 4.1 through 4.4 show how spatial variability and correlation affect the amount of benefit achieved from an incentive policy given two different sizes of budget: a low level of budget covers less than 50% enrollment, and a high level of budget covers more than 50% enrollment.

To clearly explain the findings from the numerical analysis, and to be consistent with the findings from the conceptual model in the previous section, I describe three sets of results: i) when cost variability changes from low to high for a given constant benefit variability with zero correlation ($\rho = 0$), ii) when benefit variability changes from low to high for a given constant cost variability with zero correlation, and iii) when correlation changes from positive to negative given the same level of variability of costs and benefits.

4.3.1. BC ratio targeting

Table 4.1 shows the proportion of benefits achieved relative to the maximum available benefits under BC ratio targeting with perfect information. This proportion of maximum benefits achieved is shown for different cost-benefit variability and correlations.[54] The highest benefit is achieved with a combination of high cost and high benefit variability with negative correlation ($\rho = -0.5$), while a combination of low cost and low benefit

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[54] Maximum total benefits can be achieved with 100% of land enrollment in the incentive program.

variability with positive correlation ($\rho = 0.5$) produces the lowest benefits. If cost variability increases when benefit variability stays the same and correlation is zero, the amount of benefit achieved from the incentive policy increases. For example, the benefits achieved under high cost variability (ranging from 40.4% to 46.1%) are greater than under low cost variability (ranging from 12.7% to 21.1%). This is because more relatively low cost types enroll under high cost variability than under low cost variability.

If benefit variability increases when cost variability stays the same and correlation is zero, then more relatively high benefit types enroll given the same level of cost, thus the amount of benefit achieved becomes greater as well. For example, with a low budget the benefits achieved under high benefit variability (ranging from 12.7% to 40.4%) are greater than under low benefit variability (ranging from 21.1% to 46.1%).

In terms of correlation, when benefit and cost variability is fixed, benefits are greater if benefits and costs are negatively correlated, because more low cost and high benefit types enroll than when there is positive correlation. However, the difference in benefits across correlations decreases as the variability of cost and benefit decreases. This implies that if spatial variability is low, the benefit difference associated with correlations between benefits and costs will not be as large. These results are consistent with the results from Babcock et al. (1997).

Now suppose there is asymmetric information in costs. Table 4.2 shows total benefits achieved with BC ratio targeting under asymmetric information and benefit losses relative to the benefits under perfect information for different budget levels and degrees of asymmetric information.

First, if cost variability changes from low to high when benefit variability is constant with zero correlation, the benefit achieved with high cost variability is still the highest if the budget is low and $\delta = 0.5$. This is consistent with the perfect information scenario. However, this is not the case with a high budget and $\delta = 1$. Here the highest benefit is achieved when cost variability is low, because the magnitudes of benefit loss with high cost variability are greater than with low cost variability. This is because more land with relatively low cost will be left out of the incentive program with high cost variability due to the greater information rent. Thus if the budget level and the degree of asymmetric information (δ) reach beyond a certain critical level, the benefit achieved under low cost variability becomes greater than that under high cost variability.

Second, if benefit variability increases when cost variability stays the same with zero correlation, the benefit achieved from the policy increases as well. For example, total benefits achieved under high benefit variability range from 15.5% to 65.4%, which is greater than with low benefit variability (ranging from 11.3% to 53.8%). This is consistent with the case of perfect information, even if the benefit losses caused by asymmetric information are greater with high benefit variability than with low benefit variability because of relatively greater loss of high benefit type lands with high benefit variability.

Third, in terms of correlation between costs and benefits, with perfect information the incentive program always yields larger benefits when there is negative correlation than with positive correlation. However, this result may be reversed with asymmetric information if the budget and degree of asymmetric information (δ) are sufficiently high.

For example, with a low budget and δ=0.5, the highest benefit achieved with negative correlation (33.1%) is greater than that with positive correlation (24.2%), while with a high budget and δ=1, the highest benefit achieved with negative correlation (49.3%) is lower than that with positive correlation (52.8%). This can happen because information rents with negative correlation are greater than with positive correlation, and more lands with relatively low cost and high benefit types will be excluded out of the incentive program with negative correlation, which results in greater benefit losses. Thus, if the budget and degree of asymmetric information (δ) are sufficiently high, the benefit achieved with negative correlation is lower than that with positive correlation.

A key finding in this section is that the condition which produces the highest benefit under perfect information may no longer hold under asymmetric information. This difference becomes more marked as variability and the degree of asymmetric information (δ) increases. Therefore, the policy maker's ability to screen asymmetric information becomes more important if cost and benefit variability are high, particularly with negative correlation, which are the conditions causing high benefit losses because of higher information rent than other conditions under asymmetric information. However, if cost and benefit variability are low it would not be as important because the benefit losses under asymmetric information are not as severe regardless of the correlations.

4.3.2. Acreage targeting

Table 4.3 presents the proportion of maximum benefits achieved by the incentive program under acreage targeting with perfect information for different cost-benefit variability and correlations. The table shows that the highest benefit is achieved under a combination of high cost and high benefit variability with negative correlation ($\rho = -0.5$), while the lowest benefit is achieved under a combination of low cost and high benefit variability with positive correlation ($\rho = 0.5$).When there is no correlation ($\rho = 0$), as cost variability changes from low to high leaving benefit variability unchanged, the benefit achieved from the incentive policy increases. However, the benefit is not affected when only benefit variability changes, because land enrollment under acreage targeting depends only on costs. The table also shows that benefits are always higher when there is a negative correlation between benefits and costs, regardless of spatial variability. If costs and benefits are negatively correlated, as benefit variability increases with constant cost variability, the benefit obtained from the policy increases, while it decreases with positive correlation.

Suppose now there is asymmetric information. Table 4.4 shows total benefits achieved and benefit losses with acreage targeting under asymmetric information for different budget levels and degrees of asymmetric information.

First, with zero correlation, an increase in cost variability with constant benefit variability, increases the benefit achieved when the budget is low and δ=0.5. This is consistent with the perfect information scenario, even if there are benefit losses because of asymmetric information. However, as the budget level and the degree of asymmetric information increase, the benefit achieved under high cost variability is lower than that under low cost variability, which is inconsistent with the finding under perfect information. For example, with a high budget and δ=1 with zero correlation, the benefits achieved with high cost variability (30%) are lower than those with low cost variability

(49.4%). This is because the benefit losses associated with asymmetric information become more severe with high cost variability than with low cost variability, because the underlying intuition is that the greater information rent with high cost variability causes greater acreage loss of relatively low cost types.

Second, under acreage targeting changes in benefit variability leaving cost variability fixed with zero correlation do not affect the benefit achieved from the policy. As shown in Table 4.4, the benefits achieved with zero correlation are the same across benefit variability, while they differ across cost variability.

Third, in terms of correlation between benefits and costs, the benefits achieved with negative correlation (ranging from 12.3% to 67.3%) are always greater than that with positive correlation (ranging from 10.4% to 51.2%). This is consistent with the perfect information case, even if the benefit losses due to asymmetric information become greater as costs and benefits are negatively correlated. This is because, under acreage targeting, information rents are the same across correlations given the same cost variability and budget. Total acreages enrolled are the same, but relatively high benefit types enroll more with negative correlation than positive correlation within the same acreage of lands enrolled.

An important finding is that for a small budget and a low degree of asymmetric information a combination of high cost and high benefit variability with negative correlation generates the highest benefits, but as the budget and the degree of asymmetric information increase, this is no longer the best performing combination, because of greater acreage losses of low cost and high benefit type lands with this combination than others. This is important because what we believe as an optimal condition is no longer optimal under asymmetric information. Thus, this combination requires that the policy maker have a greater ability to screen asymmetric information. However, if cost variability is low, the benefit losses induced by asymmetric information are small, so it does not much require the policy maker's ability of screening.

4.3.3. BC ratio targeting vs. acreage targeting

Table 4.5 shows the performance of acreage targeting relative to BC ratio targeting. If the ratio of benefits from acreage targeting to the benefits from BC ratio targeting is more (less) than 1, the benefits achieved under acreage targeting are higher (lower) than under BC ratio targeting.

Under perfect information BC ratio targeting produces greater benefits than acreage targeting as in Babcock et al. (1997). This result also holds under asymmetric information if cost variability is lower than benefit variability, or if the correlation between benefits and costs is zero ($\rho = 0$) or positive ($\rho = 0.5$), regardless of the budget or the degree of information asymmetry (δ). However, this result can be reversed, so that acreage targeting performs better than BC ratio targeting (the ratio is greater than 1), particularly when benefits and costs are negatively correlated. The reason is that the magnitude of benefit loss caused by asymmetric information under BC ratio targeting becomes greater than that under acreage targeting when benefits and costs are negatively correlated ($\rho = -0.5$). The benefit loss can be even more severe with negative correlation, with a larger budget, a higher degree of information asymmetry (δ), and greater cost variability. As before, the reason is that the information rent of low cost and high benefit types under BC ratio targeting becomes greater than that under acreage targeting (see section 4.2.3-1). Thus, in the presence of asymmetric information, BC ratio targeting may no longer be the optimal targeting strategy.

To summarize, a key finding is that if costs and benefits are negatively correlated, and if cost variability is greater than benefit variability, the benefit-ratio between acreage targeting and BC ratio targeting is very close to 1 under perfect information, and greater than 1 under asymmetric information, as shown in Table 4.5. Thus, while BC ratio targeting is the better option in most cases, under the conditions identified in this section, acreage targeting may be the better option.

4.4. Empirical Application: Afforestation for Carbon Sequestration in the Pacific Northwest

In this section, I apply the preceding analysis to examine how asymmetric information affects the outcomes of an incentive program for carbon sequestration through afforestation. I rely on the results from the second essay to obtain marginal costs of sequestration and their spatial variability based on their statistical characteristics. Costs are normally distributed, truncated at zero with mean 121.068 and variance 59.895. However, since the data collected does not provide the marginal distribution of benefits, I specify the beta distribution as the marginal distribution for benefits, which corresponds to the three different degrees of spatial variability assumed in the previous section. The annual carbon sequestration rate per acre used as a measure of benefits in the PNW region ranges from 0.49 to 1.71 metric tons (Mt) per acre per year, which is estimated by using carbon yield tables from Smith et al. (2006) and assuming that stands are periodically harvested.

Given this information on costs and benefits of a tree planting program for carbon sequestration, I draw 50,000 combinations of carbon benefits and costs for three different levels of benefit variability and three correlations between costs and benefits. Then I conduct a numerical analysis which estimates the carbon sequestration potential and carbon benefit loss in the presence of asymmetric information under two different incentive targeting schemes: BC ratio targeting and acreage targeting. I use budget levels ranging from $500 million to $2,500 million, which would cover around 20~80% of the total acreage enrollment for a tree planting program in the Pacific Northwest (PNW) region when there is no asymmetric information. The total area in the PNW that could be used for afforestation is assumed to be 31.2 million acres.[55] Finally, I derive carbon supply functions under asymmetric information and compare them with those under perfect information.

4.4.1. Results of Numerical Analysis

Table 4.6 and 4.7 show the total carbon benefits and loss of carbon in the PNW region for different levels of variability, correlations, and degrees of asymmetric information under two different targeting strategies. The trends of carbon benefits and benefit losses across benefit variability for different levels of budget and degrees of asymmetric information

[55] The total available agricultural land area for the PNW region is determined based on *Farms, Land in Farms, and Livestock Operations 2010 Summary* released in 2011 by the National Agricultural Statistics Service (NASS), Agricultural Statistics Board, United States Department of Agriculture (USDA). The PNW region includes Oregon and Washington.

shown in the tables are consistent with the conceptual numerical analysis conducted in the previous section.

1) *BC ratio targeting*

Table 4.6-a shows the results for BC ratio targeting under perfect information. The total annual carbon sequestration (benefits) from the incentive program range from 9.4 to 30.4 million metric tons (MMt) for a budget ranging from \$500 million to \$2,500 million. Under asymmetric information, carbon sequestration ranges from 7.7 to 22.1 MMt at $\delta = 0.5$, and from 6.1 to 17.2 MMt at $\delta = 1$. In Table 4.6-b, carbon benefit losses associated with asymmetric information range from 1.6 to 11.5 MMt, and from 3.1 to 18 MMt at $\delta = 0.5$ and $\delta = 1$, respectively. The magnitude of carbon benefit loss increases as benefit variability goes up, and is greater as the budget and degree of asymmetric information (δ) increase. This is consistent with the results from the previous section. As a result, for a large enough budget, the carbon sequestration potential with low benefit variability becomes greater than that with high benefit variability. This is shown in Figure 4.5, where these switching points (dot circle area) are placed somewhere between \$2,000~\$2,500 million for $\delta = 0.5$, and between \$1,500~\$2,000 million for $\delta = 1$ with zero correlation. This result indicates that if the budget level and the level of enrollment desired for the incentive program is less than the switching points, then more carbon sequestration is achieved with high benefit variability than with low benefit variability. This happens even if greater benefit losses occur with high benefit variability under asymmetric information.

Table 4.6 also shows how carbon benefits change with the correlation between costs and benefits. For a given level of benefit variability, the carbon benefit losses with negative correlation range from 2.3 to 18 MMt, while losses with positive correlation range from 1.6 to 10.7 MMt. Hence, the carbon benefit loss with negative correlation is greater than that with positive correlation. As a result, the carbon benefits with positive correlation become higher than those with negative correlation at a budget between \$2,000~\$2,500 million when $\delta = 0.5$, and between \$1,000~\$1,500 million when $\delta = 1$. This result indicates that even if the magnitude of carbon loss in the presence of asymmetric information is greater with negative correlation, the carbon sequestration potential with negative correlation is still greater than that with positive correlation, if total costs are less than \$1,500 million, which corresponds to around 35% of lands enrolled.

An important conclusion that follows from these results is that a combination of high benefit variability and negative correlation, which leads to the highest benefit loss under asymmetric information, requires the policy maker to have a higher capability to monitor true costs in a tree planting program, while a combination of high benefit variability and positive correlation requires less monitoring capability.

2) *Acreage targeting*

Table 4.7 shows the results for acreage targeting. With perfect information, the total annual carbon benefits from the incentive program range from 8.1 to 29.3 million metric tons (MMt) given a budget between \$500 million and \$2,500 million. Under asymmetric information, benefits range from 6.2 to 20.8 MMt at $\delta = 0.5$, and from 4.5 to 18.5 MMt at $\delta = 1$.

The amount of carbon benefit losses associated with asymmetric information ranges from 1.9 to 8.5 MMt, and from 3.6 to 10.8 MMt with $\delta = 0.5$ and $\delta = 1$, respectively (Table 4.7-b). Under acreage targeting, enrollment in the tree planting program is not affected by changes in the variability of the carbon sequestration rate. Hence, if there is no correlation between costs and benefits, the carbon benefits achieved across different level of benefit variability remain the same. However, with negative correlation the largest amount of carbon sequestration is achieved with high benefit variability (ranges from 7.8 to 20.8 MMt), while with positive correlation, the most sequestration is achieved with low benefit variability (ranges from 5.9 to 18 MMt).

Table 4.7 also shows that the carbon benefits achieved with negative correlation (ranging from 8.5 to 18.5 MMt) are consistently greater than those achieved with positive correlation (range from 6.2 to 15.5 MMt). As argued in the preceding section, this is because more lands with relatively higher carbon sequestration rate enroll for a given level of costs, even if some lands which would be enrolled under perfect information do not enroll when there is asymmetric information.

Another important finding under acreage targeting is that the carbon benefits achieved with high benefit variability at a high degree of asymmetric information ($\delta = 1$), which range from 7.9 to 18.5 MMt, are similar to those achieved with low benefit variability at low degree of asymmetric information ($\delta = 0$), ranging from 7.9 to 18 MMt. This implies that the policy maker's ability to monitor the true marginal cost in a tree planting program is less important with the combination of high benefit variability and negative correlation than with the combination of low benefit variability and positive correlation.

3) *BC ratio targeting vs. Acreage targeting*

A comparison of total carbon benefits between the two targeting tools for an afforestation program suggest that, in most cases, BC ratio targeting performs better than acreage targeting, with or without asymmetric information. In addition, the difference in carbon sequestration potential between the two targeting tools decreases as benefit variability changes from high to low. However, as shown in Figure 4.6, if benefits and costs are negatively correlated ($\rho = -0.5$) and there is asymmetric information ($\delta = 0.5,$ or 1), then as the budget level increases, the carbon sequestration potential of acreage targeting becomes greater than that of BC ratio targeting. The reason behind this is that with negative correlation the information rent of low cost and high benefit lands is greater with BC ratio targeting than with acreage targeting.

In conclusion, recognition of spatial characteristics of costs and benefits can be useful when a policy maker chooses a targeting strategy for an incentive program for carbon sequestration through afforestation. For example, if spatial variability is low, the difference in carbon sequestration between the two targeting strategies is small regardless of correlation, and thus the choice of targeting strategy may not as important. If spatial variability is high, and costs and benefits are negatively correlated, acreage targeting may be a better option than BC ratio targeting.

4.4.2. Derivation of carbon supply functions

Based on the results of the numerical analysis of carbon sequestration potential with various combinations of cost and benefit variability and correlations under both perfect and asymmetric information, I generate carbon supply functions corresponding to each combination of variability, correlation, and degree of asymmetric information. Since there are 27 different combinations in terms of variability, correlation (ρ), and degree of asymmetric information (δ), to simplify I first derive three groups of supply functions for three different degrees of asymmetric information for each targeting tool. Within each group, I derive carbon supply functions with respect to different levels of correlations, as shown in Figure 4.7. It is clear that as the degree of asymmetric information increases, carbon supply functions shift up, and costs of carbon sequestration increase.

Under BC ratio targeting with perfect information ($\delta = 0$), as correlation changes from negative to positive, carbon supply functions shift up, so that cost of carbon sequestration increases. In the presence of asymmetric information, the cost of carbon sequestration is lower with negative correlations than with positive correlations, if annual carbon sequestration is less than 19~20 MMt at $\delta = 0.5$, and 9.9~12 MMt at $\delta = 1$, respectively (Figure 4.7-a). If annual carbon sequestration exceeds those amounts, carbon sequestration costs more with negative correlation than with positive correlation. On the other hand, under acreage targeting, within the same variability of costs and benefits, supply functions with negative correlation are always flatter than with positive correlation, so that the price of carbon with negative correlation is cheaper than that with positive correlation, even with asymmetric information (Figure 4.7-b).

In Figure 4.8, I also derive carbon supply functions with respect to different levels of carbon benefit variability for a given cost variability derived from the econometric analysis.

Under BC ratio targeting with perfect information ($\delta = 0$), as carbon benefit variability changes from low to high, carbon supply functions shift down, and thus the cost of carbon sequestration decreases. With asymmetric information, if annual carbon sequestration is less than 19.4~21 MMt at $\delta = 0.5$, and 12~14 MMt at $\delta = 1$, respectively, carbon sequestration with high benefit variability costs less than with medium and low variability. If annual carbon sequestration increases more than that amount, the cost of carbon sequestration with respect to benefit variability will be reversed (Figure 4.8-a). Under acreage targeting, on the other hand, the difference in variability of carbon benefits does not change the carbon supply functions (Figure 4.8-b). A comparison of carbon supply functions derived from the two different targeting tools suggests that in most cases the cost of carbon under BC ratio targeting is cheaper than that under acreage targeting, but this can be reversed with high level of benefit variability and high degree of asymmetric information ($\delta = 1$).

4.5. Conclusion

This study is motivated by concerns about the possibility of benefit loss from incentive programs for carbon sequestration in the presence of asymmetric information. I expect that the magnitude of benefit losses under asymmetric information will depend on the joint distribution of costs and benefits, specifically on their spatial variability and the correlation between them. I examine the basic intuition behind the effects on asymmetric information on BC ratio targeting and acreage targeting using a simple conceptual model. Then I use numerical analysis to examine how the spatial variability and correlation of costs and benefits affect the benefit loss under asymmetric information. Finally, I derive carbon supply functions for an afforestation program in the PNW region with various combinations of spatial variability and correlations for a given budget level.

The main finding of this analysis is that a combination of high cost and high benefit variability with negative correlation, which is the combination that achieves the greatest benefit under perfect information, results in the greatest benefit loss under asymmetric information. This implies that the optimal targeting strategy under perfect information may not be preferred under asymmetric information. In particular, this is the case when the budget level and the degree of asymmetric information are high enough, so that under these conditions the policy maker’s ability to screen asymmetric information becomes more important. However, if cost and benefit variability are low the benefit loss under asymmetric information is not as severe, regardless of the correlations. In this case an optimal targeting strategy under perfect information is still optimal under asymmetric information, and thus it does not require highly accurate monitoring by the policy maker.

Finally, I want to note that the measurement and monitoring costs for implementing incentive program are not included. If they are taken into account, the performance of BC ratio targeting relative to acreage targeting may become lower, and the switching point that acreage targeting become more efficient than BC ratio targeting may become lower as well.

Despite of this limitation, an important contribution of this study is that, by incorporating asymmetric information issues into contract targeting strategies given spatially heterogeneous types of costs and benefits, it suggests how policy makers may choose the best targeting tool for a given level of budget in the presence of asymmetric information. A possible application of the insights derived in this study is that, in the presence of heterogeneous forest types, knowing the magnitude of benefit losses caused by asymmetric information may allow a policymaker to choose targeting strategies and the level of monitoring for a given budget level. This may help the policy maker minimize potential carbon benefit losses caused by asymmetric information. These results may apply to other environmental services as well.

4.6. References

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4.7. Tables

Table 4.1. Proportion of maximum benefit achieved under BC ratio targeting with perfect information

	Budget (M):	Low			High		
C-var	B-var	ρ=-0.5	ρ=0	ρ=0.5	ρ=-0.5	ρ=0	ρ=0.5
High	High	0.584	0.461	0.333	0.941	0.875	0.770
	Medium	0.511	0.426	0.338	0.851	0.796	0.725
	Low	0.426	0.404	0.383	0.757	0.737	0.719
Medium	High	0.396	0.321	0.242	0.907	0.845	0.760
	Medium	0.336	0.278	0.216	0.800	0.745	0.675
	Low	0.261	0.244	0.228	0.691	0.671	0.652
Low	High	0.225	0.211	0.195	0.840	0.819	0.801
	Medium	0.194	0.180	0.166	0.711	0.690	0.671
	Low	0.134	0.127	0.119	0.569	0.556	0.540

Table 4.2. Proportions of benefit and benefit losses achieved under BC ratio targeting with asymmetric information

			Total Benefits						Benefit Losses relative to perfect information					
			δ=0.5			δ=1			δ=0.5			δ=1		
Budget	C-var	B-var	ρ=-0.5	ρ=0	ρ=0.5	ρ=-0.5	ρ=0	ρ=0.5	ρ=-0.5	ρ=0	ρ=0.5	ρ=-0.5	ρ=0	ρ=0.5
Low	High	High	0.331	0.290	0.237	0.179	0.168	0.155	0.253	0.171	0.096	0.405	0.293	0.178
		Medium	0.294	0.265	0.230	0.160	0.152	0.143	0.217	0.160	0.108	0.350	0.273	0.194
		Low	0.258	0.250	0.242	0.145	0.143	0.140	0.169	0.154	0.141	0.281	0.261	0.243
	Medium	High	0.310	0.261	0.208	0.231	0.204	0.175	0.087	0.060	0.034	0.165	0.116	0.066
		Medium	0.263	0.226	0.185	0.196	0.177	0.155	0.073	0.052	0.031	0.140	0.101	0.061
		Low	0.210	0.199	0.188	0.163	0.157	0.151	0.051	0.045	0.039	0.098	0.087	0.077
	Low	High	0.216	0.202	0.189	0.206	0.194	0.183	0.010	0.008	0.006	0.020	0.016	0.012
		Medium	0.182	0.171	0.160	0.171	0.162	0.153	0.012	0.009	0.006	0.023	0.018	0.013
		Low	0.129	0.123	0.116	0.123	0.118	0.113	0.006	0.004	0.003	0.011	0.009	0.006
High	High	High	0.446	0.562	0.607	0.414	0.415	0.464	0.495	0.312	0.163	0.527	0.460	0.306
		Medium	0.485	0.536	0.551	0.353	0.358	0.393	0.366	0.260	0.174	0.498	0.438	0.332
		Low	0.494	0.499	0.500	0.294	0.305	0.314	0.262	0.238	0.219	0.463	0.433	0.405
	Medium	High	0.513	0.604	0.632	0.443	0.454	0.512	0.393	0.241	0.128	0.464	0.390	0.249
		Medium	0.552	0.568	0.566	0.393	0.421	0.463	0.248	0.177	0.109	0.407	0.324	0.212
		Low	0.538	0.535	0.531	0.399	0.408	0.417	0.154	0.137	0.121	0.292	0.263	0.236
	Low	High	0.626	0.641	0.654	0.480	0.496	0.528	0.213	0.178	0.146	0.359	0.323	0.272
		Medium	0.591	0.590	0.589	0.481	0.495	0.510	0.120	0.101	0.083	0.229	0.195	0.162
		Low	0.531	0.525	0.518	0.493	0.495	0.497	0.039	0.031	0.021	0.077	0.061	0.042

Table 4.3. Proportions of maximum benefit achieved under acreage targeting with perfect information

	Budget (M):	Low			High		
C-var	B-var	ρ=-0.5	ρ=0	ρ=0.5	ρ=-0.5	ρ=0	ρ=0.5
High	High	0.542	0.402	0.268	0.849	0.734	0.624
	Medium	0.495	0.402	0.315	0.811	0.734	0.661
	Low	0.425	0.402	0.382	0.754	0.734	0.716
Medium	High	0.353	0.242	0.135	0.795	0.667	0.544
	Medium	0.315	0.242	0.172	0.752	0.667	0.587
	Low	0.259	0.242	0.226	0.689	0.667	0.649
Low	High	0.188	0.120	0.054	0.680	0.539	0.403
	Medium	0.165	0.120	0.076	0.631	0.539	0.451
	Low	0.130	0.120	0.110	0.560	0.539	0.520

Table 4.4. Proportions of total benefit and benefit losses achieved under acreage targeting with asymmetric information

			Total Benefits						Benefit Losses relative to perfect information					
			δ=0.5			δ=1			δ=0.5			δ=1		
Budget	C-var	B-var	ρ=-0.5	ρ=0	ρ=0.5	ρ=-0.5	ρ=0	ρ=0.5	ρ=-0.5	ρ=0	ρ=0.5	ρ=-0.5	ρ=0	ρ=0.5
Low	High	High	0.361	0.249	0.140	0.220	0.141	0.067	0.181	0.154	0.128	0.322	0.261	0.201
		Medium	0.323	0.249	0.177	0.194	0.141	0.092	0.172	0.154	0.138	0.300	0.261	0.223
		Low	0.267	0.249	0.232	0.154	0.141	0.130	0.159	0.154	0.150	0.271	0.261	0.252
	Medium	High	0.295	0.198	0.104	0.239	0.156	0.076	0.057	0.044	0.032	0.113	0.086	0.059
		Medium	0.263	0.198	0.135	0.211	0.156	0.102	0.052	0.044	0.037	0.104	0.086	0.070
		Low	0.213	0.198	0.183	0.169	0.156	0.143	0.046	0.044	0.043	0.091	0.086	0.083
	Low	High	0.183	0.117	0.052	0.178	0.113	0.050	0.005	0.003	0.002	0.009	0.007	0.004
		Medium	0.161	0.117	0.073	0.157	0.113	0.071	0.004	0.003	0.003	0.008	0.007	0.005
		Low	0.127	0.117	0.107	0.123	0.113	0.104	0.004	0.003	0.003	0.007	0.007	0.006
High	High	High	0.634	0.493	0.356	0.420	0.300	0.181	0.215	0.240	0.268	0.429	0.433	0.442
		Medium	0.585	0.493	0.404	0.378	0.300	0.223	0.226	0.240	0.257	0.433	0.433	0.439
		Low	0.514	0.493	0.474	0.316	0.300	0.283	0.240	0.240	0.243	0.438	0.433	0.434
	Medium	High	0.673	0.532	0.395	0.544	0.407	0.273	0.122	0.136	0.148	0.251	0.261	0.271
		Medium	0.624	0.532	0.443	0.496	0.407	0.320	0.128	0.136	0.143	0.256	0.261	0.267
		Low	0.554	0.532	0.512	0.427	0.407	0.388	0.135	0.136	0.137	0.262	0.261	0.261
	Low	High	0.658	0.517	0.380	0.636	0.494	0.358	0.022	0.022	0.023	0.044	0.045	0.046
		Medium	0.609	0.517	0.428	0.586	0.494	0.406	0.022	0.022	0.023	0.045	0.045	0.045
		Low	0.538	0.517	0.497	0.516	0.494	0.475	0.022	0.022	0.022	0.045	0.045	0.045

Table 4.5. Benefits ratio between BC ratio targeting and acreage targeting

			Perfect info. (δ=0)			Asymmetric info. (δ=0.5)			Asymmetric info. (δ=1)		
Budget	C-var	B-var	ρ=-0.5	ρ=0	ρ=0.5	ρ=-0.5	ρ=0	ρ=0.5	ρ=-0.5	ρ=0	ρ=0.5
Low	High	High	0.929	0.874	0.805	1.092	0.858	0.593	1.230	0.843	0.435
		Low	0.998	0.997	0.997	1.035	0.994	0.960	1.066	0.992	0.929
	Low	High	0.832	0.570	0.278	0.849	0.577	0.276	0.866	0.584	0.276
		Low	0.970	0.943	0.926	0.985	0.950	0.922	1.001	0.956	0.918
High	High	High	0.902	0.839	0.810	1.421	0.878	0.586	1.014	0.724	0.391
		Low	0.997	0.995	0.996	1.039	0.989	0.946	1.076	0.984	0.899
	Low	High	0.810	0.658	0.504	1.051	0.807	0.581	1.323	0.997	0.677
		Low	0.984	0.970	0.963	1.013	0.984	0.959	1.046	1.000	0.955

Note: The ratio less (more) than 1 implies the benefits achieved under acreage targeting is less (more) than that under BC ratio targeting.

Table 4.6. Total carbon sequestration and loss of carbon by spatial variability and correlation in PNW region under BC ratio targeting

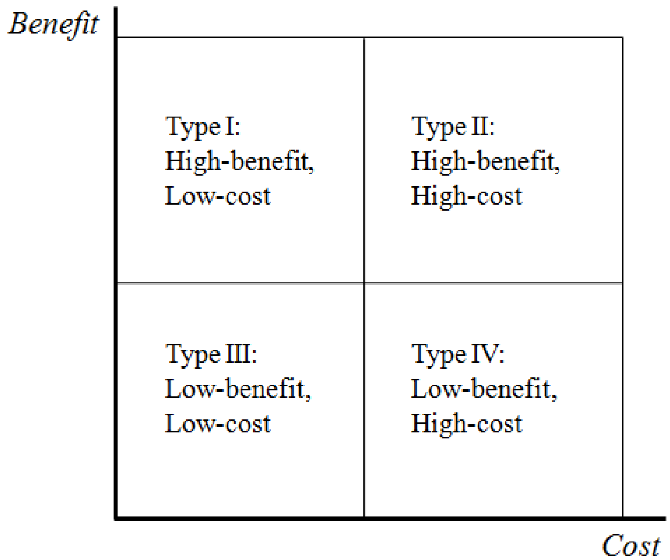
	B variability::	High			Medium			Low		
	Correlation:	ρ=-0.5	ρ=0	ρ=0.5	ρ=-0.5	ρ=0	ρ=0.5	ρ=-0.5	ρ=0	ρ=0.5
	Budget ($ million)	a. Total carbon sequestration, MMt								
Perfect Info.	$500	13.405	11.496	9.422	12.187	10.830	9.357	10.725	10.357	10.009
	$1500	24.221	22.220	19.822	22.417	21.016	19.319	20.578	20.191	19.797
	$2500	30.355	29.347	27.661	29.153	28.240	26.990	27.740	27.457	27.168
Asymmetric info., δ=0.5	$500	10.248	9.129	7.843	9.343	8.570	7.668	8.392	8.193	7.978
	$1500	17.554	17.335	16.493	16.937	16.606	15.996	16.252	16.130	16.001
	$2500	18.888	20.775	22.133	20.594	21.426	21.900	21.385	21.485	21.559
Asymmetric info., δ=1	$500	7.373	6.909	6.324	6.745	6.457	6.054	6.223	6.160	6.065
	$1500	12.057	12.921	13.320	12.108	12.551	12.828	12.254	12.341	12.426
	$2500	12.210	14.380	17.127	13.854	15.523	17.177	15.726	16.086	16.426
		b. Loss of carbon benefit relative to perfect information, MMt								
Asymmetric info., δ=0.5	$500	3.157	2.368	1.579	2.844	2.260	1.689	2.333	2.164	2.031
	$1500	6.667	4.885	3.329	5.480	4.410	3.323	4.326	4.061	3.796
	$2500	11.466	8.572	5.528	8.559	6.814	5.090	6.355	5.972	5.609
Asymmetric info., δ=1	$500	6.032	4.587	3.098	5.441	4.373	3.302	4.502	4.196	3.944
	$1500	12.164	9.299	6.502	10.309	8.465	6.491	8.324	7.850	7.371
	$2500	17.965	14.967	10.534	15.299	12.717	9.813	12.014	11.371	10.742

Table 4.7. Total Benefit by spatial variability and correlation in PNW region under Acreage targeting

B variability:		High			Medium			Low		
Correlation:		ρ=-0.5	ρ=0	ρ=0.5	ρ=-0.5	ρ=0	ρ=0.5	ρ=-0.5	ρ=0	ρ=0.5
	Budget ($ million)	a. Total carbon sequestration, MMt								
Perfect Info.	$500	12.615	10.312	8.057	11.854	10.312	8.843	10.707	10.312	9.987
	$1500	22.690	20.151	17.567	21.827	20.151	18.474	20.545	20.151	19.763
	$2500	29.253	27.423	25.584	28.646	27.423	26.216	27.711	27.423	27.135
Asymmetric info., δ=0.5	$500	10.144	8.140	6.168	9.481	8.140	6.854	8.470	8.140	7.870
	$1500	18.492	15.914	13.304	17.606	15.914	14.227	16.293	15.914	15.539
	$2500	20.834	18.361	15.836	19.983	18.361	16.725	18.719	18.361	17.989
Asymmetric info., δ=1	$500	7.758	6.111	4.449	7.214	6.111	5.028	6.369	6.111	5.894
	$1500	14.718	12.308	9.907	13.899	12.308	10.762	12.674	12.308	11.994
	$2500	18.486	15.916	13.305	17.600	15.916	14.228	16.287	15.916	15.540
b. Loss of carbon benefit relative to perfect information, MMt										
Asymmetric info., δ=0.5	$500	2.471	2.172	1.889	2.373	2.172	1.988	2.237	2.172	2.117
	$1500	4.198	4.237	4.263	4.221	4.237	4.247	4.252	4.237	4.223
	$2500	8.419	9.062	9.748	8.663	9.062	9.491	8.992	9.062	9.146
Asymmetric info., δ=1	$500	4.857	4.201	3.607	4.640	4.201	3.815	4.338	4.201	4.093
	$1500	7.973	7.843	7.660	7.928	7.843	7.712	7.871	7.843	7.768
	$2500	10.767	11.507	12.279	11.046	11.507	11.987	11.424	11.507	11.595

4.8. Figures

Figure 4.1. Forestland types in Cost-benefit relationship



Source: Babcock et al. (1997)

Figure 4.2. Changes in costs under asymmetric information with different targeting schemes

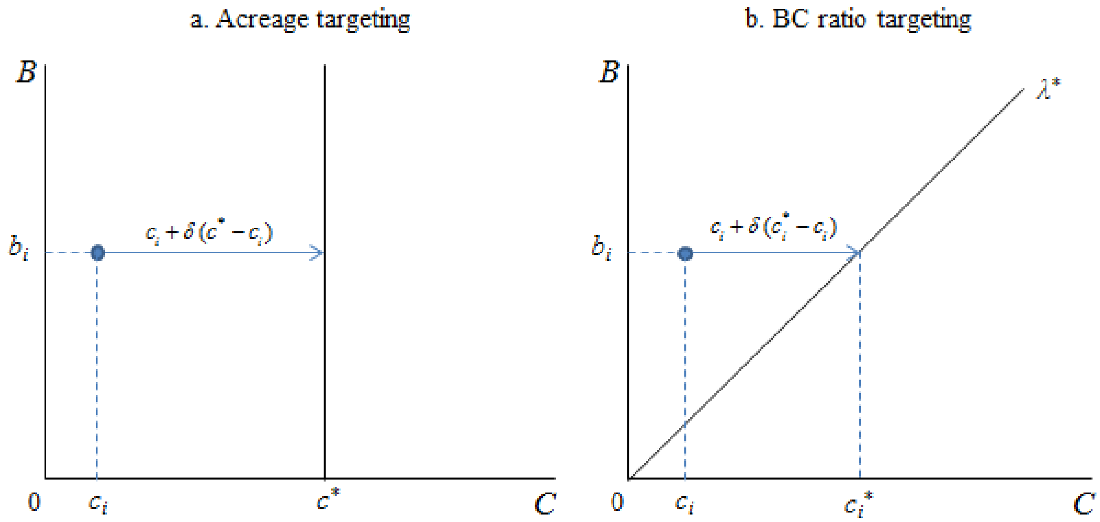
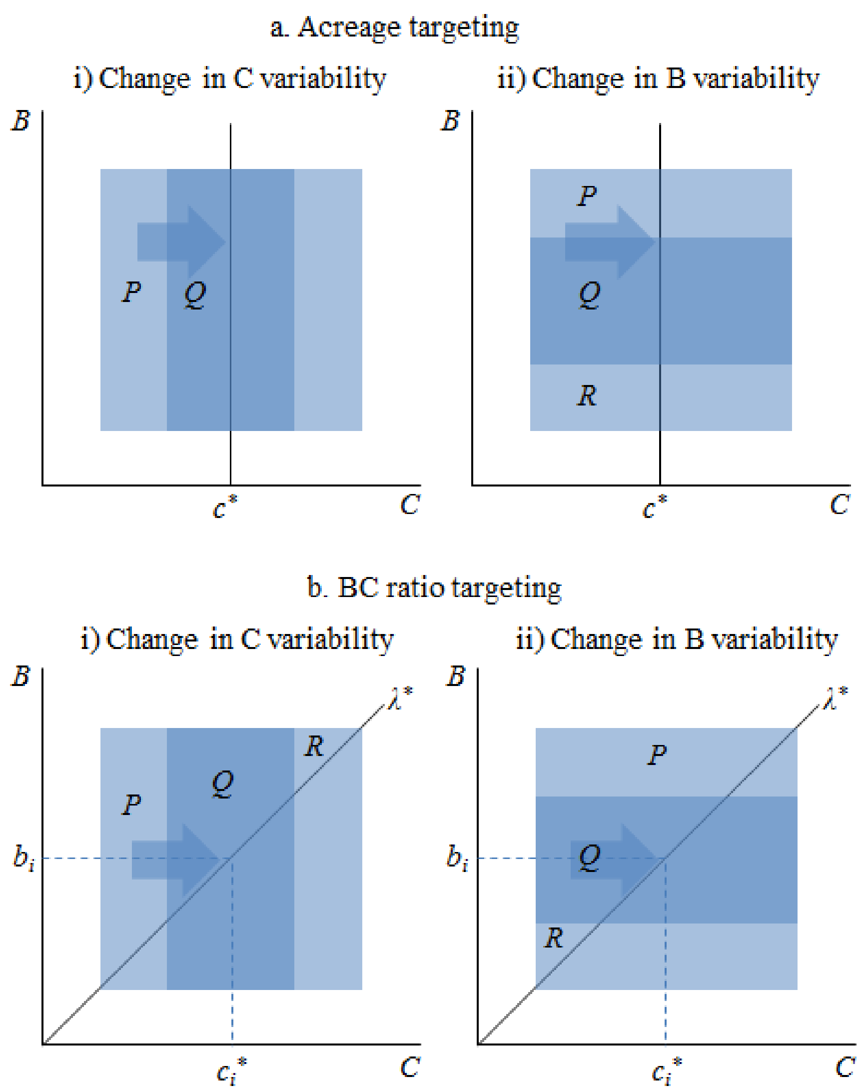


Figure 4.3. Expected effects of variability on degree of asymmetric information and benefit losses



Note: i) Arrows in the figures represent the direction of the low cost types move toward the critical level of cost.

ii) Under BC ratio targeting, $c_i^* = b_i(1/\lambda^*)$

Figure 4.4. Effect of correlation on degree of asymmetric information and benefit losses

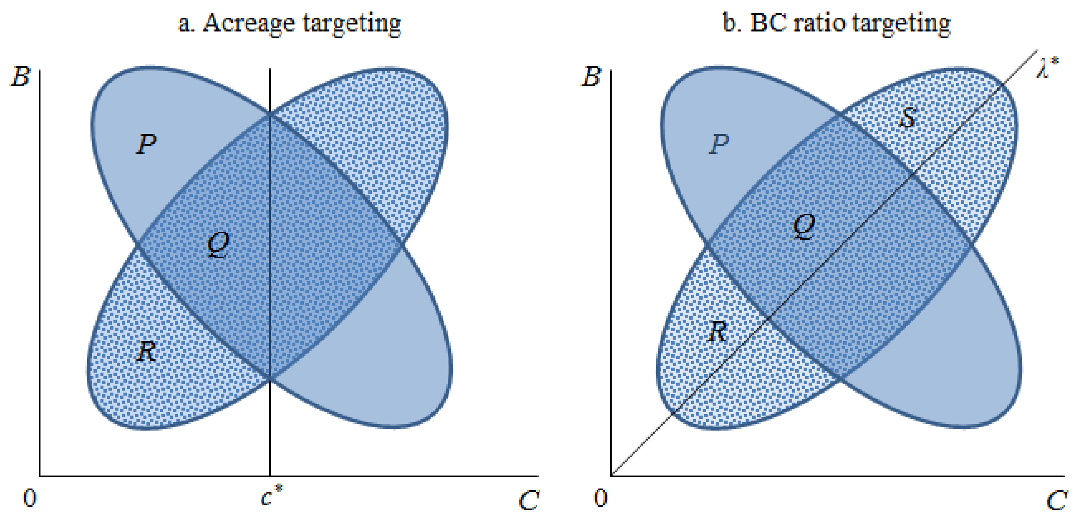


Figure 4.5. Total carbon benefits with respect to the benefit variability under BC ratio targeting

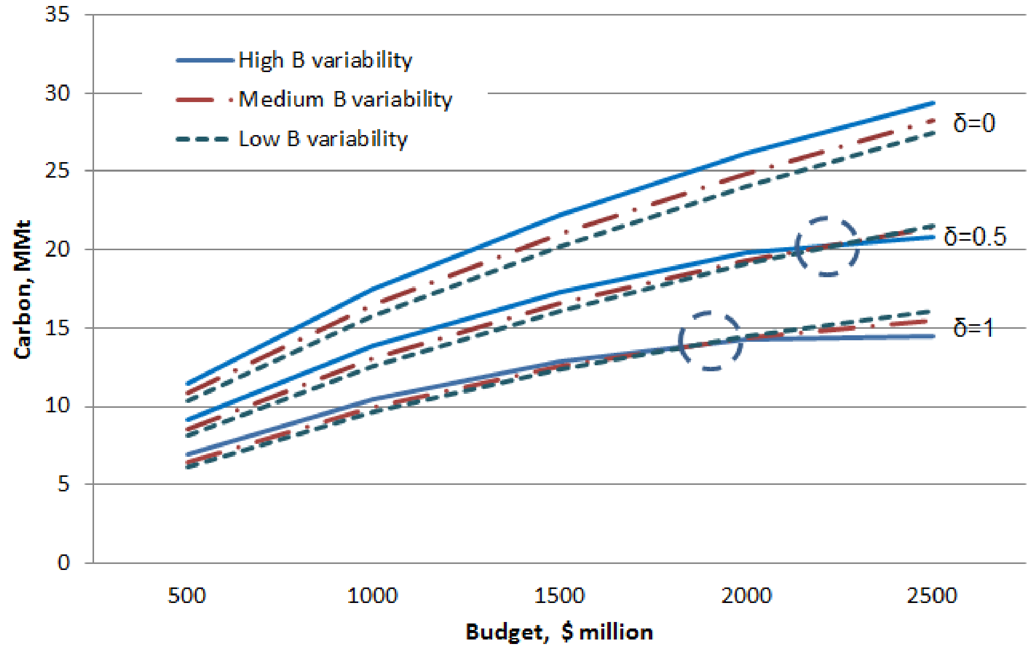


Figure 4.6. Comparison of carbon sequestration potential between BC ratio targeting and acreage targeting with negative correlation ($\rho = -0.5$)

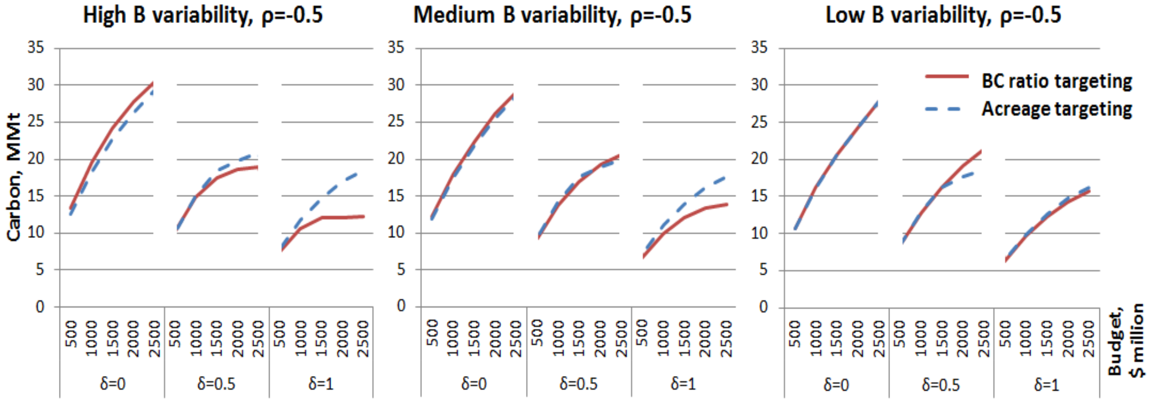


Figure 4.7. Carbon supply functions with combinations of correlations and degree of asymmetric information

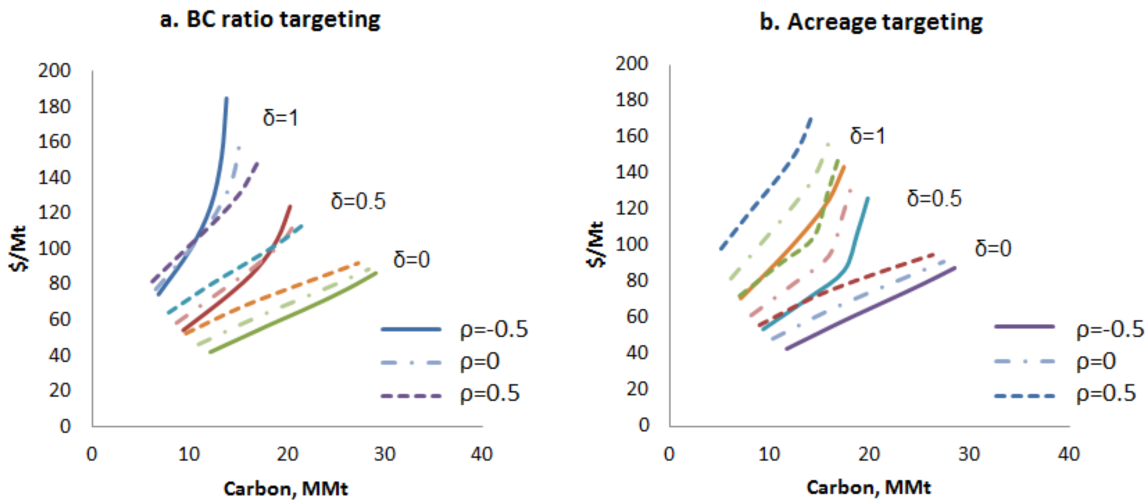
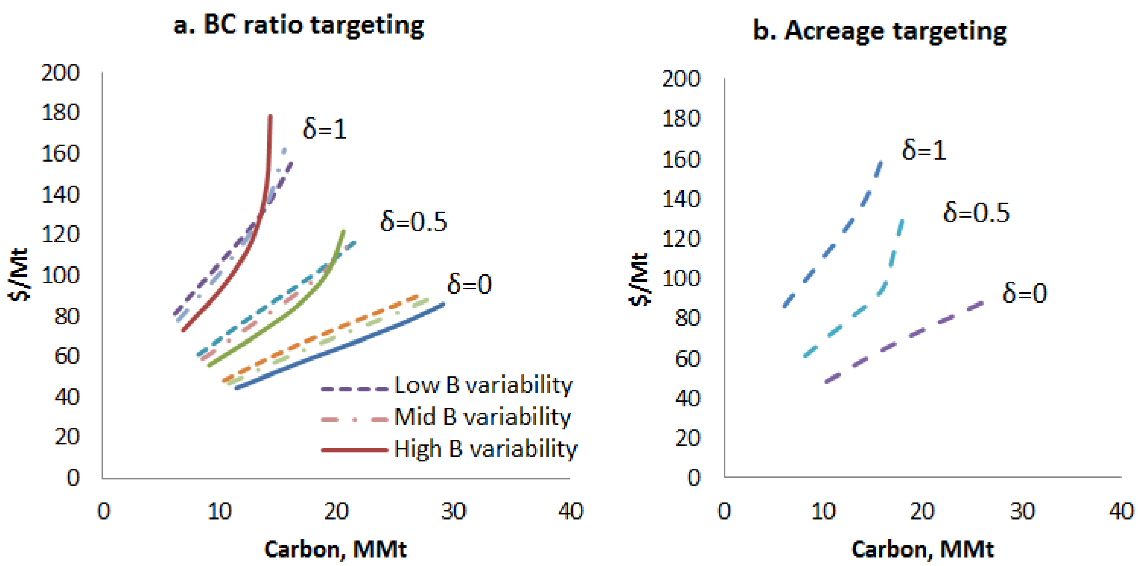


Figure 4.8. Carbon supply functions with respect to benefit variability under different targeting schemes



Note: Under acreage targeting with zero correlation, carbon supply functions are the same across benefit variability.

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