The Additionality Problem with Offsets: Optimal Contracts for Carbon Sequestration in Forests

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Abstract

Carbon offsets from forest expansion or energy efficiency improvements in developing countries are frequently discussed as a means of reducing the costs of an emissions reduction policy. However, offsets have a basic problem stemming from asymmetric information. Sellers of offsets have private information about their opportunity costs, leading to concerns about whether offsets are additional. Non-additional offsets can undermine a cap-and-trade program or, if the government purchases them directly, result in enormous government expenditures. We analyze contracts for carbon sequestration in forests that mitigate the asymmetric information problem. Landowners are offered a menu of two-part contracts that induces them to reveal their type (i.e., opportunity costs). Under this scheme, the government is able to identify ex post how much additional forest is contributed by each landowner and minimize ex ante its expenditures on carbon sequestration. To explore the performance of the contracting scheme, we conduct a national-scale simulation using an econometric model of land-use change. The results indicate that for increases in forest area between 11 and 22 million acres, government expenditures are between $1 and $6 billion lower under the contracting approach compared to a uniform subsidy offered to all landowners. This compares to an increase in private opportunity costs between $66 and $705 million dollars under the contracts.

Keywords: Carbon Sequestration; Incentive Contracting; Offsets; Additionality

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1 Introduction

As we enter the second decade of the 21st century there is an emerging consensus that carbon emissions must be limited. But there is also a strong sense that cutting emissions can be very costly, particularly if conventional sources of energy are heavily taxed or abandoned. One way to reduce the costs of a carbon reduction policy that has received a great deal of attention is offsets. The idea is to control emissions through, for example, a cap-and-trade program, but allow sources to substitute lower-cost offsets for emissions reductions. Carbon sequestration in forests is one promising type of offset. Numerous studies have found that forest sequestration can be used to offset a substantial share of carbon emissions at costs that are similar to or lower than those associated with energy-based mitigation approaches (Richards and Stokes, 2004; van Kooten et al., 2004; Stavins and Richards, 2005; Lubowski, 2002). Other offset categories include carbon storage in agricultural soils and energy efficiency improvements in developing countries. In principle, one could include all carbon sources and sinks under a cap-and-trade policy. There are practical obstacles to doing this in the case of forests and agricultural lands due to the large and diverse population of landowners and apparent political obstacles – as suggested by the Kyoto Protocol – in the case of developing countries.

Despite their potential to reduce costs, offsets have a basic problem stemming from asymmetric information. Sellers of offsets have private information about their opportunity costs of reducing or abating emissions. This implies that only the seller knows whether she would have undertaken the activity in the absence of a payment for the offset. This leads to the oft-expressed concern about "additionality": offsets are not true incremental adjustments if they would have happened anyway. Under a cap-and-trade policy, a private entity purchasing offsets cares about their price, not about whether they are additional. But, the government has an interest in ensuring the additionality of offsets since non-additional offsets effectively reduce the aggregate emissions cap. An alternative is for the government to purchase offsets directly.[1] Asymmetric information is important here as well if the government is concerned about the budgetary impacts of the policy.[2] In this case, it will want to avoid paying for non-additional offsets as well as limiting its expenditures on the offsets that are additional. However, sellers have an incentive to exploit the asymmetric information by claiming to have high opportunity costs.

In this paper, we propose and empirically investigate a contracting scheme to mitigate the asymmetric information problem. We focus our analysis on a government agency seeking to purchase offsets from private landowners, but our approach applies equally well to the situation in which the government seeks to ensure the legitimacy of privately purchased offsets. In our model, the government's objective is to maximize expected net benefits from forestation[3], where marginal benefits equal an exogenously determined carbon price and costs are defined in terms of government expenditures. The government is assumed to know the distribution over landowners' opportunity costs, but not the realization for any particular individual. The optimality conditions associated with this maximization problem induce a set of optimal contracts, one for each type of agent. Each contract entails two ingredients: a per-unit payment, and a lump-sum transfer (from the agent to the government). The essential feature of the contract scheme is that it induces agents to truthfully reveal their type (i.e., their opportunity costs). This enables the government to identify ex post how much additional forest is contributed by each landowner. Further, the government is

[1] The Conservation Reserve Program is an example of such a policy. In this case, the U.S. federal government contracted with landowners to take agricultural land out of production and put it into conservation uses.

[2] A private entity who purchases offsets would, likewise, wish to limit its expenditures. It faces the same problem as the government does with asymmetric information.

[3] Conversion of non-forest lands to forest is referred to as afforestation, while maintenance of land in forest is avoided deforestation. We use the term forestation to refer collectively to these activities.

able to minimize ex ante its expenditures on forestation. To our knowledge, our study is the first formal analysis of a carbon sequestration policy that explicitly confronts the additionality problem faced by a regulatory agency. Our proposed policy is simple, voluntary, and allows for landowner choice, features required for political feasibility and practicality.

Before giving an overview of the paper, we provide some additional motivation for our focus on carbon sequestration in forests and further justification for our concern with government expenditures. There are many ways to reduce or offset carbon emissions. Some of these activities would only be undertaken for the purpose of climate change mitigation. For example, one can assume that power utilities who switch to higher cost fuels with lower carbon content or who capture and store carbon underground do so with the goal of reducing their net carbon emissions. With carbon sequestration in forests, on the other hand, some landowners will convert agricultural lands to forest, and some will keep their lands in forest, even in the absence of additional incentives to do so. Thus, a government subsidy for forestation applied uniformly to all landowners would pay for actions landowners might have taken anyway. The costs associated with this policy could be enormous. In the U.S. an average of 1.3 million acres was deforested annually between 1982 and 1997.[4] While this represents significant carbon emissions that might be avoided at reasonable social cost, one must consider that the area of (non-federal) forest in the U.S. is approximately 400 million acres. In the extreme case, the government would subsidize all landowners when fewer than 1% of the acres would have been deforested.

Of course, the government can avoid these large expenditures if it levies taxes instead of paying subsidies. We dismiss this option as politically unviable, especially in the U.S. context.

[4] This estimate is based on National Resources Inventory (NRI) statistics for non-federal lands in the contiguous U.S. (see Lubowski (2002)).

Further, as noted above, the monitoring requirements of a cap-and-trade program make it impractical to apply to terrestrial sinks and sources on a large scale. One might also wonder if our concern about expenses is economically irrelevant, on the grounds that payments to landowners can be considered welfare-neutral: if the government costs are simply transfer payments from one set of agents in the economy to another, then they have no effect on net social benefits. We have two responses to this objection. First, the government is concerned with the budgetary effects of policies, as witnessed, for example, by debates over the size of the recent federal stimulus package in the U.S. Second, there are standard economic arguments that public funds have opportunity costs and, thus, do have implications for net social benefits.

A description of the theoretical model is contained in section 2. In section 3, we conduct an empirical simulation to examine the performance of the menu of optimal contracts. The empirical analysis draws on the national-scale econometric model of land use developed by Lubowski et al. (2006). We use the model to estimate the marginal cost distributions for forestation by state and land quality class. With this information, we compute the optimal contract menus using the theoretical results from section 2. Armed with this information, we can compare costs (both government costs and private opportunity costs) under the contracting approach to the costs of a uniform subsidy offered to all landowners. In general, we find the optimal contract scheme is considerably less expensive than the uniform subsidy. However, because the optimal contract scheme sets different subsidies for different agents, it violates the equi-marginal principle. This social cost inefficiency turns out to be small in relation to the reduction in government outlays associated with the optimal contract scheme. The implication is that the contract scheme will be preferable at the social level as well, so long as there is a modest cost of social funds. Our results have considerable practical importance, as they suggest sequestration contracts need not require huge governmental outlays.

These contracts also identify ex post how much of the forestation undertaken by each agent is additional relative to what they would have done without a contract. This is the information a regulatory agency needs to ensure proper accounting of offsets credits.

2 Theoretical statement of the problem

We suppose there is a governmental agency, which we term the "Principal," that is interested in having land placed in forest. Each unit of land placed in forest yields a benefit P^c to the Principal, which could either be viewed as revenue earned from selling sequestration credits or costs saved by avoiding the purchase of credits. One can think of this price as being induced by a carbon price.[5] The land that may be placed in forest is managed by a private entity, whom we call the "agent." In practice, the Principal will interact with a number of agents; in out model we focus on the interaction with a canonical agent. Agents are characterized by their *type*, which is private information. We denote the agent's type by $\theta \in [\underline{\theta}, \overline{\theta}]$; this value is private information. An agent's type determines his opportunity cost of placing a fraction α of his land in forest, $c(\alpha, \theta)$. We assume costs (both total and marginal) are increasing in type, $\partial c(\alpha, \theta)/\partial\theta > 0, \partial^2 c(\alpha, \theta)/\partial\alpha\partial\theta > 0$. Let the probability distribution over θ be $f(\theta)$ and the cumulative distribution function be $F(\theta)$; we assume these distribution functions are continuous in θ.

In the absence of any incentives from the Principal, agent n leaves the fraction $\alpha_n \in [\underline{\alpha}, \overline{\alpha}]$ of his acres in forest because this yields the greatest rent stream. It will be convenient to interpret the agent's type as $\theta_n \equiv \overline{\alpha} - \alpha_n$; by construction, this value lies within the compact interval $[0, \overline{\theta}]$, where $\overline{\theta} = \overline{\alpha} - \underline{\alpha}$. The agent's opportunity cost of placing a fraction α of his land in forest depends on e_n,

[5] Later in the paper, we will refer to P^c as the carbon price, even though it is defined in per-acre terms.

the increase in the fraction of land placed in forest, above and beyond the fraction that would have been placed in forest in the absence of any payment. This value equals $e_n = \alpha - \alpha_n = \alpha - \overline{\alpha} + \theta_n$. Since by assumption $c(\alpha, \theta) = c(e_n)$, we have $\partial c/\partial\alpha = \partial c/\partial\theta = c'$, and $\partial^2 c/\partial\theta\partial\alpha = c''$. We assume the Principal is unable to observe α_n *ex ante* but does know the distribution over θ.

The Principal's goal is to maximize her expected net returns

$$\Omega \equiv \int_0^{\overline{\theta}} \left\{[P^c - p(\theta)]x(\theta) + T(\theta)\right\} f(\theta) \mathrm{d}\theta,$$

where $x(\theta)$ is the fraction of land placed in forest based on the agent's actions. To maximize Ω, the Principal offers the agent a menu of contracts of the form $\left\{p(\theta), T(\theta)\right\}$, where $p(\theta)$ is interpreted as a per-unit subsidy and $T(\theta)$ is interpreted as a transfer from the agent to the Principal.[6]

Denote the profit earned by a type θ agent who acts as a type $\hat{\theta}$ agent by

$$\Pi(\hat{\theta}, \theta) = p(\hat{\theta})x(\hat{\theta}, \theta) - c(x(\hat{\theta}, \theta), \theta) - T(\hat{\theta}).$$

The incentive constraint requires that Π is maximized at $\hat{\theta} = \theta$:

$$0 = \partial\Pi(\theta, \theta)/\partial\hat{\theta} = p'(\theta)x(\theta, \theta) + [p(\theta) - \partial c(x(\theta, \theta), \theta)/\partial x](\partial x/\partial\hat{\theta}) - T'(\theta).$$

As the agent's choice of x is optimal it must satisfy $\partial c(x(\hat{\theta}, \theta), \theta)/\partial x = p(\hat{\theta})$; it follows that the incentive constraint can be written as

$$T'(\theta) = p'(\theta)x(\theta, \theta). \tag{1}$$

[6] One way to think of this transfer is $T(\theta) = p(\theta)z(\theta)$, i.e. the per-unit subsidy only applies to units of land after some fraction z.

Associated with this problem, an agent of type θ may earn *information rents*

$$\nu(\theta) = p(\theta)x - c(x,\theta) - T(\theta). \tag{2}$$

Information rents change with θ as follows:

$$\begin{aligned} \nu'(\theta) &= [p - \partial c/\partial x]\partial x/\partial\theta - \partial c/\partial\theta + [p'(\theta)x - T'(\theta)] \\ &= -\partial c/\partial\theta, \end{aligned} \tag{3}$$

where the first parenthetical term vanishes by the optimality of x and the second parenthetical term vanishes because of the incentive compatibility constraint.

Substituting the expression in (2) into the Principal's objective functional, we have

$$\Omega \equiv \int_0^{\overline{\theta}} \left\{P^c x(\theta) - [\nu(\theta) + c(x,\theta)]\right\} f(\theta)\mathrm{d}\theta.$$

Applying integration by parts to the component of the integrand involving $-\nu(\theta)f(\theta)$, and noting that $\nu(\theta)F(\theta) = 0$ at both $\theta = \overline{\theta}$ (because $\nu(\overline{\theta}) = 0$) and $\theta = 0$ (because $F(0) = 0$), we get

$$\Omega = \int_0^{\overline{\theta}} \left\{[P^c x(\theta) - c(x,\theta)]f(\theta) + \nu'(\theta)F(\theta)\right\}\mathrm{d}\theta. \tag{4}$$

Maximizing Ω at any given value of θ yields the first-order condition for an interior solution:

$$\left(P^c - \partial c/\partial x\right) f(\theta) + [\partial\nu'(\theta)/\partial x]F(\theta) = 0. \tag{5}$$

Recalling eq. (3), this first-order condition can be reduced to

$$\left(P^c - \partial c/\partial x\right) f(\theta) - [\partial^2 c/\partial\theta\partial x] F(\theta) = 0. \tag{6}$$

In addition, no agent can earn negative profits at his choice. It is straightforward to show that the efficient set of contracts will push the type $\overline{\theta}$ agent's profit—and hence its information rents—to zero (Salanié, 2005). The solution to eq. (6), combined with the condition that $\nu(\overline{\theta}) = 0$, yields the second-best fraction of land placed in forest, x^*, as a function of θ.

To simplify the optimality condition, we note that the agent will choose x so that $p = c'$, and recall from above that $\partial^2 c/\partial\theta\partial x = c''$. Using these observations, eq. (6) reduces to

$$\left(P^c - p\right) f(\theta) = c'' F(\theta). \tag{7}$$

Applying the envelope theorem to $p = c'$, we have $c'' = 1/x'(p)$; inserting into eq. (7) then yields

$$\left(P^c - p\right) x'(p) - F(\theta)/f(\theta) = 0. \tag{8}$$

For the interior solution to obtain, the second-order condition:

$$-x'(p) + (P^c - p) x''(p) < 0$$

must also be satisfied. While the first of these terms will be negative at any economically meaningful outcome, the sign of the second term depends on the curvature of marginal costs. If marginal costs are convex, as we normally think of them, then x will be concave; the second term will then be negative, and so the second-order condition will be satisfied. But if marginal costs are concave, then x will be convex, and the second-order condition can be violated.

Even if the second-order condition is met, there is no positive price that satisfies eq. (8) for any θ with $P^c x'(0) < F(\theta)/f(\theta)$, which can happen for sufficiently small values of P^c or large values of θ. On the other hand, noting that $F(\underline{\theta})/f(\underline{\theta}) = 0$, we must have either $p(\underline{\theta}) = P^c$ or $x'(p(\underline{\theta})) = 0$; we would typically expect the former branch to apply. In general, when no interior solution exists, the optimal price will be dictated by a corner solution: either $p = 0$ or $p = P^c$. Moreover, because information rents decrease with θ, we expect $p'(\theta) < 0$.

To make further progress, we suppose that θ is uniformly distributed over the interval $[0, \overline{\theta}]$. Accordingly, $f(\theta) = 1/\overline{\theta}$ and $F(\theta) = \theta/\overline{\theta} = \theta f(\theta)$. Substituting these expressions into eq. (8), we have

$$\left(P^c - p\right)x'(p) - \theta = 0 \tag{9}$$

for an interior solution.

The optimal contract scheme for a simple two-type problem is illustrated in Figure 1. In this diagram, there are two types of agents, one with low α (α_0; we term this agent 'low type'), and one with high α (α_1; we term this agent 'high type'). The types of agent are equally likely, and aside from differences in their α's the agent's costs are the same (hence, their marginal cost curves are parallel). At the optimal contract scheme, the Principal offers the agent the choice of prices p_H and p_L; the transfer payments are set so that low types choose the lower price, p_L. At this price, the low type chooses the fraction of land x_L*. Since the optimal contract scheme sets a transfer payment so as to extract all the low type's surplus, it must equal the low type's operating profit — the sum of the areas labeled a_1 and a_2. The high type is induced to accept the high price; at this price he would select the level x_H*. The incentive compatibility constraint implies the transfer payment associated with the high price renders this type of agent indifferent between 'telling the truth' (choosing the high price) and 'lying' (choosing the low price). Accordingly, the high type winds up with profits equivalent to the level he would obtain were he to misrepresent himself as a low type; if he were to misrepresent himself, he would choose the fraction x_{HL}, and earn operating profit equal to the sum of the areas labeled a_1, a_2, b_1, b_2 and d. From this operating profit he would have to forfeit the transfer payment described above, which would then leave him with a net profit equal to sum of areas b_1, b_2 and d. Total expected government expenditures under the optimal contract scheme are thus equal to this area plus the costs born by a high type at x_H* (areas $c, e_1, e_2, e_3, f_1, f_2$ and f_3), multiplied by the probability of observing a high type (i.e., $\frac{1}{2}$), plus the costs born by a low type at at x_L* (area b_1), multiplied by the probability of observing a low type (also $\frac{1}{2}$). By contrast, the same expected level of acreage could be induced if all agents were offered the price p_a (which corresponds to the expected price, $\frac{p_L+p_H}{2}$). At that price, low types would select x_L^{**} and high types would select x_H^{**}. Since the Government knows that all agents would offer at least α_0 without payment, it seems reasonable that the price p_a only be offered for levels above α_0. Accordingly, expected Government expenditures would be

$$\frac{p_a(x_L^{**}-\alpha_0)}{2}+\frac{p_a(x_H^{**}-\alpha_0)}{2};$$

this corresponds to the average of the sum of areas a_2, g_2, b_3, b_1, b_2 and c (for low types) and the sum of areas $a_2, g_2, b_3, b_1, b_2, c, d, e_1, e_2, e_3$ and g_3 (for high types). Comparing these two expenses, we see that the Principal would save an amount equal to the area a_2, g_2, b_3, b_2 and c on low types; on high types, the difference in expenses corresponds to the difference between areas a_2, g_2, b_3, g_3

and areas f_1, f_2, f_3. It is straightforward, though tedious, to verify that the government's expected costs are smaller under the optimal contract scheme, by a non-trivial amount. This cost savings comes at the expense of somewhat higher private costs, in that these costs would be lower at the common price of P_a (because of the equi-marginal principle). Even so, so long as the social cost of funds is sufficiently large, the imputed benefits accruing from limiting government expenditures will outweigh the welfare cost attributable to asymmetric costs at the margin.

In the empirical application below, we interpret a landholder as having one unit of land, and so the amount of an agent's land in forest also equals the fraction of the agent's land in forest. With this interpretation, the amount of forest at a larger geographical level, such as a state, is found by aggregating over all agents within the cohort. As we treat all agents within a particular state and land class as *ex ante* identical, multiplying the predicted share of an agent's land in forest by the total amount of land in the land class for that state will yield the expected amount of land allocated to forest.

3 Empirical Analysis of Carbon Sequestration Contracts

We conduct a national-level simulation of the carbon sequestration contracts. Two key ingredients for the simulation are the α distributions and the forest response functions $x(p)$. These are derived using the econometric model of land use developed by Lubowski et al. (2006) to derive the supply function for carbon sequestration in forests. These authors estimate a discrete-choice model of private land-use decisions using parcel-level data. The random utility framework is naturally suited to our principal-agent problem. Landowners are assumed to allocate their land to the use that maximizes utility. Utility has a deterministic component, observed by all, and a random component. The landowner observes the realization of the random variable, but the researcher only knows its distribution. Thus, the random utility model assumes asymmetric information between the researcher and the landowner. We adopt the same information structure for our principal-agent problem, where the agent has perfect information and the principal knows only the distribution of the random component of landowner utility.

In the Lubowski et al. model, utility is represented by net returns, a measure of the variable profits per acre from each land use. Land parcels begin in one of six uses (cropland, pasture, forest, urban, Conservation Reserve Program,[7] range) and are assumed to be allocated to the use generating the highest level of net returns. Because of the random component of net returns, land-use decisions are a probabilistic phenomenon from the perspective of the principal. Estimation of the model yields land-use transition probabilities of the following form:

$$P_{ijkt} = f(X_{c(i)t}, Y_i; \beta_{jk}), \tag{10}$$

where i indexes parcels, j indexes the starting use, k indexes the ending use, and t indexes time. Thus, eq. (10) signifies the probability that parcel i changes from use j to k during the time period beginning in t.[8] Probabilities are a logistic function f of observable variables $X_{c(i)t}$ and Y_i, where $c(i)$ is a function that maps from parcel i to the county in which it is located. Thus, $X_{c(i)t}$ is a vector of county-level variables (specifically, average county-level net returns to each use) and Y_i is a vector of parcel-level variables (specifically, measures of plot-level land quality that are used to scale county average returns and to proxy for conversion costs). β_{jk} is a vector of estimated

[7] The Conservation Reserve Program (CRP) is a federal cropland retirement program.

[8] Lubowski et al. (2006) estimate the land-use model with data from the National Resources Inventory (NRI), a panel survey of land use in the U.S. conducted at 5-year intervals over the 1982 to 1997. Due to the structure of the data, the probabilities correspond to land-use changes over a 5-year period.

parameters specific to the j-to-k transition.

According to the sampling scheme underlying the land-use data, each parcel i represents a certain number of acres A_i. If parcel i is initially in use j, this corresponds to A_{ij} acres in this use. If k indexes an alternative use, the expected amount of A_{ij} allocated to use k by the end of the 5-year time period beginning in t is $A_{ij} \times P_{ijkt}$. More generally, if A_{it} is a vector of acres by use in period t and P_{it} is a 6×6 matrix of transition probabilities, then $A_{it+N} = A_{it} \times P_{it}^N$ gives the expected acres in each use N periods in the future. Because forests require several decades or more to grow to maturity, our application is necessarily concerned with land-use change over long periods of time. We adopt a planning horizon of 100 years (i.e., N = 20 periods). Obviously, land-use allocations this far into the future are subject to great uncertainty. We represent this uncertainty by varying the net returns to alternative uses $X_{c(i)t}$ over historical ranges and using the associated transition probability matrices to compute the area of forest land 100 years in the future.[9]

We adopt states (or groups of states) as our unit of analysis. States with little private forest (North Dakota, South Dakota, Nebraska, Kansas, Nevada, and Arizona, and the western portions of Oklahoma and Texas) are dropped and small states are combined (the southern New England states, the northern New England states, and the mid-Atlantic states of New Jersey, Delaware, and Maryland). As well, based on climatic similarities, we reconfigure Oregon and Washington as the western and eastern portions of these states, and combine the eastern portions of Oklahoma and Texas. Henceforth, the term ”state” will be used to refer to one of the thirty-five states, groups of states, or portions of states considered in the analysis.

Lubowski (2002) assembled data from a variety of sources to estimate county average net

[9] There are other approaches to representing this uncertainty, such as deriving forecast errors using the covariance matrix for the estimated parameters in the econometric model.

returns per acre to crops, pasture, forest, urban, and range over the period 1978 to 1997.[10] For each state, we identify the minimum and maximum real return to each use over this period, and use this to represent the range of possible net returns in the future. This yields 2^5 = 32 combinations of minimum or maximum net returns to the five uses, each forming a vector denoted X_m where m = 1,...,32. Returning to the transitions probabilities, if we substitute a particular vector X_m into eq. (10), we obtain

$$P_{ijkt} = f(X_m, Y_i; \beta_{jk}), \tag{11}$$

for all j and k. Or, we can combine this set of 32 transition probabilities into the matrix P_{im}. This matrix is defined for each vector X_m and each value of Y_i. Y_i is a vector of dummy variables indicating whether parcel i is in one of four land quality categories.[11] This means that for each state we define transition probability matrices P_{qm} for four quality classes q = 1,...,4 and 32 net return combinations m=1,...,32.

For a given state, denote by A_{q0} the total acres of quality q land in each use in the initial period 0. Then, using the relationship from above, we determine the acres of quality q land 20 periods in the future as

$$A_{qm20} = A_{q0} \times P_{qm}^{20}, \tag{12}$$

where m indicates that the net return vector X_m was used to compute P_{qm}. The element of A_{qm20} of central importance to us is the one corresponding to the area of forest 100 years in the future. This variable, when expressed as a percentage of the maximum possible forest area, defines

[10] Net returns to land in the CRP are not estimated. Land-use changes involving CRP land are not modeled in terms of net returns, but handled using a different procedure discussed in Lubowski et al. (2006).

[11] Land quality is defined in terms of the Land Capability Class (LCC) system used by the U.S. Department of Agriculture. Under this system, land is assigned a rating from I to VIII, where I is the best land for agriculture. Lubowski et al. (2006) defined four land quality classes that combine LCCs I and II, III and IV, V and VI, and VII and VIII.

α_{qm}, the share of a state's land allocated to forest in the future in the absence of any carbon sequestration incentives. The maximum possible forest area is defined as the total area of private land in crops, pasture, forest, and range.[12] This measure excludes urban land, which we assume cannot be converted back to undeveloped uses, and federal lands, which are managed by U.S. government agencies. In our analysis, we assume α is uniformly distributed within each state and land quality category. The upper and lower bounds of these distribution are $\underline{\alpha}_q = \mathbf{min}_m(\alpha_{qm})$ and $\overline{\alpha}_q = \mathbf{max}_m(\alpha_{qm})$.

Table 1 lists these values. Across states, the average value of $\underline{\alpha}_q$ increases from 0.126 for the highest quality land (q = 1) to 0.461 for the lowest quality land (q = 4). Agriculture tends to be more profitable than forestry on higher quality lands and, thus, when agricultural returns are high small shares of high quality land are forested. The average value of $\overline{\alpha}_q$ falls from 0.854 for q = 1 to 0.697 for q = 4. If returns to forestry are high enough, the highest quality land will be put into forest. However, some of the lowest quality land is infeasible for forestry, even with very favorable returns.

The next step in the analysis is to derive the response function $x(p)$. We assume this function is a quadratic:

$$x(p) = \alpha + \delta_0 p + \delta_1 p^2. \tag{13}$$

Note that an increasing concave response function ($\delta_0 > 0 > \delta_1$) implies an increasing convex marginal cost function associated with increases in forest area. We need estimates of the coefficients δ_0 and δ_1 for each land quality category in each state. The intercept of this function represents the amount of forest land that would be allocated at a price of zero, the distribution for

[12] The NRI does not identify lands owned by states and counties and, thus, they are included in our measure of maximum forest area. These public lands do not represent a large share of the land base in any state and, in most cases, are forested.

which we derived above. To estimate the δ coefficients, we modify the transition probabilities in P_{qm} by means of a per-acre subsidy or tax p:

$$P_{qjk} = f(X_m + \mathbf{p}; \beta_{\mathbf{jk}}). \tag{14}$$

The vector p is defined so that forest net returns are increased by a per-acre subsidy in the case of transitions from non-forest to forest uses. Further, net returns to non-forest uses are diminished by a per-acre tax in the case of transitions from forest to non-forest uses. Thus, afforestation is encourage while deforestation is discouraged.

With P_{qm} thus modified, we project land use 100 years into the future for each q and m and subsidy/tax values p = 25,50,...,250. For each land quality category, this gives us 32 observations of x, the share of the maximum forest area that is forested after 100 years, for each of the 11 values of p. These $32 \times 11 = 352$ observations of x and p are used to estimate the price coefficients of $x(p)$ for each land quality category in each state.

The estimation results are presented in Table 2. A first set of estimates produced using all 352 observations in each regression yielded counterintuitive results in some cases (specifically, a negative coefficient on price). To investigate further, we estimated the coefficients δ_0 and δ_1 separately for each value of m using the 11 observations on x and p. This refined approach yielded negative estimates of δ_0 in about 20 percent of the cases. Most likely, these cases involve large differences in the net returns to alternative uses, which can result when we combine minimum and maximum values of net returns. Such combinations can produce complicated cross-effects on the transition probabilities (note that the probability of the j-to-k transition is a function of the net returns to *all* land uses). Accordingly, we dropped the subsets of observations yielding a negative

δ_0 value, and re-estimated the price coefficients. With this approach, the coefficient δ_0 is positive in all cases and the coefficient δ_1 is negative in most cases.

The assumed quadratic relation $x(p) = \alpha + \delta_0 p + \delta_1 p^2$ implies $x'(p) = \delta_0 + 2\delta_1 p$. Inserting this expression into eq. (9) yields the quadratic relation

$$\big(P^c - p\big)(\delta_0 + 2\delta_1 p) = \theta. \tag{15}$$

The optimal set of prices $p(\theta)$ solves eq. (15). Assuming $\delta_0 + 2\delta_1 p > 0$, as is the case in the numerical results discussed below, the solution requires $p < P^c$.[13] But the participation constraint precludes negative prices (which would yield smaller amounts of forest, at non-negative cost, than could be obtained without spending anything).[14] Thus, the optimal price must satisfy the bounds $0 \le p(\theta) \le P^c$.

In general, there will be two solutions to the quadratic equation in (15):

$$p(\theta) = -\frac{1}{4\delta_1}(\delta_0 - 2\delta_1 P^c) \pm \frac{1}{4\delta_1}\sqrt{(\delta_0 - 2\delta_1 P^c)^2 + 8\delta_1(\delta_0 P^c - \theta)} \tag{16}$$

The optimal price will be the smallest positive solution, which is induced by the positive branch from eq. (16).[15] Taking the positive branch and simplifying, we find the rule for determining the

[13] Note that $\delta_0 + 2\delta_1 p = x'(p)$, which we would expect to be non-negative. This restriction needs to hold for all prices under consideration. If $\delta_1 > 0$ then the condition $\delta_0 + 2\delta_1 p > 0$ for all non-negative prices; if $\delta_1 < 0$ then the condition may be reduced to $\delta_0 + 2\delta_1 P^c > 0$.

[14] A negative price means the agent is charged for every unit of land put into forest. Besides being counter-intuitive, such an arrangement would require a positive transfer payment to the agent, to the extent that the net payment to the agent was non-negative.

[15] The radical term on the right-hand side of eq. (16) is positive, so if $\delta_1 < 0$ the expression following the $\pm$ sign is negative, and hence must be added to the first term. But if $\delta_1 > 0$ the first term in eq. (16) is negative, so the solution must entail adding the second expression. In either case, the solution requires using the positive branch.

optimal price (when an interior solution applies):

$$p(\theta) = \frac{1}{2}[P^c - \frac{\delta_0}{2\delta_1}] + \frac{\sqrt{(\delta_0 + 2\delta_1 P^c)^2 - 8\delta_1\theta}}{4\delta_1}. \tag{17}$$

If $\delta_1 < 0$ this rule will apply for all values of θ. But if $\delta_1 > 0$, for sufficiently large values of θ no rational solution will exist. In such a case, there is no positive price that satisfies the optimality condition, and so the appropriate choice is $p(\theta) = 0$.

The solution is completed by deriving the optimal transfer function $T(\theta)$, which is induced by eq. (1). Differentiating the right-side of eq. (17) with respect to θ, and making use of eq. (17), we obtain

$$p'(\theta) = -\frac{1}{\delta_0 + 2\delta_1[2p(\theta) - P^c]}. \tag{18}$$

Then, combining eqs. (13) and (18), we obtain the differential equation that describes the optimal transfer function:

$$T'(\theta) = -\frac{\alpha + \delta_0 p(\theta) + \delta_1 p(\theta)^2}{\delta_0 + \delta_1[2p(\theta) - P^c]}. \tag{19}$$

The final step is to apply the boundary condition, $\nu(\bar{\theta}) = 0$. To use this condition, one needs to know the costs associated with placing an increment e in forest. By definition, $x = \alpha + e$, so $e = \delta_0 + \delta_1 p$. Inverting this relation yields $p(e)$:

$$p(e) = -\frac{\delta_0}{2\delta_1} + \frac{\sqrt{\delta_0^2 + 4\delta_1 e}}{2\delta_1}, \tag{20}$$

where we take the positive root so as to obtain the smallest positive price.[16] Since the agent will

[16] If $\delta_1 > 0$ the intercept is negative while the second fraction is positive, so we must add the second fraction. If $\delta_1 < 0$ the intercept is positive but the second fraction is negative, so again we want to add the second fraction.

choose e so as to maximize profit, we know $c'(e) = p$. Thus, integrating the right-hand side of eq. (20) will yield costs

$$c(e) = -\frac{\delta_0 e}{2\delta_1} + \frac{(\delta_0^2 + 4\delta_1 e)^{3/2}}{12\delta_1^2} - \frac{\delta_0^3}{12\delta_1^2}. \tag{21}$$

Once one has determined $p(\overline{\theta})$ the associated net revenues can be calculated using eqs. (20) – (21); setting the transfer $T(\overline{\theta})$ equal to these net revenues then solves the boundary condition $\nu(\overline{\theta}) = 0$. With $T(\overline{\theta})$ determined, it is then straightforward to numerically solve the differential equation (19).

Following this algorithm, we are able to derive optimal contracts for each land class in each state. These contracts can then be used to calculate expected amount of land in forest, by state and land class, and the associated cost to the Principal. We can also use information regarding the distribution over α and the $x(p)$ function to determine the constant subsidy that would deliver that amount of land in forest.[17] This allows us to compare the expected costs under the optimal contract with the constant subsidy scheme.

4 Simulation Results

The results of the empirical analysis of carbon contracts are presented in Tables 3 and 4. Table 3 gives the forest shares for each land quality category and state when carbon prices are \$0 and \$100 per acre. The \$0 case corresponds to the baseline with no carbon sequestration contracts. Thus, the first entry, 0.522, indicates that 52.2% of the highest quality land (category 1) in Alabama is expected to be allocated to forest in 100 years without any carbon sequestration incentives. As above, the share is the percentage of the maximum possible area that can be allocated to forest.

[17] There is a subtlety here: because no agent has a value of $\alpha < \underline{\alpha}$ there is no reason for the Principal to pay the constant subsidy on all units of land placed in forest. Rather, the constant subsidy would most sensibly be paid on all units of land *above* $\underline{\alpha}$; this is scheme we use in the results discussed below.

Across states, the average baseline forest shares are similar for lands of qualities 1 and 2 (49% and 45%, respectively) and higher for quality 3 and 4 lands (each 58%). The northern New England group of states (Maine, New Hampshire, Vermont) have the highest baseline forest shares for all land quality categories, while Wyoming has the lowest baseline shares. The northern New England states are currently heavily forested and remain so in the baseline. In many parts of Wyoming, trees do not grow well due to limited moisture. Other states in the Rocky Mountain region also have relatively low baseline forest shares.

Under the carbon sequestration contracts, forest shares increase for the majority of states and land quality categories. The largest response is on the lowest quality lands (category 4), where forest shares increase by about 6% on average. The next largest increase is on quality 1 lands (4% on average), followed by quality 2 and 3 lands with about 1% average increases. In some cases, the solution to the government's maximization problem is to not offer any contracts. This generally obtains when the conversion function $x(p)$ is concave and a fair bit of land would be kept in forest even without payments (i.e., $\underline{\alpha}$ is relatively large), which happens most commonly for quality 2 and 3 lands. Considering individual states, the largest forest increases on high quality lands (categories 1 and 2) occur in Missouri and Georgia, respectively. On low quality lands (categories 3 and 4), the largest increases occur in Kentucky and Wyoming, respectively. Other Rocky Mountain states see large increases in forest shares on low quality lands, which are in abundant supply in this region.

Table 4 presents government expenditures under the contracts compared to a subsidy that pays landowners the same amount per acre. At a given carbon price, the increase in forest area tends to be larger with the subsidy than with the contracts. Thus, to make the expenditures comparable, we set forest area equal to the area under the contracts and calculate the corresponding subsidy that would yield this area. This is done using the results in Table 2. For each state and land quality, we determine the per-acre subsidy that yields the increase in forest area achieved under the contract. The increases in forest area are listed in Table 4 for each state (results are aggregated across land qualities) and carbon prices of $50, $100, and $150 per acre. The costs of the contracts are calculated by summing the payments to landowners across types and subtracting the transfer payments they make back to the government. To compute the costs under the subsidy policy, we multiply the per-acre subsidy by the forest area provided by each landowner type net of the area that the highest cost type (the lowest alpha in Table 1) would provide for free. Because it knows the lower bound on the alpha distribution, the government knows the smallest forest share than any landowner will provide with no incentive. The subsidy only needs to be offered on forested acres above this point. As with the contract expenditures, we aggregate the subsidies paid to each of the landowner types to arrive at the results in Table 4.

Our key finding is that government expenditures are dramatically lower under the contracts than under a subsidy policy. At a carbon price of $50, the optimal contracts increase forest area by 11.4 million acres nationwide, at a cost to the government of $203 million. To achieve the same increase in forest area with a subsidy policy, the government would have to spend about $1.1 billion, over five times as much. For carbon prices of $100 and $150, the relative advantage of the contracting approach diminishes somewhat (expenditures are 3.8 and 3.4 times higher under subsidies, respectively), but is still substantial. On a state-by-state basis, there is considerable variation in relative expenditures. Although subsidies are always more expensive for the government than contracts, they differ only by a factor of 2 in Wyoming, while in western Oregon and Washington the factor is between 17 and 59 depending on the carbon price. These differences can be traced back to the slope of the marginal cost curves in Tables 1 and 2.

While government expenditures under the contracts are much lower than under a uniform subsidy, one naturally wonders about the difference in private opportunity costs under the two approaches. Because the uniform subsidy satisfies the equi-marginal principle, we know that it will minimize the private opportunity costs associated with the increases in forest area. In contrast, under the contracts prices vary by type. A comparison of these costs for each state is given in Table 5. For a carbon price of $100 per acre, private opportunity costs are $1.05 billion on a national scale under the contracts, compared to $734 million under the subsidy policy. The cost differences are $66 million and $705 million under carbon prices of $50 and $150 per acre, respectively. As with government expenditures, there is considerable variation among states in the differences between private opportunity costs. At the $100 carbon price, there is a ten-fold difference in western Oregon and Washington of $100 and less than a 1% difference in Wyoming.

5 Conclusion

In this paper, we have proposed a method for designing contracts that encourage carbon offsets from forestation at minimal cost to the government, subject to the landholders having private information about their opportunity costs of placing land in forest. These contracts typically leave some rents in landowners' hands, and so are second-best in nature. But, assuming that the government is concerned with the budgetary impacts of the policy, the contracts generally do a much better job of inducing the expansion or maintenance of forests than does a simple, constant per-unit subsidy. On a national scale, we find that for given increases in forest area government expenditures with contracting are between 20% and 30% of those with subsidies. In absolute terms, contracts lower expenditures between $906 million and $6.3 billion. Since the contracting scheme does not satisfy the equi-marginal, private opportunity costs are necessarily higher than under the uniform subsidy.

However, these differences are small (between \$66 million and \$705 million) relative to the reductions in expenditures. Thus, the contracting scheme is preferable from society's perspective provided there is a modest cost of social funds.

A major concern with offsets is additionality. Whether it purchases offsets directly or monitors their use in offsetting reductions by regulated emissions sources, the government has an interest in ensuring that offsets are truly incremental adjustments. Because it induces truth-telling, our contracting approach allows the government to determine ex post whether an offset is additional. Thus, our approach provides a regulatory agency with the information it needs to ensure that offsets are credited in a way that will not undermine an emissions reduction policy or result in enormous government expenditures. Our approach requires that the government knows the distribution of opportunity costs, but not the costs of any individual. Further, our proposed policy is simple, voluntary, and allows for landowner choice, features required for political feasibility and practicality.

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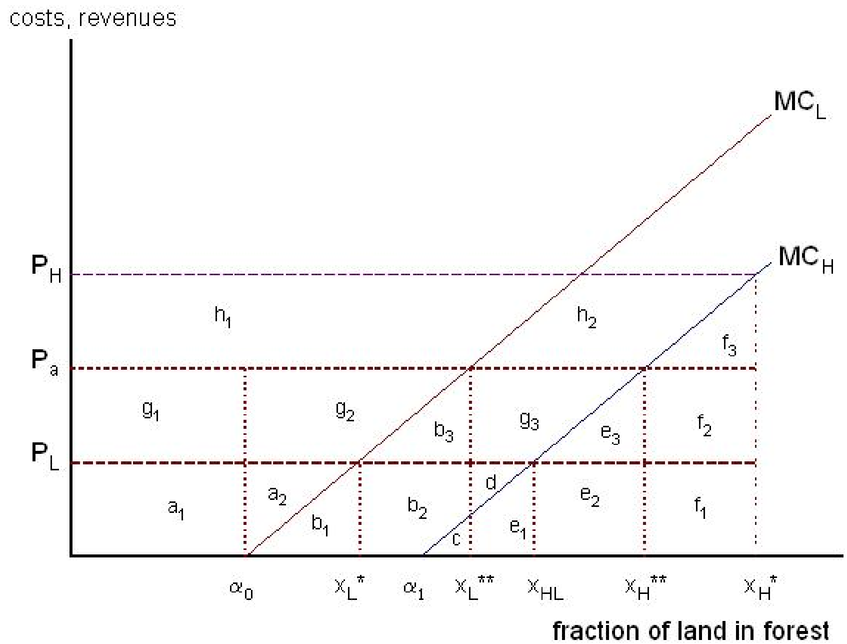

costs, revenues
MC_L
MC_H
P_H
P_a
P_L
h_1
h_2
f_3
g_1
g_2
b_3
g_3
e_3
f_2
d
a_1
a_2
b_1
b_2
c
e_1
e_2
f_1
α_0
x_L*
α_1
x_L**
x_HL
x_H**
x_H*
fraction of land in forest

Table 1. Lower and upper bounds of the α distribution, by state and land quality category

State	Land quality 1 lower	Land quality 1 upper	Land quality 2 lower	Land quality 2 upper	Land quality 3 lower	Land quality 3 upper	Land quality 4 lower	Land quality 4 upper
AL	0.274	0.769	0.365	0.678	0.620	0.813	0.652	0.804
AR	0.186	0.738	0.213	0.621	0.525	0.786	0.600	0.791
CA	0.000	0.917	0.000	0.744	0.008	0.801	0.031	0.568
CO	0.013	0.882	0.027	0.703	0.070	0.440	0.200	0.298
CT, MA, RI	0.214	0.939	0.348	0.814	0.585	0.855	0.653	0.881
DE, MD, NJ	0.103	0.900	0.184	0.753	0.435	0.824	0.514	0.861
FL	0.233	0.890	0.187	0.740	0.478	0.766	0.439	0.657
GA	0.171	0.907	0.108	0.773	0.520	0.847	0.538	0.825
ID	0.025	0.923	0.090	0.764	0.192	0.789	0.355	0.458
IL	0.052	0.881	0.123	0.710	0.444	0.745	0.544	0.743
IN	0.088	0.842	0.201	0.673	0.506	0.741	0.649	0.775
IA	0.044	0.816	0.092	0.630	0.339	0.652	0.497	0.715
KY	0.060	0.922	0.117	0.777	0.239	0.809	0.586	0.799
LA	0.190	0.869	0.079	0.726	0.518	0.829	0.499	0.735
ME, NH, VT	0.399	0.883	0.476	0.756	0.693	0.839	0.709	0.879
MI	0.184	0.904	0.318	0.758	0.627	0.833	0.650	0.798
MN	0.129	0.761	0.271	0.628	0.597	0.768	0.655	0.767
MS	0.284	0.852	0.323	0.700	0.596	0.801	0.666	0.828
MO	0.045	0.932	0.019	0.836	0.287	0.849	0.422	0.853
MT	0.024	0.783	0.046	0.602	0.158	0.324	0.187	0.246
NM	0.015	0.837	0.044	0.915	0.082	0.874	0.103	0.209
NY	0.106	0.856	0.121	0.728	0.412	0.829	0.478	0.845
NC	0.195	0.939	0.262	0.811	0.503	0.846	0.588	0.852
OH	0.092	0.725	0.224	0.614	0.531	0.787	0.625	0.800
Eastern OK & TX	0.088	0.867	0.101	0.695	0.259	0.556	0.387	0.573
PA	0.181	0.930	0.247	0.792	0.563	0.848	0.611	0.813
SC	0.256	0.923	0.362	0.781	0.616	0.842	0.631	0.844
TN	0.139	0.682	0.235	0.598	0.466	0.748	0.622	0.793
UT	0.023	0.896	0.050	0.718	0.142	0.527	0.156	0.198
VA	0.165	0.885	0.037	0.740	0.380	0.817	0.446	0.844
WV	0.196	0.668	0.356	0.635	0.569	0.782	0.694	0.877
WI	0.166	0.831	0.282	0.684	0.567	0.801	0.641	0.805
WY	0.021	0.773	0.049	0.599	0.071	0.197	0.106	0.135
Eastern OR & WA	0.040	0.874	0.024	0.748	0.126	0.882	0.109	0.638
Western OR & WA	0.002	0.876	0.041	0.801	0.150	0.897	0.249	0.881

Table 2. Price coefficients for the forest response function, by state and land quality category

State	Land quality 1 price	Land quality 1 price squared	Land quality 2 price	Land quality 2 price squared	Land quality 3 price	Land quality 3 price squared	Land quality 4 price	Land quality 4 price squared
AL	0.00191	-0.00000354	0.00057	0.00000034	0.00036	-0.00000020	0.00078	-0.00000180
AR	0.00272	-0.00000494	0.00099	0.00000049	0.00061	0.00000004	0.00084	-0.00000163
CA	0.00317	-0.00000452	0.00086	-0.00000036	0.00078	-0.00000058	0.00220	-0.00000345
CO	0.00200	-0.00000273	0.00157	0.00000069	0.00091	0.00000583	0.00245	-0.00000100
CT, MA, RI	0.00146	-0.00000080	0.00035	0.00000017	0.00058	-0.00000096	0.00060	-0.00000151
DE, MD, NJ	0.00209	-0.00000278	0.00045	0.00000062	0.00049	-0.00000055	0.00054	-0.00000121
FL	0.00169	-0.00000242	0.00106	-0.00000015	0.00076	-0.00000014	0.00170	-0.00000288
GA	0.00282	-0.00000622	0.00301	-0.00000782	0.00107	-0.00000227	0.00129	-0.00000313
ID	0.00302	-0.00000467	0.00114	0.00000095	0.00131	0.00000341	0.00243	-0.00000276
IL	0.00278	-0.00000441	0.00047	0.00000282	0.00018	0.00000135	0.00054	-0.00000095
IN	0.00303	-0.00000485	0.00035	0.00000270	0.00022	0.00000099	0.00058	-0.00000128
IA	0.00306	-0.00000500	0.00066	0.00000277	0.00040	0.00000143	0.00047	-0.00000027
KY	0.00143	-0.00000321	0.00044	0.00000218	0.00180	-0.00000048	0.00070	-0.00000146
LA	0.00270	-0.00000453	0.00181	-0.00000275	0.00110	-0.00000224	0.00175	-0.00000353
ME, NH, VT	0.00143	-0.00000148	0.00033	0.00000011	0.00042	-0.00000096	0.00047	-0.00000130
MI	0.00263	-0.00000438	0.00027	0.00000150	0.00025	-0.00000025	0.00059	-0.00000138
MN	0.00264	-0.00000462	0.00030	0.00000212	0.00018	0.00000039	0.00064	-0.00000140
MS	0.00200	-0.00000382	0.00050	0.00000114	0.00039	-0.00000027	0.00063	-0.00000138
MO	0.00404	-0.00001000	0.00116	-0.00000368	0.00062	-0.00000123	0.00135	-0.00000251
MT	0.00293	-0.00000492	0.00201	0.00000018	0.00078	0.00000572	0.00345	-0.00000299
NM	0.00246	-0.00000238	0.00169	-0.00000285	0.00117	-0.00000036	0.00156	-0.00000047
NY	0.00191	-0.00000332	0.00099	-0.00000119	0.00067	-0.00000127	0.00091	-0.00000216
NC	0.00185	-0.00000144	0.00085	-0.00000083	0.00101	-0.00000135	0.00087	-0.00000185
OH	0.00313	-0.00000613	0.00057	0.00000167	0.00023	0.00000072	0.00064	-0.00000137
Eastern OK & TX	0.00300	-0.00000564	0.00143	-0.00000048	0.00105	0.00000260	0.00231	-0.00000301
PA	0.00187	-0.00000337	0.00039	0.00000135	0.00029	-0.00000031	0.00061	-0.00000148
SC	0.00229	-0.00000422	0.00082	-0.00000140	0.00063	-0.00000122	0.00087	-0.00000194
TN	0.00277	-0.00000434	0.00077	0.00000114	0.00053	0.00000099	0.00073	-0.00000148
UT	0.00246	-0.00000352	0.00106	0.00000197	0.00090	0.00000580	0.00298	-0.00000059
VA	0.00235	-0.00000385	0.00208	-0.00000418	0.00132	-0.00000214	0.00138	-0.00000301
WV	0.00233	-0.00000455	0.00031	0.00000072	0.00032	-0.00000040	0.00062	-0.00000144
WI	0.00294	-0.00000502	0.00047	0.00000148	0.00027	0.00000030	0.00057	-0.00000122
WY	0.00291	-0.00000427	0.00238	0.00000024	0.00069	0.00000803	0.00366	-0.00000190
Eastern OR & WA	0.00292	-0.00000607	0.00112	-0.00000296	0.00137	-0.00000294	0.00323	-0.00000815
Western OR & WA	0.00174	-0.00000380	0.00022	-0.00000039	0.00026	-0.00000064	0.00056	-0.00000150

Table 3. Forest shares under the contract policy, by carbon price, state, and land quality category

State	Land quality 1 $0/ac	Land quality 1 $100/ac	Land quality 2 $0/ac	Land quality 2 $100/ac	Land quality 3 $0/ac	Land quality 3 $100/ac	Land quality 4 $0/ac	Land quality 4 $100/ac
AL	0.522	0.553	0.522	0.522	0.717	0.720	0.728	0.743
AR	0.462	0.517	0.417	0.417	0.656	0.656	0.696	0.711
CA	0.459	0.508	0.372	0.379	0.405	0.410	0.300	0.339
CO	0.448	0.470	0.365	0.365	0.255	0.255	0.249	0.435
CT, MA, RI	0.577	0.593	0.581	0.581	0.720	0.726	0.767	0.773
DE, MD, NJ	0.502	0.528	0.469	0.469	0.630	0.633	0.688	0.692
FL	0.562	0.582	0.464	0.476	0.622	0.633	0.548	0.601
GA	0.539	0.582	0.441	0.491	0.684	0.698	0.682	0.704
ID	0.474	0.520	0.427	0.427	0.491	0.491	0.407	0.573
IL	0.467	0.508	0.417	0.417	0.595	0.595	0.644	0.650
IN	0.465	0.518	0.437	0.437	0.624	0.624	0.712	0.722
IA	0.430	0.483	0.361	0.361	0.496	0.496	0.606	0.612
KY	0.491	0.502	0.447	0.447	0.524	0.554	0.693	0.702
LA	0.530	0.576	0.403	0.426	0.674	0.690	0.617	0.667
ME, NH, VT	0.641	0.662	0.616	0.616	0.766	0.771	0.794	0.799
MI	0.544	0.586	0.538	0.538	0.730	0.732	0.724	0.733
MN	0.445	0.492	0.450	0.450	0.683	0.683	0.711	0.725
MS	0.568	0.598	0.512	0.512	0.699	0.703	0.747	0.757
MO	0.489	0.558	0.428	0.435	0.568	0.572	0.638	0.656
MT	0.404	0.452	0.324	0.324	0.241	0.241	0.217	0.502
NM	0.426	0.462	0.480	0.495	0.478	0.489	0.156	0.255
NY	0.481	0.503	0.425	0.433	0.621	0.626	0.662	0.671
NC	0.567	0.591	0.537	0.544	0.675	0.688	0.720	0.732
OH	0.409	0.471	0.419	0.419	0.659	0.659	0.713	0.722
Eastern OK & TX	0.478	0.526	0.398	0.417	0.408	0.408	0.480	0.596
PA	0.556	0.577	0.520	0.520	0.706	0.707	0.712	0.719
SC	0.590	0.623	0.572	0.579	0.729	0.737	0.738	0.751
TN	0.411	0.470	0.417	0.417	0.607	0.607	0.708	0.720
UT	0.460	0.492	0.384	0.384	0.335	0.335	0.177	0.449
VA	0.525	0.559	0.389	0.415	0.599	0.616	0.645	0.664
WV	0.432	0.478	0.496	0.496	0.676	0.678	0.786	0.794
WI	0.499	0.553	0.483	0.483	0.684	0.684	0.723	0.731
WY	0.397	0.447	0.324	0.324	0.134	0.134	0.121	0.453
Eastern OR & WA	0.457	0.499	0.386	0.394	0.504	0.516	0.374	0.446
Western OR & WA	0.439	0.455	0.421	0.422	0.524	0.524	0.565	0.568

Table 4. Government expenditures for increases in forest area, by carbon price and state									
	$50/ac			$100/ac			$150/ac		
	Increase	Costs		Increase	Costs		Increase	Costs	
	in forest	Contract	Subsidy	in forest	Contract	Subsidy	in forest	Contract	Subsidy
State	(1000 ac)	($ million)		(1000 ac)	($ million)		(1000 ac)	($ million)	
AL	101	1.5	13.5	215	8.9	47.0	280	23.2	101.5
AR	126	1.9	14.0	279	11.6	51.9	370	30.8	118.6
CA	302	4.4	57.1	650	27.8	187.8	897	77.2	399.8
CO	606	10.3	33.1	984	62.6	164.4	958	158.6	387.3
CT, MA, RI	13	0.2	2.8	24	1.0	8.6	32	2.7	17.1
DE, MD, NJ	26	0.4	5.6	54	2.3	17.8	73	6.4	36.2
FL	133	2.0	22.7	306	13.3	81.6	439	39.1	187.6
GA	369	5.3	47.5	746	30.1	160.0	921	73.2	332.9
ID	346	5.6	20.1	556	33.0	94.5	511	79.3	212.9
IL	259	3.8	40.3	554	23.4	136.9	744	63.6	291.0
IN	207	3.1	27.0	459	19.3	97.1	626	52.8	215.5
IA	297	4.4	39.6	659	27.7	141.7	894	75.3	312.5
KY	77	1.1	15.6	160	6.9	49.5	225	19.7	102.7
LA	206	3.0	30.1	443	18.6	104.0	591	49.9	225.2
ME, NH, VT	49	0.7	8.9	96	4.0	28.0	122	10.1	55.5
MI	113	1.7	17.3	244	10.2	59.2	328	27.4	126.1
MN	314	4.7	39.1	688	28.6	140.2	920	76.4	311.0
MS	97	1.4	14.7	201	8.4	49.3	262	21.8	103.3
MO	334	4.7	56.0	641	25.9	169.9	780	62.0	333.5
MT	1857	38.0	93.0	2063	171.5	390.2	1887	382.5	860.6
NM	749	12.1	67.1	1788	87.7	321.5	1925	249.8	777.4
NY	98	1.4	24.5	187	7.9	73.8	244	20.9	144.1
NC	106	1.5	23.6	217	9.5	74.5	312	27.3	156.2
OH	213	3.2	23.4	466	19.2	86.3	608	50.1	195.4
Eastern OK & TX	563	8.5	69.3	1277	55.5	268.4	1568	153.7	607.2
PA	51	0.7	10.8	99	4.1	33.0	127	10.6	65.0
SC	85	1.2	14.8	176	7.3	48.6	229	19.2	99.6
TN	123	1.9	13.5	278	11.7	51.0	376	31.8	118.9
UT	1174	25.3	59.7	1351	116.0	254.3	1328	270.7	580.0
VA	162	2.3	26.7	335	13.9	88.1	436	36.5	181.3
WV	37	0.5	5.5	77	3.2	18.5	97	7.9	38.3
WI	169	2.5	20.6	371	15.6	74.3	498	41.9	166.6
WY	1669	38.0	83.6	1729	159.3	339.3	1630	354.6	753.0
Eastern OR & WA	347	5.0	52.1	690	27.8	166.9	846	67.1	344.0
Western OR & WA	21	0.3	15.4	30	1.3	31.5	33	2.9	48.3

Table 5. Private opportunity costs of increases in forest area, by carbon price and state

State	$50/ac Increase in forest (1000 ac)	$50/ac Costs ($ million) Contract	$50/ac Costs ($ million) Subsidy	$100/ac Increase in forest (1000 ac)	$100/ac Costs ($ million) Contract	$100/ac Costs ($ million) Subsidy	$150/ac Increase in forest (1000 ac)	$150/ac Costs ($ million) Contract	$150/ac Costs ($ million) Subsidy
AL	101	1.4	0.2	215	8.5	2.4	280	22.6	9.4
AR	126	1.8	0.3	279	11.2	3.8	370	30.2	15.0
CA	302	3.9	0.5	650	26.2	6.5	897	74.3	26.7
CO	606	10.2	8.7	984	62.5	60.0	958	158.3	154.1
CT, MA, RI	13	0.2	0.0	24	1.0	0.2	32	2.6	0.6
DE, MD, NJ	26	0.3	0.0	54	2.1	0.4	73	6.1	1.6
FL	133	1.8	0.3	306	12.6	4.2	439	37.8	17.5
GA	369	4.9	0.7	746	28.9	8.1	921	71.4	29.4
ID	346	5.6	4.4	556	32.8	30.0	511	79.1	73.6
IL	259	3.4	0.4	554	22.2	5.1	744	61.6	20.9
IN	207	2.8	0.4	459	18.6	5.2	626	51.5	21.2
IA	297	4.1	0.6	659	26.6	7.3	894	73.4	29.6
KY	77	1.0	0.1	160	6.5	1.3	225	19.0	5.9
LA	206	2.8	0.4	443	17.7	4.9	591	48.5	19.5
ME, NH, VT	49	0.6	0.1	96	3.7	0.7	122	9.8	2.8
MI	113	1.5	0.2	244	9.7	2.4	328	26.6	9.7
MN	314	4.3	0.7	688	27.5	8.1	920	74.7	32.2
MS	97	1.3	0.2	201	8.0	1.9	262	21.1	7.4
MO	334	4.2	0.6	641	24.6	6.6	780	60.1	24.1
MT	1857	38.0	37.3	2063	171.4	170.2	1887	382.4	380.5
NM	749	11.7	5.8	1788	86.6	72.4	1925	247.7	219.5
NY	98	1.1	0.1	187	7.2	1.1	244	19.7	4.2
NC	106	1.3	0.1	217	8.8	1.6	312	26.0	6.6
OH	213	3.0	0.5	466	18.6	6.3	608	49.2	24.5
Eastern OK & TX	563	7.9	2.1	1277	53.7	26.5	1568	150.5	87.4
PA	51	0.6	0.1	99	3.8	0.7	127	10.1	2.6
SC	85	1.1	0.1	176	6.9	1.5	229	18.5	5.9
TN	123	1.7	0.3	278	11.3	3.9	376	31.2	15.9
UT	1174	25.2	24.9	1351	116.0	115.1	1328	270.6	268.8
VA	162	2.1	0.2	335	13.2	2.9	436	35.2	11.2
WV	37	0.5	0.1	77	3.0	0.8	97	7.7	3.0
WI	169	2.3	0.4	371	15.0	4.5	498	40.9	18.3
WY	1669	38.0	37.8	1729	159.3	158.8	1630	354.6	353.8
Eastern OR & WA	347	4.5	0.8	690	26.6	8.9	846	65.2	32.8
Western OR & WA	21	0.2	0.0	30	1.0	0.1	33	2.5	0.4