Exploring tax-based payment approach for forest carbon sequestration

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Abstract:

We seek to determine if the tax-based payment approach is a valid alternative to existing incentive payment approaches for forest carbon sequestration. To achieve the objective, we test a hypothesis that waiving the property tax rate on forestland provides incentives to landowners for afforesting non-forested land or sustaining forests at risk of deforestation. We used a land use change model based on the Bureau of Economic Analysis (BEA) 88 area as a case study to test the hypothesis. The estimated effects of the waived property tax on forestland from the land use model were then used to simulate changes in afforestation and deforestation under the current level of property tax rate and under the hypothetical zero property tax. The ex-ante forecasts were then used to estimate the amount of carbon sequestered using a carbon model. Finally the estimated carbon sequestrations under the two scenarios were applied to estimate costs of supplying carbon sequestration using the tax-based payment approach. We summarize our empirical results with two key findings. First, the results show that an increase in net return from forestland by waiving the property tax on forestland increases the shares of forestland, which in turn increases accumulation of carbon in the forest ecosystem. Second, our finding suggests that annualized cost of supplying forest-based carbon sequestration was estimated to be $101.48 per ton, should the tax-based payment approach be adopted in the BEA 88. On a per-ton basis, this cost is on the high end of the estimated cost of U.S. forest-based carbon sequestration ($30 to $90 per ton) in the previous literature. Despite its lower cost efficiency, the tax-based payment approach is still worth consideration because the administrative resources and systems needed for utilizing the property tax as a tool to internalize the positive externality of the carbon sequestration of forestland are already in place and thereby can avoid costs in creating complex new institutional arrangements associated with existing incentive payment approaches.

Keywords:

Forest-based carbon sequestration; positive externality; incentive payment; property tax rate

JEL Code(s):

Q23, Q24, H23

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1. Introduction

1.1. Background

There is a growing concern that carbon emissions resulting from human activities contribute to climate change. In response to the concern, global efforts have been made to reduce carbon emissions (Canadell et al. 2007; Henstra and McBean 2009). Among different types of global efforts, much attention has focused on forest-based carbon sequestration by preventing deforestation and encouraging afforestation as a potential means of alleviating carbon emissions (Brand 1998; Metz et al. 2001; Stavins and Richard 2005; Plantinga and Richards 2008; Gorte 2009; Andersson 2009).[1] The reasons for the attention are obvious. First, the potential of forestland for mitigating carbon emissions is substantial. For example, the U.S. forestland was estimated to hold a carbon sequestration potential of 905 million metric tons in 2011, which equals an offset capacity of 16.1% of total U.S. carbon emissions (or 13.5% of total greenhouse gas emissions) in 2011 (USEPA 2013). Second, forest-based carbon sequestration has cost advantages compared to other carbon emission mitigation efforts (e.g., developing alternative energy sources to fossil fuel and carbon recovery from the energy conversion process of fossil fuel power plants) (Hendriks et al. 1989; Moulton and Richards 1990; Hall et al. 1991; Baral and Guha 2004; Plantinga and Richards 2008; Gorte 2009).

Despite the potential of forest-based carbon sequestration as means of easing carbon emissions, mitigating deforestation for carbon sequestration is a complex issue that has to contend with deforestation pressures for agriculture and urban development (Geist and Lambin 2001; UNFCCC 2006; Chomitz 2007; Myers Madeira 2008). The primary source of

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[1] The forest-based carbon sequestration is the process of capturing carbon in aboveground live trees, belowground live and dead trees, standing dead trees, understory vegetation, down dead wood, the forest floor, and soil organic carbon.

complication is not necessarily the deforestation pressure itself but the fact that the value of the carbon sequestration of the forestland is not considered in the process of deforestation for development. Economists commonly refer to the value of carbon sequestration as a positive externality and the phenomenon as market failure. In efforts to internalize the positive externality of the carbon sequestration of forestland, incentive payment approaches for forest carbon sequestration have been explored (e.g., Stainback and Alavalapati 2004; Bharrat 2008; Silva-Chavez 2005).

Among the efforts, many studies have focused on the efficiency in the different incentive payment approaches for forest carbon sequestration (i.e., practice-based payment and performance-based payment approaches) (Michael et al. 2006; Lubowski et al. 2006). A practice-based payment approach offers equal incentives based on acre of forestland enrolled in the incentive payment program, assuming spatial homogeneity in the implementation costs and positive externalities from forest-based carbon sequestration (Mason and Plantinga 2011; Plantinga 2013; Kim and Langpap 2014). In contrast, a performance-based payment approach offers discriminative incentives on a per ton basis, assuming spatial heterogeneity in costs and benefits (Antle 2003; Zhao et al. 2003; Fraser 2009; Gibbons et al. 2011; Kim and Langpap 2014).

Despite the abundant literature on the efficiency of the incentive payment approaches for forest carbon sequestration, they have not been adopted beyond the scale of pilot projects. The pilot projects have been launched at the state level with the financial assistance from federal agencies in relatively short period of time. For example, the Michigan Department of Natural Resources has provided a temporary incentive payment for private forest owners to enhance a forest’s carbon sequestration capacity through the support of the US Forest Service during 2009-

2010 (State of Michigan 2014). The states, such as West Virginia, Tennessee, Maryland, North Carolina, Pennsylvania, Massachusetts, and Oregon also have implemented similar incentive payment systems in recent years (MONOMET 2009; USEPA 2012).

The main challenge in designing and adopting the incentive payment programs for forest carbon sequestration is the institutional burden of creating new programs on top of the financial burden of implementing the programs (Baldwin and Richards 2010; IPCC 2011). Offering landowners incentives in the form of reducing the property tax rate on forestland can be a good alternative to the incentive payment programs for forest carbon sequestration. The reason is that the administrative resources and systems needed for utilizing the property tax are already in place and thereby can avoid costs in creating complex new institutional arrangements (Boyd et al. 2000; Dinan 2012). Thus, the government's financial burdens could be alleviated by reducing the additional cost or efforts for new incentive payment design. For these reasons, a tax-based payment approach with a form of indirect financial incentives can be taken into consideration as the possible alternative to the incentive payment programs.

1.2. Objective and hypothesis

Here we seek to determine if the tax-based payment approach is a valid alternative to existing incentive payment approaches for forest carbon sequestration. To achieve the objective, we test a hypothesis that waiving the property tax rate on forestland provides incentives to landowners for afforesting non-forested land or sustaining forests at risk of deforestation. We used a land use change model to test the hypothesis. The estimated effects of the waived property tax on forestland from the land use model were then used to simulate changes in afforestation and deforestation under the current level of property tax rate and under the hypothetical zero property tax. Alternatively, we could hypothesize to reduce different rates of property taxes but we simulated with zero property tax to evaluate the maximum capacity of the tax-based payment approach. The *ex-ante* forecasts were then used to estimate the amount of carbon sequestered using a carbon model. Finally the estimated carbon sequestrations under the two scenarios were applied to estimate costs of supplying carbon sequestration using the tax-based payment approach.

1.3. Significance of the analysis

Our research contributes to the literature in two ways. First, our analysis of tax-based payment approach for forest carbon sequestration provides a clue for using the tool of property tax as alternative incentive payment approach. Among the many studies that evaluate the effectiveness of incentive payment approaches for forest carbon sequestration (referred in the *1.1. Background* section), few, if any, studies explicitly consider tax-based payment approach as a candidate tool for handling the institutional burden of creating new programs of incentive payment systems. In contrast, tax deduction tools have been commonly used in protecting land through different acquisition strategies (e.g., conservation easements and fee simple acquisitions). For example, landowners may sell at below market value by way of making a charitable donation in which the donation is usually claimed as a tax deduction (Boyd et al. 2000; Lindstrom 2000, 2007). Similar to such a tax deduction as an incentive to land protections, we explore the potential of tax incentive as means of easing carbon emissions by exploring tax-based payment approach for forest carbon sequestration.

Second, our estimate of the costs of supplying forest-based carbon sequestrations using tax-based payment approach has clear implications. The estimates of the simulated changes in forest-related land use by the tax-based payment approaches were converted to changes in forest-based carbon sequestration. These information can be used by local governments to anticipate how much reduced budget from the waived property tax can contribute to how much supply of forest-based carbon sequestration.

2. Conceptual Framework

To derive costs of carbon sequestration through the tax-based payment approach, changes in forest-related land use and associated changes in carbon sequestration under tax-based payment scenarios need to be estimated. The land use changes were estimated using a land use model to link the tax-based payment with land use changes based on maximizing net returns from different land uses. The following is the conceptual base of the land use change model.

Landowners are assumed to make land use decisions that maximize their utility among a set of available alternative land uses. The utility function for each alternative land use is composed of two parts: (*i*) a deterministic component indicating observable attributes affecting land use decisions and (*ii*) a stochastic component (often referred to as random factors or error terms) indicating unobservable attributes affecting land use decisions (McFadden 1973; Domencich and McFaden 1975; Manski, 1977; Baltas and Doyle 2001; Lubowski et al. 2002; Cooper 2003; Wang and Kockelman 2005).

By considering both deterministic and stochastic components of landowners' land use decisions under the random utility theory, the utility of landowner i (i=1,2,…I) for land use k (k=0,1,…K) U_{ik} is expressed as:

$$U_{ik} = V_{ik}(X_{ik}) + \varepsilon_{ik} \ , \tag{1}$$

where V_{ik} is the utility from the deterministic component and ε_{ik} is the stochastic component. Typically, the utility V_{ik} is a function of the vectors of exogenous variables X_{ik}. Here, X_{ik} can generally be specified as (*i*) pecuniary attributes like expected net returns and (*ii*) non-pecuniary attributes like natural characteristics or socioeconomic characteristics from the land use *k* by the landowner *i* (Hyberg and Holthausen 1989; Pattanayak et al. 2002).

Because V_{ik} is the utility from the deterministic component such as X_{ik}, the landowner chooses a land use that yields the highest V_{ik}. The land use decision is made under uncertainty due to the stochastic components ε_{ik} in Eq. (1) (Baltas and Doyle 2001). Thus, a landowner's land use decision can be written in the following probability function:

$$\begin{aligned}\Pr_{ik=0} &= \Pr[V_{ik=0}(X_{ik=0}) + \varepsilon_{ik=0} > V_{ik\neq 0}(X_{ik\neq 0}) + \varepsilon_{ik\neq 0}] \\ &= \Pr[V_{ik=0}(X_{ik=0}) - V_{ik\neq 0}(X_{ik\neq 0}) > \varepsilon_{ik\neq 0} - \varepsilon_{ik=0}]\end{aligned} \tag{2}$$

$\Pr_{ik=0}$, the probability of a landowner *i* choosing the land use *k=0* is obtained under the assumption that the distribution for $\varepsilon_{ik\neq 0} - \varepsilon_{ik=0}$ follows an independent and identical Gumbel distribution (type I extreme value distribution).[2] Under the assumption, the decision probability can be derived as a multinomial logit model used for multiple land use choices (McFadden 1974; Maddala 1983; Baltas and Doyle 2001; Carrión-Flores et al. 2009) as follows:

$$\Pr_{ik} = \frac{\exp(\beta_k^{'} X_{ik})}{\sum_{k=0}^{K} \exp(\beta_k^{'} X_{ik})} \ , \tag{3}$$

where $\beta_k^{'}$ is a regression coefficient associated with the *k*th land use. The multinomial logit model has the advantage of estimating empirically because the expected share of each land use is

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[2] Multinomial logit models, and certain other types of logistic regression, can be phrased as latent variable models with error variables distributed as Gumbel distributions (type I generalized extreme value distributions).

estimated as a linear combination of exogenous explanatory variables (Wu and Segerson 1995; Hardie and Parks 1997: Plantinga et al. 1999; Ahn 2008; Chakir 2009).

3. Empirical Model

3.1. Land use model

The multinomial logit model was estimated using the study area of the Bureau of Economic Analysis (BEA) 88 area, which covers 17 counties in Tennessee and 1 county in Kentucky (see Fig. 1) in 2001, 2006, and 2011 as following:

$$\Pr_{ikt} = \frac{\mathrm{e}^{\beta_0+\beta_1 elv_i+\beta_2 slp_i+\beta_3 D_i+\boldsymbol{\beta_4 \mathrm{X}_{ikt\text{-}5}}}}{\sum_{k=0}^{4} \mathrm{e}^{\beta_0+\beta_1 elv_i+\beta_2 slp_i+\beta_3 D_i+\boldsymbol{\beta_4 \mathrm{X}_{ikt\text{-}5}}}}, \qquad (4)$$

where *i* is a pixel; *k* represents different land uses with *k* = 0, 1, 2, 3, 4 for other land uses, forestland, pastureland, cropland, and urban land, respectively; *t* is 2006 and 2011; elv_i is average elevation of a pixel *i*; slp_i is average slope of a pixel *i*; a year dummy variable D_i (1 if *t* = 2011, 0 otherwise) for a pixel *i*; and $\mathbf{X}_{\mathbf{ikt\text{-}5}}$ is a vector of annual net returns per acre for the four land uses (i.e., forestland, pastureland, cropland, and urban land).

The rest of this paper is organized as follows. The next section describes expected net returns for the four land uses as major components of exogenous variables in the land use model. The following section discusses the carbon simulation model to project site-specific carbon sequestration levels for the forestland. Then, we present the description of how costs of supplying the carbon sequestration with tax-based payment approach are estimated, which is followed by the description of study area and data, discussion of estimation results, and conclusions.

3.2. Annual net returns for four land uses

The expected annual return per acre for forestland (i.e., deciduous forest and evergreen forest) was calculated from the soil expectation value (SEV), which is the bare land value with successive crops and was calculated for a perpetual series of harvest ages (Medema and Horn 1986; Bettinger et al. 2009). Because forestland yield income periodically at the end of a harvest unlike annual cropland income, SEV is often useful for finding the present value of a perpetual periodic series to determine the potential value of the forestland (Schlosser 2004).

The SEV of a type of forestland *f* (*f* = deciduous forest, evergreen forest) per acre for a county *j* in 2001, for example, was estimated as follows:

$$\frac{P_f \cdot Q_{fjt}}{(1+r)^t - 1},\ t = harvest\ age\,, \tag{5}$$

where P_f is the stumpage price of a type of forestland *f* in 2001, Q_{fjt} is the harvest volume per acre for a forestland type *f* in a county *j* at harvest age *t*, and *r* is the discount rate of 5%. Following the conventional forester's decision making (Binkley 1987), the harvest age *t* in Eq. (5) was determined by setting the average stumpage value (i.e., $(P_f \cdot Q_{fjt}) / t$) equals to the annual incremental change in stumpage value (i.e., $\Delta(P_f \cdot Q_{fjt})/\Delta t$) for a forestland type *f* in a county *j*. Once the harvest age *t* was determined, Q_{fjt} was estimated by averaging the plot-level harvest volume per acre based on Forest Inventory and Analysis (FIA) database (Woudenberg et al. 2010). We applied the same method to calculate SEVs for both types of forestland *f* in a county *j* for different P_f.

Once the SEVs were estimated for the two types of forestland at the county level, weighted averages of the SEVs based on shares of the two types of forestland for each county for

2001 and 2006 were calculated. Then, the annualized value of weighted average of the SEV per acre (A_{SEV}) for the forestland was calculated as follows:

$$A_{SEV} = \mathrm{SEV} \Big/ \left(\frac{\left[1 - (1/(1+i)^n) \right]}{r} \right), \tag{6}$$

where r is the discount rate and n is for a period of 100 years—it can be flexible, but should be adequately long. Then, the property tax amounts, which vary by county, were subtracted from A_{SEV} to estimate the expected annual return per acre of forestland after tax.

We used county-level pastureland rent per acre for the expected return from pastureland. As the county-level pastureland rent is available for the period of 2008-2012, the data for 2001 and 2006 was predicted. For the prediction of 2001 and 2006 county-level pastureland rent per acre, a fixed effect model with panel data of 2008-2012 was employed by regressing county-level pastureland rent on state-level pastureland rent and number of cattle and pastureland size at the county level. The regression model is specified under the premise that the pastureland rent is positively related with the changing number of cattle and the size of pastureland (Sedivec 1995; NCFMEC 2011). The pastureland rents at the state level for a county in Kentucky and for 17 counties in Tennessee are, respectively, available for 2008-2012 and 1994-2012 and pastureland size at the county level is available for 1997, 2002, 2007, and 2012. The data for the years in between were filled by assuming annual linear increases for the period betwee1997-2012 for the estimation of the fixed effect model and its prediction of 2001 and 2006 county-level pastureland rent per acre. Then, we subtracted the property tax amounts from the predict values for 2001 and 2006 to estimate the expected annual returns per acre from pastureland after the tax.

The expected annual return per acre for crop land was estimated based on net cash farm income of the operation and harvest acres of crop at the county level using the following three steps. First, the ratio of non-feed and livestock expenses to total farm production expenses was derived from determining the proportion of livestock and poultry expenditures, including expenditures for their feed and for total production expenditures. Specifically, the sum of the purchases of feed, livestock, and poultry was divided by total farm production expenses. Second, the ratio of the non-feed and livestock expenses to total farm production expenses from the first step was multiplied by the net farm cash income of the operations. This means that the proportion of livestock net cash farm income to be removed from the total net cash farm income of the operation; thus, this resulting values in the second step were subtracted from the county level net cash farm income of the operation in order to leave the net cash farm income from cropland only, not from feed and livestock. Then, the property tax amounts were subtracted to estimate the expected annual returns per acre for cropland after tax for 2001 and 2006. The second step was implemented under the assumption that the net farm cash income is directly and positively correlated with farm production expense (Schnepf 2014).

The expected annual returns per acre for urban land was derived from land value ratio per acre multiplied by median housing value at the census-block group level. The land value ratio per acre was obtained by dividing the ratio of land value to median housing value by lot size. While the median housing value is available at the census-block group level for 2001 and 2006 from the U.S. Census data (Census 2000; ACS 2009, 2012), the land value ratio per acre is only available from tax assessment data at the parcel level. Ideally, the land value ratio per acre data would have been available from all 18 counties; however, discrepance in how different counties administer these data made this impractical.

To predict the land value ratio per acre for the counties where the parcel-level tax assessment data is not available, we regressed the land value ratio per acre on population density of 2010 at the census-block group level and the distances between centroids of the census-block groups to the nearest various landmarks (i.e., city center with population greater than 10,000, local, state, and national park, golf course, hospital, school, and local, state, and interstate highway) (ESRI, 2011). The regression model was specified under the premise that (*i*) the weight of the land value of the total assessed single family house value is greater in more urbanized areas with greater population density and closer to the city center and its associated facilities (Colwell and Munneke 1997; Haughwout et al. 2008; Albouy and Ehrlich 2012) and (*ii*) the land value ratio does not fluctuate over time (Bourassa et al. 2011).

For the regression model, we used 2013 parcel-level data from 2 of the 18 counties within the study area (i.e., Blount and Roane counties in Tennessee) and also 5 counties in Tennessee that are outside of the study area (i.e., Franklin, Fentress, Morgan, Monroe, and Pickett). The 5 county parcel-level data outside of study area were used in the regression model to incorporate the land value ratios for the 18 counties that were not captured by the parcel-level data from 2 counties. Once we predicted the land value ratio per acre, we annualized at the discount rates of 5% using Eq. (6). Finally, we subtracted property tax amounts from the annualized value to estimate the expected annual return per acre for urban land after the tax. (See Table 1 for the simple statistics of the net return values of all four land uses.)

3.3. Carbon simulation model

We applied a daily version of Century model (referred to as "DayCent model"), to trace gas fluxes (e.g., CO_2, N_2O, NO_x, N_2, and CH_4) for forestland (Parton et al. 1998; Kelly et al. 2000; NREL 2000; DelGrosso et al. 2001). The DayCent Model has been used extensively to simulate the effect of environmental changes (i.e. maximum and minimum air temperature, precipitation and atmospheric CO_2 levels) and management practices including grazing intensity, forest clearing practices, burning frequency, fertilizer rates, and crop cultivation practices on natural and managed plant-soil ecosystems at the site, regional, and global level (Peng et al. 1998; Bill Parton et al. 2001).

The DayCent model includes submodels of plant production, decomposition of dead plant material and soil organic matter, soil water and temperature dynamics, and traces daily gas fluxes (Metherell et al. 1993; Bill Parton et al. 2001). We used the plant production submodel for the forest group to simulate the growth of evergreen and deciduous forestland for the purpose of our study. Based on dominant species of each land use of the study area, we simulated the growths of Duke Forest Loblolly Pine for evergreen forestland and Oak Ridge for deciduous forestland (Williams 2005; TN EPPC 2013; Walker et al. 2014).

Given two types of forestlands, we processed input data (i.e., weather data, soil data, and plant rotation schedules and management practice data) for the plant production submodel for forestland during 1990-2200 using the following procedure. First, we used a daily weather data that contain maximum and minimum air temperature, precipitation, and atmospheric CO_2 levels of Tennessee. The same weather data for Tennessee was used for the entire study area under the assumption that Bell County, Kentucky shares the similar weather patterns for the 17 counties in Tennessee. Then, we applied soil data that contains six soil types (i.e., clay loam, clay, loam, sandy clay loam, sandy loam, and sandy clay) for the BEA 88. Next, we employed plant rotation schedules and management options that are appropriate for the study area. We specified rotation years for Duke Forest Loblolly Pine and Oak Ridge to be 50 and 75 years, respectively, following the forest harvesting decision rule described in the section *3.2. Annual net returns for* *four land uses*. We selected clear cutting as a forest management option following the standard management option in the CENTURY user's manual (Metherell et al. 1993; Peng et al. 1998).

Given the weather data, soil data, and plant rotation schedules and management practice data discussed above, we ran the DayCent model for 12 times (i.e., 2 types of tree species × 6 soil types) separately and obtained the daily total carbon densities in metric ton per acre during 1990-2200 by summarizing the carbon densities from carbon pools on forestland (i.e., live trees, standing dead trees, understory vegetation, down dead wood, forest floor, and soil organic matter). For calculation of annualized carbon sequestration for forest based on the summarized carbon densities from carbon pools on forestland (referred to as "carbon stock"), discounted and weighted present value of tons sequestered of the entire study area, BEA88, was computed using the following process (Richards and Stoke, 2004).

First, we calculated present value of carbon (PVC) sequestered per acre for tree types and soil types as shown below:

$$PVC_{fs} = \sum_{t=0}^{n} \frac{Y_{fst}}{(1+r)^{t}}, \tag{7}$$

where, PVC_{fs} is present value of carbon stock in tons for tree type *f* and soil type *s*; Y_{fst} is annual carbon stock for *f* and *s* at time *t* during 1990-2200 (n=210); *r* is discount rate. Second, we calculated weighted average of present value of carbon sequestration for the entire area based on shares of 2 tree types and 6 soil types as shown below:

$$WPVC = \sum_{f=1}^{2} \sum_{s=1}^{6} w_f \cdot w_s \cdot PVC_{fs}, \tag{8}$$

where *WPVC* is weighted average of present value of carbon sequestration, w_f is a ratio of each tree type and w_s is a ratio of each soil type. Third, to achieve annualized carbon sequestration, we annualized *WPVC* with 100 years and at the 5% discount rate. The weighted average value of 2 tree types and 6 soil types yields 0.568 carbon tons per acre for the forestland of the study area (see Table 2 for the annualized carbon sequestration for 2 tree types and 6 soil types).

3.4. Opportunity cost of supplying the amounts of carbon sequestration

The econometric estimates of the multinomial logit model of the land use expressed in Eq. (4) were used to predict land allocations for t = 2011 based on observed net returns of four land uses at t = 2006 as a baseline scenario. Under the hypothetical scenario, we predicted land allocations for t = 2011 based on net returns of forestland without imposing any property tax. The predicted areas of forestland under the baseline and under the hypothetical scenario were converted to annualized carbon sequestration based on the forest carbon model described in the section above. From the procedure, the opportunity cost of supplying carbon sequestration that corresponds to the tax waiver was obtained.

4. Study Area and Data Sources

The study area pertains to BEA 88, which covers 18 counties in Kentucky and Tennessee (see Fig. 1). BEA 88 is one of the 179 economic areas in the U.S. that consist of metropolitan statistical areas, or a similar area, as a core trading center (Harris et al. 2000; Johnson and Kort 2004). We focus BEA 88 as a case study for three reasons. First, BEA 88 serves as regional centers of economic activity including newly recognized metropolitan areas and the surrounding counties, thereby can reflect well changes in economic growth and population, and current regional economic activity in the U.S. regions (Harris et al. 2000). Second, BEA 88 has a local importance of the U.S carbon sequestration since it is located in the Appalachian region which accounts for around 20% of the U.S. forestland (Smith et al. 2009). Third, the application of the tax-based payment approach is practically feasible for the area under the current property tax system because counties in BEA 88 have similar tax systems that can be easily modifiable without too much challenges associated with institutional heterogeneity.

Four datasets were used (i.e., land use, net returns, census, and geographic data). The land use data, including five types of land uses (i.e., forestland, pastureland, cropland, urban land and other uses) in 2006 and 2011 were obtained from the National Land Cover Database (NLCD) (Homer et al. 2007; Fry et al. 2006; Jin et al. 2013), where 21 mutually exclusive land use categories are available at a resolution of 30 m × 30 m. The NLCD classifications of deciduous forest and evergreen forest were merged as "forest use"; developed open space, developed low intensity, developed medium intensity, and developed high intensity were categorized as "urban use"; cultivated crops were categorized as "crop use"; pasture/hay and grassland/herbaceous were categorized as "pasture use"; and the rest of classifications were categorized as "other use".[3] The 30 m × 30 m areas of the five categories were aggregated within each 1 km × 1 km pixel to calculate the share of each land use.

The net return for each land use was measured at higher levels of spatial resolution than the 1 km × 1 km pixel level. For the net returns of the forestland use, stumpage price for Tennessee was obtained from Timber Mart-South, which is a quarterly market price survey report of the major timber products by the Frank W. Norris Foundation (TMS 2001, 2006, 2011). The stumpage price for Kentucky was collected from Growing Gold by the Kentucky Division of Forestry (KDF 2001, 2006, 2011). The information on harvest volume and rotation age at the

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[3] Example of "other use" include open water, barren land rock/sand/clay, dwarf scrub, shrub/scrub, woody wetlands, and emergent herbaceous wetlands.

county-level by two species (i.e., deciduous forest, evergreen forest) was from General Technical Reports published by the USDA Forest Service (Smith et al. 2006).

The median housing value at the census-block group level for 2000 as a proxy for 2001 data were from the Decennial Census of the US Census Bureau (Census 2000) and its average estimates during the period of 2005-2009, as proxy data for 2006 were obtained from the American Community Survey of the US Census Bureau (ACS 2009, 2012). The 2013 parcel-level data (i.e., assessed land value, assessed values for single family house, and lot size) for the 7 counties were from the Office of Local Government GIS in Tennessee.[4] The county-level total crop sale, farm income, cropland size, pastureland size, and number of cattle for 1997, 2002, 2007, and 2012 were from National Agricultural Statistical Service (NASS, 2014). The population density data for 2000 is from Decennial Census of the US Census Bureau (Census 2000).

In connection with geographic data, average elevation and slope were measured using the data set that consists of raster grids of elevation and slope values derived from 30 m × 30 m Digital Elevation Model (DEM) data provided by the U.S. Geological Survey (USGS 2013). Based on the DEM data, the average elevation and slope for 1 km × 1 km pixels was calculated using the Zonal Statistics tool in ArcGIS 10.1 (ESRI, 2012). The distances to various landmarks (e.g., city, park, hospital, and highway) are measured between the parcel centroids of 1 km × 1 km and either the centroids of the nearest city, park, or the nearest point of the polylines representing a highway using spatial join in ArcGIS (ArcGIS Resource Center, 2013).

The property tax rate data for Tennessee and Kentucky are, respectively, from the Tax Aggregate Report (TAR 2001, 2006, 2011) and the Property Tax Rate Book (PTR 2001, 2006, 2011). The tax rates in Tennessee vary by “residential and farm” and “industrial and commercial”

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[4] The 7 counties include Blount, Franklin, Fentress, Morgan, Monroe, Pickett, and Roane.

categories. The category for residential and farm composed of different tax rate by county was used for the tax rates for all four land uses. In the case of Kentucky, all types of real estates in a county are taxed using the same rate, and thus the tax rate is not different for all four land uses. We accommodated differences of tax rates between the pixels inside and outside of the city boundary as the pixels inside of the city boundary are imposed to pay both city and county property taxes while the pixels outside of the city boundary are only imposed to pay county tax.

For the data for carbon simulation model, the information for spatial domain was measured by tool from ArcGIS 10.1 (ESRI, 2012). The annual weather data for Tennessee were acquired from the DAYMET model maintained by the Oak Ridge National Laboratory (Thornton at al. 2014). The soil property data used in DayCent model were from SSURGO database (USDA-NRCS 2012). The plant rotation schedules and management practice data are based on the Field Crop Budgets (UTIA 2014), along with the CENTURY User Manual (Metherell et al. 1993; Peng et al. 1998).

5. Estimation results

In Table 3, we report the marginal effects of the explanatory variables that are calculated using the parameter estimates for the multinomial logit model of the land use allocations. Overall, the model correctly predicts 75.3% of land use allocations. The marginal effects of net returns of forestland, pastureland, cropland, and urban land are all positive and significant at the 5% (hereafter, referred to as “significant” for the significance level of 5%) on the probabilities of allocating forestland, pastureland, cropland, and urban land, respectively. Specifically, an increase in net return for own land use by $1 per acre increases shares of *(i)* the forestland by 1.13% point, *(ii)* the pastureland by 13.56% point, *(iii)* the cropland by 0.001% point, and *(iv)* the urban land by 0.01% . The cross marginal effects of net returns from pastureland, cropland, and urban land on the forestland shares are all negative and significant. In particular, increases in net returns for pastureland, cropland, and urban land by $1 per acre decrease the shares of forestland by 6.5% point, 0.02% point, and 0.01% point, respectively. These findings of own and cross marginal effects of net returns imply that a land use was chosen more frequently for the land use with higher net return, confirming our conceptual framework.

The positive and significant marginal effects of slope and elevation on the forestland use suggest that *(i)* the pixels with steeper slope and *(ii)* the pixels with higher elevation were more likely to be chosen for the forestland than the rest of the land uses. These findings characterize the forestland of the study region in terms of slope and elevation.

Given the marginal effects, we predicted area allocated to each of the four land uses under the baseline and under the tax-based payment scenario. The predicted forestland increased from 2,808,831 acres (or 57.64% of the total area) under the baseline to 2,815,166 acres (or 57.77% of the total area) under the tax-based payment scenario. The increase of 6,335 acres of forestland (or 0.13% of the total area) in 2011 was due to the increase of net return from forestland that was triggered by waiver of the total property tax amount $365,167 across the study area in 2006 (i.e., average of $0.13 per acre of property tax not collected from 2,808,980 acres of forestland of the study area in 2006). We obtained $57.64 per acre as the per-acre cost of preventing deforestation and encouraging afforestation by dividing $365,167 (i.e., the waiver of the total property tax amount) by 6,335 acres (i.e., the increased area of forestland due to the increase of net return from forestland). Then, we obtained $101.48 per ton of annualized cost of supplying carbon sequestrations by dividing $57.64 per acre (i.e., the annual cost for preventing deforestation and encouraging afforestation) by 0.568 carbon tons per acre (i.e., the annualized carbon sequestration rate per acre obtained from the carbon model discussed in *3.3 Carbon simulation model* section).

5. Conclusions

We summarize our empirical results of the BEA 88 case study with two key findings. First, the results show that an increase in net return from forestland by waiving the property tax on forestland increases the shares of the forestland, which in turn increases accumulation of carbon in forest ecosystem. These results suggest that *(i)* waiving the property tax rate on forestland provides incentives to landowners for afforesting non-forested land or sustaining forests at risk of deforestation and *(ii)* prevented deforestation and encouraged afforestation through the waived property tax on forestland is a valid alternative to existing incentive payment approaches for forest carbon sequestration.

Second, our finding suggests that annualized cost of supplying forest-based carbon sequestration was estimated to be $101.48 per ton, should the tax-based payment approach be adopted in the BEA 88. On a per-ton basis, this cost is on the high end of the estimated cost of U.S. forest-based carbon sequestration ($30 to $90 per ton) in the previous literature (Stavins and Richard 2005). The reason for the high cost for the tax-based payment approach is that, if adopted, the tax-based payment approach has to be applicable to all of the forestland because implementation of property tax has to be non-discriminative. In contrast, existing incentive payment approaches may be more cost effective because selective payment can be made based on the estimated opportunity cost of each forestland. Despite its lower cost efficiency, the tax-based payment approach is still worth consideration because the administrative resources and systems needed for utilizing the property tax as a tool to internalize the positive externality of the carbon sequestration of forestland are already in place and thereby can avoid costs in creating complex new institutional arrangements associated with existing incentive payment approaches.

Although our study provides useful insights on whether offering incentives in the form of removing the property tax rate on forestland is potential alternative to existing incentive payment approaches for forest carbon sequestration, we do not provide information that helps understanding cost-efficiency of the program. A complementary analysis comparing costs of supplying forest-based carbon sequestration between different incentive payment designs and the tax-based payment approach would help understanding the cost-efficiency between the two types of payment approaches. Future analysis comparing these two approaches would be beneficial in generating more complete information for the assessment of the tax-based payment approach.

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Table 1. Variable names, descriptions, and statistics

Variable	Description	Mean (Standard deviation)
Net Return for forestland	Expected annual return for forest use (i.e., weighted average of the soil expectation value based on shares of the deciduous and evergreen forestland for each county) ($ per acre)	20.179 (4.541)
Net Return for pastureland	Expected annual return for pasture use (i.e., county-level pastureland rent per acre) ($ per acre)	20.399 (1.326)
Net Return for crop	Expected annual return for crop use (i.e., net cash farm income of the operation and harvest acres of crop at the county level) ($ per acre)	33.491 (172.104)
Net Return for urban	Expected annual returns for urban use (i.e., land value ratio per acre multiplied by median housing value at the census-block group level) ($ per acre)	417.714 (603.318)
Slope	Average slope at pixel-level (degrees)	10.606 (4.621)
Elevation	Average elevation at pixel-level (meters)	392.081 (107.431)
Year dummy variable	1 if year is 2011, 0 otherwise	0.5000 (0.500)

Table 2. Annualized carbon sequestration for 2 tree types and 6 soil types (ton per acre)

Soil properties	Duke Forest Loblolly Pine for evergreen forestland (8.1%)	Oak Ridge for deciduous forestland (91.9%)	Weighted average of forestland (i.e., evergreen and deciduous)
Clay loam (8.4%)	0.762	0.577	0.592
Clay (16%)	0.829	0.627	0.643
Loam (29.6%)	0.754	0.570	0.585
Sandy Clay loam (5.7%)	0.647	0.490	0.503
Sandy loam (17.1%)	0.664	0.503	0.516
Sandy Clay (23.3%)	0.717	0.521	0.537
Weighted average	0.737	0.553	**0.568**

Table 3. Marginal effects of the multinomial logit model for the land use allocations

Variables	Forestland ME1	Pastureland ME 2	Cropland ME 3	Urban land ME 4	Other uses ME 5
Net return for forestland	0.01126*	-0.01447*	-0.00031*	0.00429*	-0.00075*
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Net return for pastureland	-0.06510*	0.13562*	-0.00131	-0.01609*	-0.05307*
	(0.004)	(0.006)	(0.002)	(0.005)	(0.007)
Net return for cropland	-0.00018*	0.00019*	0.00000*	-0.00002*	0.00002*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Net return for urban land	-0.00006*	-0.00005*	-0.00000	0.00013*	-0.00001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Slope	0.06847*	-0.04478*	-0.00004	-0.01098*	-0.01267*
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
Elevation	0.00036*	0.00033*	-0.00002*	-0.00003	-0.00064*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year dummy variable	-0.10337*	0.25043*	-0.00161	-0.02403*	-0.12142*
	(0.014)	(0.008)	(0.006)	(0.010)	(0.024)

* Indicates statistical significance at the 5% level and numbers in parentheses are standard errors.

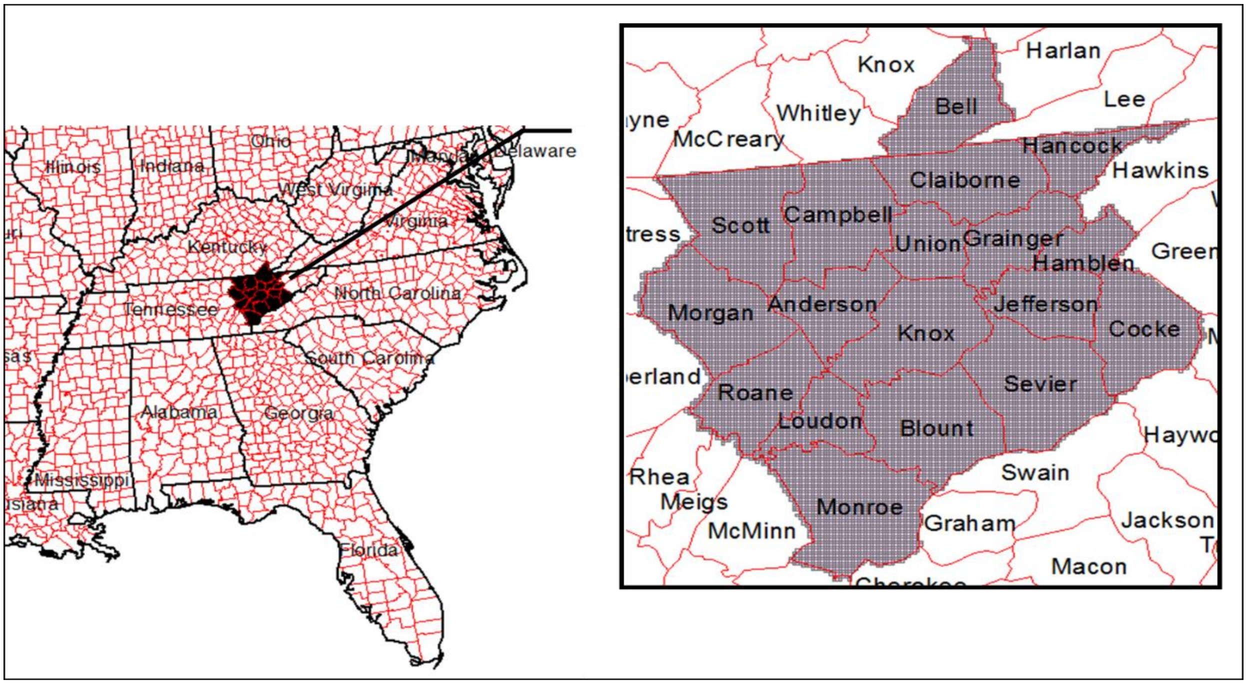

Fig. 1. Bureau of Economic Analysis (BEA) 88 area