Agricultural Landowners' Response to Incentives for Afforestation

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ABSTRACT

Previous research has shown that afforestation of agricultural land is a relatively low-cost option compared to energy-based approaches for mitigating net carbon dioxide emissions, and that financial incentives affect landowner behavior and can be used to increase carbon sequestration on private land. In this paper we use stated preference data from private landowners in the Pacific Northwest region of the U.S. to examine the key factors affecting participation in an incentive program for carbon sequestration through afforestation. We also estimate the corresponding potential for carbon sequestration and its cost. Our results suggest that incentive payments would significantly and positively affect landowners' level of enrollment in a tree planting program.

Keywords: Afforestation, Carbon sequestration, Carbon supply function, Incentives, Stated preference.

JEL Codes: Q23, Q28, Q54

1. Introduction

Climate change due to the accumulation of greenhouse gases (GHG) in the atmosphere is one of the major issues in the global economy (Stern 2007). The forest sector can play an important role in mitigating GHG emissions by sequestering carbon from the atmosphere in standing live trees as well as 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). Because forests have relatively larger potential for carbon sequestration than other land use choices (Gorte 2009), afforestation, or planting trees on land not previously in forestry, is often promoted as a strategy for increasing carbon sequestration (Moulton and Richards 1990; Adams et al. 1999). For instance, it has been established that afforestation of crop land can sequester between 2.2 and 9.5 metric tons of carbon-dioxide equivalent per acre per year (Mt CO_2 eq./acre/year) (US EPA 2005), and afforestation of pasture land can sequester between 2.7 and 7.7 Mt CO_2 eq./acre/year (Lewandrowski et al. 2004).[1]

Much of the economics 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 option for mitigating CO_2 emissions. For instance, Parks and Hardie (1995) use Natural Resource Inventory data and an engineering cost model to simulate the impacts of subsidies for sequestering carbon in new forests established on agricultural land. They derive a carbon supply function to develop criteria for enrolling lands in a national carbon sequestration program. Sectoral optimization model approaches, such as the U.S. agricultural sector model (USMP, Lewandrowski et al. 2004) and the forest and agricultural sector optimization model (FASOM, Adams et al. 1993; Alig et al. 1997), have explicitly modeled the links between

[1] The ranges in sequestration reflect variation in tree growth rates as well as in above- and underground carbon sequestration rates across species and locations (Gorte 2009).

agricultural land, forest land, and timber markets, and examined the potential for offsetting changes in land use resulting from price feedbacks.[2] 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.

Plantinga et al. (1999) argue that these studies tend to underestimate the marginal costs of carbon sequestration by simply assuming that landowners will participate in an 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), and Lubowski et al. (2006) estimate econometric models of observed land use decisions as a function of relative returns to different land uses and other relevant factors such as land quality. The estimates from these land use models are used to simulate how landowners might respond to the effects of hypothetical economic incentives such as a subsidy for carbon sequestration. These responses are then used to calculate the opportunity costs of afforestation and hence carbon sequestration cost functions. By relying on observed land use choices, this approach accounts for additional factors affecting land enrollment decisions, such as irreversibilities and the resulting option values, the cost of acquiring forest management skills, and non-market benefits derived by landowners (Plantinga et al. 1999).

[2] The USMP is a spatial and market equilibrium model that simulates farm-sector impacts resulting from changes in commodity market conditions, agricultural technologies, and government policies related to commodity production, resource use, environmental quality, and trade. The FASOM is an intertemporal market and spatial equilibrium model in which agriculture and forestry compete for the use of land. It considers endogenous decisions on afforestation, deforestation, and forest management, and tracks changes in the net levels of carbon sequestration occurring over time.

Although these econometric models estimated from revealed preference data account for additional factors affecting land enrollment decisions, they mostly cannot incorporate information about individual landowners' characteristics and land characteristics. 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. For instance, Van Kooten et al. (2002) and Shaikh et al. (2007) use survey data to examine the effects of incentives to encourage landowners to plant trees on agricultural lands in Western Canada. This approach allows researchers to incorporate key factors affecting individual landowners' land use decisions and to improve the accuracy of examining the cost of carbon through afforestation, and thus can serve as a valuable complement to revealed preference studies, optimization models (Adams et al. 1993; Callaway and McCarl 1996) and bottom-up engineering approaches (Richards et al 1993).[3]

This paper adds to this literature by using stated preference data from private landowners in the U.S. We use a survey to elicit agricultural landowners' willingness to participate in an incentive program for carbon sequestration through afforestation. We examine the key factors affecting participation and measure the potential extent of participation in a tree planting program. We also estimate the corresponding potential for carbon sequestration and its cost. In contrast to most other stated preference afforestation studies, we follow Siikamaki and Layton (2007) and use a continuous measure of enrollment as opposed to a simple dichotomous measure of participation.[4] This continuous measure allows landowners to choose a level of enrollment based on different levels of incentives offered, as well as on various other heterogeneous factors, such as personal characteristics and spatial characteristics of their agricultural lands.

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[3] A stated preference approach has also been used to examine participation in other types of incentive programs, such as agri-environmental and farmland preservation programs (Lynch and Lovell 2003; Ma et al. 2012) or biodiversity conservation (Langpap 2004; Siikamaki and Layton 2007; Matta et al. 2009).

[4] Siikamaki and Layton (2007) focus on forest protection in Finland.

The rest of this paper is organized as follows. In section 2 we discuss the survey procedure and describe the variables used in our empirical models. In section 3 we describe the econometric approach used for estimation, and in section 4 we present the estimation results. In section 5 we present simulation results for changes in carbon sequestration associated with changes in annual incentive payments. Finally, in section 6 we summarize and discuss implications from our analysis.

2. Survey data

2.1. *Survey*

We relied on a mail survey of private landowners in western Oregon and Washington to generate data on their responses to an afforestation incentives program.[5,6] 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 land they own, annual net agricultural returns and productivity of their agricultural lands, the spatial characteristics of their agricultural lands, reasons for owning land, and their understanding and attitudes about the importance of environmental services provided by their lands.

The names and addresses of agricultural landowners were provided by county tax assessor's offices, and we randomly chose 1,000 landowners to participate in the survey. To help

[5] The counties selected for the survey are Benton, Jefferson, Columbia, Lane, Polk, Coos, Crook, Deschutes, Douglas, Josephine, Lake, Marion, Linn, and Clatsop in Oregon, and Grays Harbor, Pierce, Whatcom, San Juan, Clallam, Jefferson, Skamania, and Kitsap in Washington.

[6] A mail survey was deemed the most cost-effective approach to obtain a sample of adequate size. A second survey was separately conducted in the southeast (North Carolina and Georgia). Given the low response rate for this survey, we do not include the corresponding data in our main analysis. However, we present the results obtained from this second survey in the appendix, and use them as a robustness test for our main results. The two regions were chosen to conduct surveys because of their suitability for tree planting, favorable climate conditions (abundant precipitation and long growing seasons), and relatively large timber markets.

design the questionnaire and establish an appropriate bid range for carbon prices, a draft of the survey was reviewed by a group of experts and an in-person pretest was conducted with a group of twenty agricultural landowners. 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. [7] Additionally, we provided a separate sheet with information to help respondents understand the detailed incentive scheme. This sheet briefly explained the role of carbon dioxide in climate change, how afforestation can sequester carbon, amounts sequestered by Douglas-Fir over time, and how this determines how much a landowner could earn by planting Douglas-Fir on their agricultural land. A copy of the description of the incentive payments and the enrollment question is shown in Figure 1.[8]

The survey design and mailing procedure were conducted following Dillman's (1978, 2007) survey design method. The final sets of survey questionnaires were mailed out in January 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.[9] 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. Out of the 1,000 surveys initially mailed out, 206 were undeliverable or were returned unfilled due to recipients being absent, disabled, or not being agricultural landowners in the relevant study area. Of the remaining 794 surveys that reached potential responders, we received 372 usable surveys. This gives an effective response rate of 47% (372÷794).

[7] Experts from the USDA Forest Service, the Departments of Statistics and Applied Economics, and the College of Forestry at Oregon State University provided feedback.
[8] A copy of the entire survey is available from the authors upon request.
[9] There is substantial evidence that prepaid monetary incentives can achieve higher response rates (Little and Hubbard 1988; James and Bollstein 1990; Brennan 1992; Salant and Dillman 1994).

A follow-up phone and mail survey of a sample of non-respondents was conducted to assess and control for potential selection bias induced by non-responses. This survey collected information on size of agricultural land, landowners' demographic characteristics, and their understanding and attitudes about the importance of environmental services provided by their lands. Out of 100 non-respondents initially contacted by phone, 27 answered the follow-up phone survey. An additional 100 non-respondents were then contacted by mail, and 26 returned the follow-up mail survey.

To elicit the survey participants' enrollment response, we designed a hypothetical incentive scheme that is consistent with components of the USDA Conservation Reserve Program (CRP), including a 15-year contract, a 50% cost-share subsidy for establishing trees, and annual rental payments.[10] Each respondent was asked to state either the amount of acreage or the proportion of total acreage owned he/she would enroll in a Douglas-fir tree planting program, given a fixed per acre annual incentive payment.[11] Answers given in acreage were later converted to proportions based on the total acreage owned. This question was posed three times to each participant with three different and increasing levels of payments.[12] We relied on the in-person pretest and expert review to calculate the range of annual rental payments per acre offered to participants. Specifically, we multiplied annual carbon sequestration rates for Douglas-fir by the price of carbon, which ranged from \$12.50 to \$150 per metric ton, with 12 breaks across four different versions of the survey.[13] Table A2 in the Appendix shows the different payment levels

[10] The duration of CRP contracts is usually 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).
[11] Douglas fir is the most common tree species with the highest carbon accumulation rate over time in the Pacific Northwest region (Lewandrowski et al. 2004; Smith et al. 2006; Lubowski et al. 2006).
[12] Sequential responses to increasing payment levels may not be independent (we thank an anonymous reviewer for pointing this out). We assess the potential bias through robustness checks in section 4.3.
[13] This range of carbon prices was chosen to be consistent with the average of the maximum carbon price used in the

and how they were calculated. Annual carbon accumulation rates within the duration of the contract were calculated by using the carbon accumulation table created by Smith et al. (2006).

2.2. *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 include the annual rental payment, average annual net returns from agricultural lands, land characteristics, landowners' management attributes, and demographic characteristics.

The annual rental payment per acre offered to each landowner, which is the main variable we use to examine the landowners' response to incentives for enrolling in a tree planting program, ranges from \$16 to \$192.[14] We also include in the model each landowner's average annual net returns to agricultural lands to account for the opportunity cost of converting from agricultural lands to forests (Shaikh et al. 2007).

Variables describing land characteristics include dummies for high- and low-productivity land. These variables were constructed from survey responses to questions about a landowner's proportions of high- and low-productivity land. We expect that high productivity lands are less likely to be enrolled in a tree planting program, whereas low productivity lands are more likely to be enrolled. We also control for the size of agricultural land holdings, as they can affect the opportunity costs of participation. Finally, we control for whether the predominant land respondents would enroll is cropland or grassland by constructing a dummy variable set equal to

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U.S. Agricultural Sector Model (Lewandrowski et al. 2004) and in U.S. EPA (2005).

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

one if all or most of stated enrollment (in acreage or proportion) is cropland and set equal to zero if it is grassland.

Additionally, spatial characteristics of lands associated with their location can affect the decision to enroll in a tree planting program. For instance, Zhou and Kockelmen (2008) recognized that variables such as central business district access and distance to the nearest highway, as well as a parcel's neighborhood attributes, can affect the relative returns to different land uses and thus land use and management decisions. Finally, the risk of fire can also affect land use and management decisions (Amacher et al. 2005; Konoshima et al. 2008), as landowners located in fire-prone areas may be less willing to convert part of their land to forest. However, the effects of spatial characteristics have not been examined in the existing afforestation literature because of a lack of information on the spatial configuration of land parcels. To identify the spatial characteristics of each land parcel included in our survey, we directly asked landowners whether their agricultural lands are within a mile from their residence and from a highway, and whether they are adjacent to a forest, other agricultural lands, or fire hazards.

Landowners' management attributes variables include the landowners' opinions on the importance of providing environmental services to 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 with a 5-point scale ranging from 'not important' to 'very important'. We include dummy variables to indicate whether the respondent considers it important to provide each environmental service. The dummy variable is set equal to one if the stated importance level is greater than 3, and to zero otherwise. We also control for landowners' reasons for owning agricultural land. We create dummy variables to identify landowners who consider each reason important. The dummy variables for each reason are set equal to one for landowners who give that reason a ranking of at least 4, and to zero otherwise. A priori expectations about these variables are unclear, so the sign and magnitude of their effects on enrollment are an empirical question.

We control for additional factors that reflect landowners' preferences and attitudes about conservation as well as their previous experience with afforestation, forestry, and incentives programs, and thus could affect the enrollment decision. We include dummy variables that identify landowners who have adopted conservation farming practices, have received incentive payments in the past, own forest land, have experience with afforestation, have plans for future afforestation, have family ownership of their land, and are members of a non-governmental conservation or environmental organization. Finally, we control for a variety of landowners' demographic characteristics that may have an effect on landowner's preferences and budget constraint and thus impact their enrollment decision. Following previous literature on voluntary program participation, we control for age, gender, education, income, and occupation (Ervin and Ervin 1982; Bell et al. 1994; Nagubadi et al. 1996; Langpap 2004). Summary statistics and a description of all these variables are presented in Table 1.

3. Econometric model

The primary goal of the econometric analysis is to predict the amount of agricultural land enrolled in a tree planting program as a function of incentive payments and various other factors affecting the landowners' decision. Because we elicited landowners' willingness to participate in a tree planting program using an open-ended question, our sample includes a small number of lower- and upper-censored responses (seventeen and seven, respectively). Therefore, we rely on a Tobit model for estimation, which assumes that the dependent variable is observed only if it is above or below a given cut-off level (Moeltner and Layton 2002; Cho et al. 2005).[15] The dependent variable in our model is given by the proportion of total agricultural land (cropland plus grassland) that each landowner *i* is willing to allocate for a tree planting program. Hence, we specify the following two-sided censored regression model (see, e.g., Greene 2012):

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

where y_i^* denotes the latent enrollment variable for landowner *i*, y_i is the stated proportion of total agricultural land enrolled, X_i is a vector of explanatory variables, β is a parameter vector which is common to all landowners, and ε_t is a normally distributed error term.

Each respondent was asked to provide a stated enrollment level for three different levels of incentive payments, and we added cropland and grassland enrollments into a fraction of total agricultural land enrolled.[16] Therefore, we have three observations for each landowner *i*. Hence, we can apply panel econometric methods that account for landowner-specific unobserved heterogeneity. This approach also controls for potential group-wise heteroskedasticity induced by variation in the payment levels. Because the number of observations for each respondent is small, the fixed effects estimator will be inconsistent due to the incidental parameters problem (Wooldridge 2001). Hence, we use a random effects Tobit model:

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

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 $i \neq j$.

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[15] We assume that the true distribution of willingness to participate in the incentive program is censored at zero (Halstead et al., 1991).

[16] Only thirteen respondents included acreage or proportions for both cropland and grassland. The remaining respondents replied with only one of the two options.

4. ESTIMATION RESULTS

The empirical version of model (1) is given by

$$y_{it} = \beta_0 + \beta_1 Payment_{it} + \beta_2 Land_i + \beta_3 Demographic_i + \beta_4 Owner_i + v_i + \varepsilon_{it} \qquad (3)$$

$i = 1, \ldots, N$; $t = 1, 2, 3$, where y_{it} is the stated proportion of lands landowner i would be willing to enroll in a tree planting program, $Payment_{it}$ is the per acre payment offered to each agricultural landowner, $Land_{it}$ is a vector of land characteristics, $Demographic_i$ is a vector of landowner's demographic characteristics, $Owner_i$ is a vector of landowners' attributes, βs are parameter vectors to be estimated, v_i is unobserved landowner heterogeneity, and ε_{it} is a random disturbance term.

An important caveat to keep in mind when estimating model (3) is that we obtain three observations from each survey respondent. The variation in the variables controlling for parcel and landowner characteristics is therefore relatively limited, and this may affect the accuracy with which we can measure the effects of these variables. Furthermore, correlation between error terms for each respondent that is not accounted for by panel methods may induce bias in our estimates. We assess the robustness of our estimates to this potential bias in section 4.3.

4.1. *Sample Selection*

Given the nature of our data, we test and control for potential sample selection bias. If the factors affecting survey response, landowners' decision to participate in the program proposed in the survey, and enrollment choices are correlated then the parameter estimates may be biased. To test and correct for this potential source of bias, we collected information about non-respondents through a follow-up phone and mail survey.

Additionally, survey respondents were asked if they would be willing to participate in an incentives program given the right incentives and conditions, or whether they would be unwilling to participate regardless of the conditions. Those respondents who identified themselves as unwilling to participate in a tree planting program regardless of the conditions were instructed not to answer the enrollment questions and hence were excluded from the sample, because their enrollment choices would not reflect a response to a price signal. There were 178 such protest respondents, leaving 194 unique responses available for estimation, or an effective sample of 24% of the 794 surveys that reached landowners.[17]

We conduct a two-step Heckman test for sample selection bias (Heckman 1979; Desvousges et al. 1987; Whitehead et al. 1993; Messonnier et al. 2000; Cho et al. 2005). A probit model of participation was estimated as a first step. The model is based on demographic and property characteristics of participants and non-participants (including non-respondents and protest responses).[18] The resulting parameter estimates are used to calculate the Mills ratio, which indicates the probability of a landowner having responded and, for those who responded, the probability that they are willing to enroll in the hypothetical incentive program. In the second step, the inverse Mills ratio is included as an additional regressor in the censored Tobit model. If the coefficient for the Mills ratio is not significantly different from zero, the null hypothesis of no bias cannot be rejected.

4.2. *Results*

The estimated parameters for model (3) are not easy to interpret because they represent the change in the latent variable y^* with respect to a change in the independent variables. Hence, instead we discuss the corresponding marginal effects associated with the change in explanatory

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[17] If the model is estimated with the 178 protest responses included with zero enrollment, estimated marginal effects for most variables are smaller in magnitude than those presented here, but have the same sign and statistical significance.

[18] Specifically, independent variables are landowner age, gender, education, and income, size of property, type of land use, and importance given to providing environmental services (soil erosion, water quality, wildlife habitat, carbon sequestration).

variables. The estimated coefficients can be found in the appendix. The first column of Table 2 shows the marginal effects of each independent variable on the expected willingness to plant trees within a 15-year contract, calculated at the sample mean, from the random effects Tobit model.[19]

The marginal effect of the annual payment is positive and statistically significant. It indicates that a $1 increase in the annual incentive payment would increase the proportion of land enrolled by 0.208 percentage points. To provide some perspective on the magnitude of this effect, we note that a representative landowner would enroll 12.1 acres (16.9% of the mean size of 71.4 acres) with the mean payment of $104/acre during the duration of the contract. A 10% increase in the payment, to $114/acre, would increase enrollment to 13.6 acres, which represents an 11% increase. Similarly, for the entire PNW region, the model predicts that 5.3 million acres would be enrolled at the mean payment of $104 per acre for 15 years. A 10% increase, to $114/acre, would result in an enrollment of 5.9 million acres (a 11.3% increase).

The marginal effects with respect to land characteristics show that the stated average annual returns of agricultural lands have a negative effect on the willingness to participate. As expected, landowners who own highly productive land would allocate less land for afforestation, and landowners who own low productivity land allocate more land for afforestation. The marginal effects for variables representing spatial characteristics of agricultural lands suggest

[19] The survey also asked landowners' willingness to enroll in a program with a 30 year contract. For the sake of clarity in presentation and discussion of results and given space considerations, we chose to focus the discussion on only one type of contract. We chose the results for the fifteen year contract because this contract length is more consistent with major existing conservation programs such as the CRP and because many respondents who indicated willingness to participate and provided responses for a 15 year contract did not provide responses for a 30 year contract (perhaps revealing less familiarity with a longer contract). Results are broadly consistent with those presented here for the 15 year contract, but the marginal effect of the incentive payment is somewhat smaller and some variables that are significant with the 15 year contract are not with the 30 year contract (for instance agricultural returns, proximity to fire hazards, importance of carbon sequestration, and previous experience with or future plans for afforestation). Results are available upon request.

that lands adjacent to fire hazards are less likely to be allocated to a tree planting program. The remaining spatial characteristics do not have a statistically significant effect on the willingness to participate in afforestation.

The marginal effects for variables indicating attitudes about providing environmental services show that landowners who believe sequestering 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, preserving water quality, and providing wildlife habitat, do not have a statistically significant impact on the level of participation in afforestation. In addition, landowners who own their agricultural lands to protect nature, have previous experience with afforestation, have planned future afforestation, and who are members of a non-governmental conservation or environmental organization allocate more agricultural land to a tree planting program.[20]

The marginal effects for the variables describing landowners' demographic characteristics suggest that male landowners are more willing to allocate their agricultural land for afforestation, but landowners with a graduate degree are less willing to allocate land for afforestation. Other characteristics do not have a statistically significant effect on landowners' willingness to participate in a tree planting program.[21] Finally, the coefficient of the inverse Mills ratio is not statistically significantly different from zero, suggesting there is no evidence of sample selection bias.

4.3. *Robustness*

[20] We tested whether these groups of landowners are also less sensitive to differences in payment amounts by including interaction terms between carbon payments and the indicator variables for these landowner characteristics. We found that respondents who own land to protect nature are less sensitive to payment changes (p = 0.03). However, other interaction terms are not statistically significant (p – values range from 0.37 to 0.89).

[21] However, an F-test of the joint significance of the demographic variables allows us to reject the null hypothesis that they are not statistically significant at a 9% confidence level (p=0.087).

To check the robustness of these results we estimate several alternative versions of the model. First, a potential shortcoming of the random effects Tobit model is that it assumes v_i and X_i are uncorrelated. An alternative that relaxes this assumption is a Chamberlain random effects (CRE) Tobit model (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:

$$
\begin{aligned}
& y_{it} = \max(0, \psi + X_{it}^{'}\beta + \bar{X}_i \xi + a_i + \varepsilon_{it}, 100) \\
& \varepsilon_{it} \mid X_i, a_i \sim N(0, \sigma_\varepsilon^2), \quad t = 1,2,3 \\
& a_i \mid X_i \sim N(0, a_a^2)
\end{aligned}
\tag{4}
$$

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 $i \neq j$.[22] Additionally, we estimate as standard (pooled) Tobit model with standard errors clustered at the respondent level. The second and third columns of Table 2 show the marginal effects corresponding to these two models. The results are qualitatively and quantitatively very similar to those for the random effects Tobit model.

Second, given that the three payments offered to each respondent were sequentially increasing, the second and third responses may be affected by the preceding payment levels, making the observations dependent in ways that are not fully accounted for by panel methods. We used two approaches to test whether this may significantly bias our estimates. First, we

[22] An alternative approach to accounting for the panel nature of the survey data due to the fact that each respondent generated three observations would be to use a multivariate panel censored regression model for estimation, as in Layton and Siikamäki (2009). For tractability we use the RE and CRE Tobit models.

estimated three separate random effects Tobit models, one for each of the payment levels. Second, we randomly drew one observation from each respondent and estimated a random effects Tobit model. We repeated this process two hundred times and estimated average marginal effects. The results are generally consistent with those presented in Table 2. This suggests that any bias caused by sequential responses to ordered payment amounts is relatively small.

Finally, we estimated a series of models with more parsimonious specifications to check whether our results change when groups of variables that are not significant in our main specification are left out. Specifically, we excluded some demographic variables, such as income, occupation, and retirement status, as well as some land owner concern variables, ownership objectives, and spatial characteristics. The marginal effects for these models are presented in Table 3. With the exception of the variables indicating ownership for amenity purposes and single family ownership of the land, which become significant in the more parsimonious models, the qualitative and quantitative results are largely consistent with those presented in Table 2.

4.4. *Afforestation in the Southeast*

As an additional robustness test, we repeat the preceding analysis using data from an afforestation survey conducted in the southeast. This survey did not elicit a high enough response rate to justify as detailed an analysis as that conducted with data from the Pacific Northwest, but here we use it to gain insight into whether our key results hold for landowners from a different region.[23] The marginal effects for the three model specifications are reported in Table A1 in the appendix. They suggest that the result for the main parameter of interest, the annual payment, holds for landowners in the southeast as well. However, the marginal effect is larger, indicating that landowners in this region are potentially more responsive to incentive payments. This is

[23] The response rate is 27%. Summary statistics for the region are available upon request.

consistent with results from previous studies (Lewandrowski et al. 2004; Alig 2010). Differences in the effects of various control variables likely reflect dissimilarities across the two regions in factors that are not accounted for in the data. Finally, we estimated a model with the pooled data from both surveys and the results are consistent with those presented here.

5. Carbon sequestration

5.1. *Carbon Supply Function*

We use the estimated parameters from the random effects Tobit model to conduct a simulation of landowners' response to different levels of annual payments, ranging from $0/acre to $200/acre, as part of a 15-year contract. The area of agricultural land used in the simulation is 31.2 million acres, assuming that the adoption rates predicted for the estimation sample apply to the entire region.[24] We then use the simulation results to estimate a carbon sequestration supply function. The annual carbon sequestration rate is estimated by using carbon yield tables for Douglas-fir under periodic harvesting provided in Smith et al. (2006). These tables specify regional estimates of mean carbon stocks (in metric tons/acre) accumulated in live trees, standing dead trees, understory, down dead wood, the forest floor, soil, and non-soil sinks for different stand ages on reforested and afforested land.[25] We derive the carbon supply function based on the procedure used by Stavins and Richards (2005), who calculate the annualized present value of carbon tons sequestered as $PVC \times \left[r/1-(1+r)^{-T} \right]$, where $PVC = \left[\sum_{t=0}^{n} Y_t / (1+r)^t \right]$ is the present value of carbon tons sequestered (not including storage), Y_t is the additional flow of carbon at time *t*, and

[24] Given random sampling of survey recipients and no evidence of sample selection bias, our estimation sample should be representative of the region. We apply the available agricultural land area based on the common forest region defined by Smith et al. (2006).
[25] These estimates do not 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.

$r = 5\%$ is the discount rate.[26,27] We use a time horizon of 100 years to facilitate comparison with other studies.

The simulated participation rates and the corresponding carbon supply function are displayed in Fig. 2.[28] The simulation results show that as the annual payment rate goes up the rate of participation in a tree planting program increases, and thus carbon sequestration rates increase as well. As shown in the figure, however, the participation rate increases at a decreasing rate for sufficiently high annual payments, and therefore so does carbon sequestration. Although it is not possible to know exactly what drives this relationship, one potential explanation is that opportunity costs of participation are low when little or no land is enrolled, but increase as more (and better) land is enrolled. The carbon supply function in Fig. 2-b indicates that at carbon prices of $30/Mt and $50/Mt, a total of 8.8 million metric tons (MMt) and 18.3 MMt of carbon, respectively, would be sequestered in the region.

For purposes of comparison with other studies we scaled up these results from the regional level to the national level following the procedure used in Stavins and Richards (2005). The accuracy of the scaled-up results is limited, and accordingly we mention them only to provide context. They should therefore be interpreted with this caveat in mind. The comparison suggests that the marginal costs of carbon estimated here are higher than those obtained using bottom-up engineering approaches and optimization models, but below the marginal costs

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

[27] The discounting approach to calculating the present value of the amount of carbon sequestered assumes that marginal benefits of sequestration associated with additional units of carbon are constant (Stavins and Richards 2005). Although this approach is standard in computing marginal costs of carbon sequestration and enables comparisons across studies, it is not valid to discount physical flows of carbon sequestration without knowledge of the corresponding relative benefits in different years. Improved accounting of the benefits of sequestration over time is needed in the literature to derive comparable estimates of marginal costs of sequestration. We thank an anonymous reviewer for pointing this out.

[28] Although the survey instrument used carbon dioxide (CO_2) when referring to carbon sequestration because this is likely the most familiar term for respondents, all results in the paper are expressed in terms of carbon (C) to facilitate comparison with other studies (note that 1 ton of C = 3.67 tons of CO_2).

estimated from the stated preference approach conducted by Shaikh et al. (2007). These differences may be partially due to the hypothetical nature of the questions underlying our stated preference approach or to the additional consideration of individual owner-specific characteristics and land-related characteristics, which had been treated as unobservable in other studies.

5.2. *Sensitivity Analysis*

We derived the carbon supply function assuming participating landowners would plant Douglas fir, a fast growing tree species. Hence, we could be overestimating the resulting levels of carbon sequestration if instead participating landowners planted other species. Thus, for comparison purposes we also derive the carbon supply function by assuming landowners plant mixed tree species. We calculate the annual carbon sequestration rate of the mixed tree species based on the average annual growth rate of carbon presented in Smith et al. (2006) weighted by the proportion of tree species in the region. The results, presented in Fig. 3, show that planting mixed tree species makes the supply function steeper, since the annual carbon sequestration rate with mixed tree species is lower than with a fast growing species.

We also derive the carbon supply function assuming no harvest takes place, in contrast to periodic harvesting. The results, shown in Fig. 3 as well, indicate that the sequestration rate when there is no harvest is greater than with harvest. Hence the carbon supply function with no harvest is flatter than with harvest, as shown also in Lubowski et al. (2006).

Finally, it is important to assess the sensitivity of our results to alternative discount rates. The discount rate does not affect predicted enrollment (it is not part of the econometric model of participation). However, it does affect the marginal cost calculations. A higher discount rate lowers the present value of both annualized carbon sequestration and the annualized rental payment (Lubowski et al. 2006). However, it is not clear how the ratio between annualized payment and annualized carbon sequestration would change with different discount rates. Fig. 4 shows that as the discount rate goes up the present value of carbon sequestration decreases faster than the present value of the annual payment, and thus the carbon supply function becomes steeper.[29]

6. Conclusion

A variety of methodological approaches have been used to assess the costs of sequestering carbon through afforestation of agricultural lands: a bottom-up engineering approach, optimization, revealed preference, and, less frequently, stated preference. This study conducts the first stated-preference analysis for landowners in the U.S., thus providing a methodological complement and a benchmark for comparison for results based on a revealed preference approach. We analyze agricultural landowners' willingness to participate in a tree planting program and examine the key factors affecting their stated level of enrollment in the program. Using data collected from a mail survey conducted in the Pacific Northwest, we estimate the proportion of agricultural lands that landowners are willing to enroll as a function of incentive payments for carbon sequestration and various additional factors, including spatial characteristics of lands and landowners' characteristics. We use our estimation results to simulate regional-level carbon sequestration response to incentive payments.

The estimation results show that the annual payment for carbon sequestration positively affects landowners' stated level of enrollment in a tree planting program. We also find that variables representing productivity of land, spatial characteristics, and reasons for owning

[29] The present value of carbon sequestration decreases faster than that of the annual payment because of a relatively higher growth rate of carbon accumulation in the first three decades. Thus the ratio of annualized payment to annualized amount of carbon sequestration increases when the discount rate increases.

agricultural lands affect landowners' level of enrollment in the program, whereas landowners' demographic characteristics, with the exception of gender and graduate education, do not. Regional-level simulations of carbon sequestration in response to incentive payments show that planting fast growing tree species with no harvest has the highest carbon sequestration potential, and that the carbon supply function shifts up as the discount rate increases.

An overview of the results presented in the literature on carbon sequestration through afforestation suggests that the estimated costs of sequestration may vary with the methodological approach underlying the estimation. Our results confirm this assessment. The scaled-up cost of carbon sequestration estimated in this study is higher than that obtained from bottom-up engineering approaches and optimization models. It is also higher than that obtained using a revealed preference approach. One possible explanation for these differences is that landowner and parcel characteristics, which are not observed in revealed preference data, bias estimates of responsiveness to relative returns and thus of the marginal cost of sequestration. The cross-study variation in estimated costs highlights the need for further research into the causes underlying these differences and their methodological and policy implications. Additionally, they suggest the potential advantages of constructing data sets that combine observed land use choices with information on parcel and demographic characteristics from the landowners making these choices, thus combining the key advantages of the revealed and stated preference approaches. Finally, the stated caveats regarding the scaling up of regional results necessary for these kinds of comparisons highlight the need for bigger-scale studies that cover several regions, thereby making national level comparisons more accurate.

In addition to complementing existing revealed preference results, this study provides additional insights into landowners' willingness to plant trees on their agricultural lands by considering parcel characteristics as well as landowner attributes, such as their attitude about provision of environmental services, motives for land ownership, previous experience with afforestation, incentive programs, and conservation farming, as well as demographic characteristics that may affect afforestation decisions but cannot be controlled for with other approaches. This type of information may give policy makers a better sense of how to identify target groups who are more likely to participate in a tree planting program.

References

Adams, R.M., Adams, D.M., Callaway, J.M., Chang, C.C., McCarl, B.A., 1993. Sequestering Carbon on Agricultural Land: Social Cost and Impacts on Timber Markets. Contemporary Policy Issues 11 (1), 76–87.

Adams, D.M., Alig, R.J., McCarl, B.A., Callaway, J.M., Winnett, S.M., 1999. Minimum Cost Strategies for Sequestering Carbon in Forests. Land Economics 75, 360–374.

Alig, R.J., 2010. Economic Modeling of Effects of Climate Change on the Forest Sector and Mitigation Options: A Compendium of Briefing Papers. Gen. Tech. Rep. PNW-GTR-833. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station.

Alig, R.J., Adams, D., McCarl, B., Callaway, J.M., Winnett, S., 1997. Assessing Effects of Mitigation Strategies for Global Climate Change with an Intertemporal Model of the U.S. Forest and Agriculture Sectors. Environmental and Resource Economics 9, 259–274.

Amacher, G.S., Malik, A.S., Haight, R.G. 2005. Not Getting Burned: The Importance of Fire Prevention in Forest Management. Land Economics 81 (2), 284–302.

Bell, C. D., R. K. Roberts, B. C. English, and W. M. Park. 1994. A Logit Analysis of Participation in Tennessee's Forest Stewardship Program. Journal of Agricultural and Applied Economics 26(2), 463–472.

Brennan, M. 1992. The Effect of a Monetary Incentive on Mail Survey Response Rates: New Data. Journal of the Market Research Society 34 (2), 173–177.

Callaway, J.M., and B.A. McCarl. 1996. The Economic Consequence of Substituting Carbon Payments for Crop Subsidies in US Agriculture. Environmental and Resource Economics 7(1), 15 – 43.

Cho, S.H., Newman, D.H., Bowker, J.M. 2005. Measuring Rural Homeowners' Willingness to Pay for Land Conservation Easements. Forest Policy and Economics 7, 757–770.

Desvousges, W.H., Smith, V.K., Fisher, A., 1987. Option Price Estimates for Water Quality Improvements: A Contingent Valuation Study for the Monongahela River. Journal of Environmental Economics and Management 14 (3), 248–267.

Gorte, R.W. 2009. U.S. Tree Planting for Carbon Sequestration. CRS Report for Congress, Congressional Research Services.

Dillman, D.A., 1978. Mail and Telephone Surveys: The Total Design Method. New York Wiley-Interscience. 375p.

Dillman, D.A., 2007. Mail and Internet Surveys: The Tailored Design Method. 2nd Edition. John Wiley: Hoboken, NJ.

Ervin, C. A., and D.E. Ervin. 1982. Factors Affecting the Use of Soil Conservation Practices: Hypotheses, Evidence, and Policy Implications. Land Economics 58, 277–292.

Greene, W.H., 2012. Econometric Analysis. 7th Edition. Prentice Hall: Boston, MA.

Halstead, J.M., Lindsay, B.E., Brown, C.M., 1991. Use of the Tobit Model in Contingent Valuation: Experiment Evidence from the Pemigewasset Wilderness Area. Journal of Environmental Management 33, 79–89.

Heckman, J., 1979. Sample Selection Bias as a Specification Error. Econometrica 47, 153–161.

IRB, 2003. Exclusions from Income: Cost-sharing Payments: Conservation Reserve Program. Rev. Rul. 2003-59, I.R.B. 2003-24, 1014.

James, J.M., Bollstein, R., 1990. The Effect of Monetary Incentives and Follow-up Mailings on the Response Rate and Response Quality in Mail Surveys. Public Opinion Quarterly 54, 346–361.

Kristensen S., Thenail, C., Kristensen, L., 2001. Farmer's Involvement in Landscape Activities: An Analysis of the Relationship between Farm Location, Farm Characteristics and Landscape Changes in Two Study Areas in Jutland, Denmark. Journal of Environmental Management 61 (4), 301–318.

Konoshima, M., Montgomery, C.A., Albers, H.J., Arthur, J.L., 2008. Spatial-Endogenous Fire Risk and Efficient Fuel Management and Timber Harvest. Land Economics 84 (3), 449–468.

Langpap, C. 2004. Conservation Incentives Programs for Endangered Species: An Analysis of Landowner Participation. Land Economics 80(3), 375–388.

Langpap, C., Wu, J., 2008. Predicting the Effect of Land-Use Policies on Wildlife Habitat Abundance. Canadian Journal of Agricultural Economics 56, 195-217.

Lynch, L., Lovell, S.J., 2003. Combining Spatial and Survey Data to Explain Participation in Agricultural Land Preservation Programs. Land Economics 79(2): 259 – 276.

Lewandrowski, J., Peters, M., Jones, C., House, R., Sperow, M., Eve, M., Paustian, K., 2004. Economics of Sequestrating Carbon in the U.S. Agricultural Sector. ERS USDA, Technical Bulletin Number 1909.

Little, E.L., Hubbard, R., 1988. Promised Contributions to Charity and Mail Survey Responses: Replication with Extension. Public Opinion Quarterly 52 (2), 221–230.

Lubowski, R.N., Plantinga, A.J., Stavins, R.N., 2006. Land-Use Change and Carbon Sinks: Econometric Estimation of the Carbon Sequestration Supply Function. Journal of Environmental Economics and Management 51 (2), 135–152.

Ma, S., Swinton, S.M, Lupi, F., Jolejole-Foerman, C., 2012. Farmers' Willingness to Participate in Payment-for-Environmental-Services Programmes. Journal of Agricultural Economics 63(3): 604 – 626.

Mansfield, C., Pattanayak, S.K., McDow, W., 2000. What Drives Voluntary Preservation? Significant Natural Heritage Areas in North Carolina. RTI International, USA.

Matta, J.R., Alavalapati, J.R.R., Mercer, D.E., 2009. Incentives for Biodiversity Conservation Beyond the Best Management Practices: Are Forestland Owners Interested? Land Economics 85(1): 132 – 143.

Messonnier, M.L., Bergstrom, J.C., Cornwell, C.M., Teas-ley, R.J., Cordell, H.K., 2000. Survey Response-Related Biases in Contingent Valuation: Concepts, Remedies, and Empirical Application to Valuing Aquatic Plant Management. American Journal of Agricultural Economics 83 (2), 438–450.

Moeltner, K., Layton, D.F., 2002. A Censored Random Coefficient Model for Pooled Surveys Data with Application to the Estimation of Power Outage Costs. Review of Economics and Statistics 84 (3), 552–561.

Moulton, R.J., Richards, K.R., 1990. Costs of sequestering carbon through tree planting and forest management in the United States. US Department of Agriculture, Forest Service, General Technical Report WO-58, Washington, DC, 1990.

Nagubadi, V., K. McNamara, W. Hoover, and W. Mills, Jr. 1996. Program Participation Behavior of Nonindustrial Forest Landowners: A Probit Analysis. Journal of Agricultural and Applied Economics 28(2), 323–336.

National Agricultural Statistics Service, 2014. Quick Stats: Farms & Land & Assets. Available at: http://quickstats.nass.usda.gov/

Parks, P.J., Hardie, I.W., 1995. Least-Cost Carbon Reserves: Cost-Effective Subsidies to Convert Marginal Agricultural Land to Forests. Land Economics 71, 122–136.

Plantinga, A.J. 1997. The Costs of Carbon Sequestration in Forests: A Positive Analysis. Critical Reviews in Environmental Science and Technology 27, 268–278.

Plantinga, A.J., Mauldin, T., Miller, D.J., 1999. An Econometric Analysis of the Costs of Sequestering Carbon in Forests. American Journal of Agricultural Economics 81, 812-824.

Richards, K.R., Moulton, R.J., Birdsey, R.A., 1993. Costs of Creating Carbon Sinks in the US. Energy Conservation Management 34, 905–912.

Richards, K.R., Stokes, C., 2004. A Review of Forest Carbon Sequestration Cost Studies: A Dozen Years of Research. Climatic Change 63 (1-2), 1–48.

Salant, P., Dillman, D.A., 1994. How to Conduct Your Own Survey. New York: John Wiley and Sons.

Shaikh, S.L., Sun, L., Van Kooten, G.C., 2007. Are Agricultural Values a Reliable Guide in Determining Landowners' Decisions to Create Forest Carbon Sinks? Canadian Journal of Agricultural Economics 55 (1), 97–114.

Siikamaki, J., Layton, D.F., 2007. Potential Cost-Effectiveness of Incentive Payment Programs for the Protection of Non-Industrial Private Forests. Land Economics 83 (4), 539–560.

Smith, J.E., Heath, L.S., Skog, K.E., Birdsey, R.A., 2006. Methods for Calculating Forest Ecosystem and Harvested Carbon with Standard Estimates for Forest Types of the United States. Gen. Tech. Rep. NE-343. Newtown Square, PA: U.S. Department of Agriculture, Forest Service, Northeastern Research Station.

Stavins, R.N. 1999. The Cost of Carbon Sequestration: A Revealed-Preference Approach. The American Economic Review 89: 994–1009.

Stavins, R.N., Richards, K.R., 2005. The Cost of U.S. forest-based Carbon Sequestration. Pew Center on Global Climate Change.

Stern, N. 2007. The Economics of Climate Change. The Stern Review. New York, NY: Cambridge University Press.

U.S. Department of Agriculture (USDA), Climate Change Program Office, Office of the Chief Economist, 2011. U.S. Agriculture and Forestry Greenhouse Gas Inventory: 1990-2008. Technical Bulletin No. 1930.

U.S. Department of Agriculture (USDA), Farm Service Agency, 2012. Conservation Reserve Program.

U.S. Department of Agriculture (USDA) Economic Research Service, 2014. Agricultural Productivity in the U.S. Available at: http://www.ers.usda.gov/data-products/agricultural-productivity-in-the-us.aspx#.VD9smPldVdI

U.S. Environmental Protection Agency (US EPA), Office of Atmospheric Programs, 2005. Greenhouse Gas Mitigation Potential in U.S. forestry and Agriculture, EPA 430-R-05-006, Washington, DC.

Van Kooten, G.C., Shaikh, S.L., Suchanek, P., 2002. Mitigating Climate Change by Planting Trees: The Transaction Costs Trap. Land Economics 78 (4), 559–572.

Whitehead, J.C., Groothuis, P.A., Blomquist, G.C., 1993. Testing for non-response and sample selection bias in contingent valuation. Economics Letters 41, 215–220.

Wooldridge, J.M., 2010. Econometric Analysis of Cross Section and Panel Data. 2nd edition. The MIT Press.

Zhou, B., Kockelman, K.M., 2008. Neighborhood impacts on land use change: a multinomial logit model of spatial relationships. The Annals of Regional Science 42, 321–340.

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Appendix

Table A1: Marginal effects for the Southeast

Table A2: Calculation of Incentive Payments