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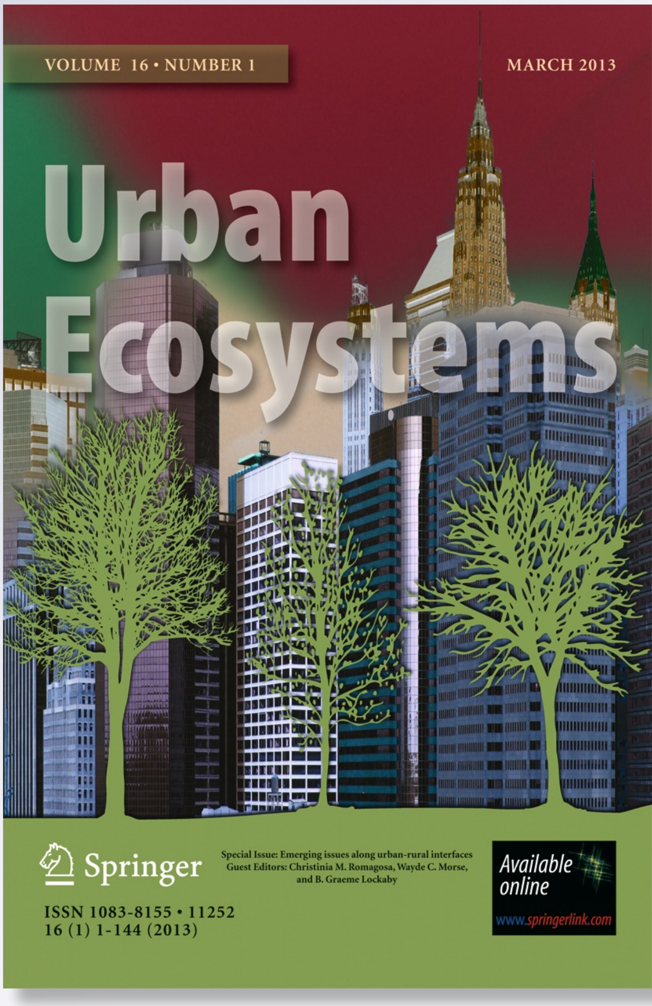

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Impacts of property tax on land use change decisions in Georgia

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Abstract In this paper, we report a study on how property taxes influence land use change decisions of Georgia private landowners. We analyze National Resources Inventory plot-level land use data and county-level socio-economic data using a panel random parameter logit model. Our results indicate that property taxes have significantly negative impacts on private landowners' land-use change decisions, but these impacts are relatively small.

Keywords Property tax · Random parameter logit · Markov transition matrix · Land use change · Urbanization

Introduction

Property tax is the primary revenue source for local government and for most public school systems in the United States. It is an ad valorem tax levied on an individual's real properties. Property tax on lands, levied on lands and items that are permanently built or attached to the lands, is based on the property's fair market value. Due to economic pressures from economic development and population growth, fair market value of rural lands often exceeds the capitalized income-producing capability of rural land uses, making individual landowners endure a higher tax burden and influencing their land management and use decisions (Hickman 1982).

Georgia is the ninth most populous state and is currently one of the fastest growing states in the United States (United States Census Bureau 2000). From 1945 to 2002, Georgia has experienced significant land use changes in rural and developed uses: a 9.60% decrease in rural lands and a 564.92% increase in developed lands. Changes in land use have produced

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significant economic and environmental effects such as traffic congestion, increases in property tax rates, lower air and water quality, and loss of biodiversity.

To find out how property tax policy influences private landowners' land use and land use transition decisions, we pursue a series of discrete choice (DC) analyses based on the first-order Markov transition probabilities in five major land use categories. In conjunction with classic land use theory, Markov transition probabilities are specified as functions of land-use net returns, property tax levied on different land use types, and land quality measures. Our results indicate that land use transitions are responsive to variations in property tax in an inelastic fashion.

Methodology

Following Lubowski (2002) and Polyakov and Zhang (2008), for a parcel of land n in use i at time t, a risk-neutral profit-maximizing landowner will choose use j at time t+1 that yields the highest expected present discounted value of an infinite stream of net returns minus conversion costs. Let R_{it} or R_{jt} be the instantaneous net benefits from any acre of land in use i or j respectively, at time t, and C_{jit} be the cost of converting one acre of land from use i to use j at time t, then land use conversion from i to j happens if:

$$R_{jt} - C_{jit} > R_{it} \tag{1}$$

When faced with more than one possible use j, the landowner will choose the alternative with the highest positive value of $R_{jt} - C_{jit} - R_{it}$.

We define a utility function of converting parcel n from land use i to j as:

$$U_{i(t+1)j|i} = R_{ntj} - R_{nti} - C_{ntj|i} = V_{n(t+1)j|i} + \varepsilon_{ntj} \tag{2}$$

to capture both observable and unobservable factors that might affect the landowners' returns and conversion costs to different land uses. $V_{nt+1j|i}$ is a representative utility that contains factors of observable attributes of initial and final land uses x_{nti} and x_{ntj}, and the observable attributes of parcels S_{nt} that are related to either returns or conversion costs. The random expression ε_{nti} is used to capture unobservable or non-quantitative factors that could affect land use conversion decisions. It is assumed to be independently and identically distributed (IID) and follows Type I extreme value distribution. Land use change happens when $U_{it+1j|i} > 0$, and land initial use in i will convert to j instead of k when

$$V_{n(t+1)j|i} + \varepsilon_{ntj} > V_{n(t+1)k|i} + \varepsilon_{ntk} \tag{3}$$

where

$$V_{n(t+1)j|i} + \varepsilon_{ntj} = U_{n(t+1)j|i}$$

and

$$V_{n(t+1)k|i} + \varepsilon_{ntk} = U_{n(t+1)k|i}(j \neq k).$$

The probability of converting land use j to land use i is:

$$P_{n(t+1)j|i} = prob\left(U_{n(t+1)j|i} > U_{n(t+1)k|i}\right) = prob\left(V_{n(t+1)j|i} + \varepsilon_{ntj} > V_{n(t+1)k|i} + \varepsilon_{ntk}\right) \tag{4}$$

Based on McFadden's (1973) conditional logit model, and following Polyakov and Zhang (2008), the empirical model is specified as:

$$P_{n(t+1)j|i} = \frac{\exp(\alpha_{ij} + \tau_{tj} + \boldsymbol{\beta}'\boldsymbol{X}_{ntj} - \boldsymbol{\beta}'\boldsymbol{X}_{nti} + \gamma_j'\boldsymbol{S}_{nt} - \gamma_i'\boldsymbol{S}_{nt})}{\sum_{k=1}^{J} \exp\left(\alpha_{ik} + \tau_{tk} + \boldsymbol{\beta}'\boldsymbol{X}_{ntk} - \boldsymbol{\beta}'\boldsymbol{X}_{nti} + \gamma_k'\boldsymbol{S}_{nt} - \gamma_i'\boldsymbol{S}_{nt}\right)} \tag{5}$$

where α_{ij} are the conversion-specific constants, τ_{tj} are fixed year effects, $\boldsymbol{\beta}$ is a vector of coefficients for the attributes characterizing alternative land uses, and $\boldsymbol{\gamma}_j$ is a vector of coefficients for the plot-specific attributes of land use j. To prevent indeterminacy in the model, we set $\tau_{Ti}=0$, $\tau_{t,J}=0$ and $\gamma_J=0$, where subscript T represents land use period in 1992–1997, and J represents lands for developed use. For lands keeping their initial uses, we set the conversion-specific constants $\alpha_{ii}=0$. Components of representative utility specific to initial land use ($\boldsymbol{\beta}'\boldsymbol{X}_{nti}$ and $\gamma_i'\boldsymbol{S}_{nt}$) cancel out due to appearance in both numerator and denominator. So the final form of the empirical model is

$$P_{n(t+1)j|i} = \frac{\exp\left(\alpha_{ij} + \tau_{tj} + \boldsymbol{\beta}'\boldsymbol{X}_{ntj} + \gamma_j'\boldsymbol{S}_{nt}\right)}{\sum_{k=1}^{J} \exp\left(\alpha_{ik} + \tau_{tk} + \boldsymbol{\beta}'\boldsymbol{X}_{ntk} + \gamma_k'\boldsymbol{S}_{nt}\right)} \tag{6}$$

When the parameters of attributes of alternative land uses are assumed to be random and to vary among sample points, the conditional logit model of Eq. 6 can be specified as:

$$P_{n(t+1)j|i}(\beta_n) = \frac{\exp\left(\alpha_{ij} + \tau_{tj} + \boldsymbol{\beta}'\boldsymbol{X}_{ntj} + \gamma_j'\boldsymbol{S}_{nt}\right)}{\sum_{k=1}^{J} exp\left(\alpha_{ik} + \tau_{tk} + \boldsymbol{\beta}'\boldsymbol{X}_{ntk} + \gamma_k'\boldsymbol{S}_{nt}\right)} \tag{7}$$

The inclusion of the random parameter in the empirical model allows us to measure implicitly some unobservable point-level effects, and helps us lessen deviations from using county-level socioeconomic factors rather than the approximate point-level values due to the limitation of data information (Lewis et al. 2011).

Data

We use panel land use data for Georgia from National Resources Inventory (NRI) sample plots. Six broad categories of non-federal lands are chosen to represent five land use types: (irrigated and non-irrigated) croplands, pasture, forests, lands in Conservation Reserve Program (CRP), and developed lands. Data are collected at the beginning and the end of each of the five-year periods from 1987 to 1997, representing 21,384 sample sites covering 31.1 million acres.

Land quality is used to control for land heterogeneity, which has been documented to have a major influence on the use of lands for agriculture and forests (Hardie and Parks 1997; Ahn et al. 2000, 2002). The U.S. Department of Agriculture (USDA) classifies non-federal lands, except developed uses and waters, into eight land capability classes (LCC) to summarily measure the suitability of land for crop production, where LCC I is the most productive and LCC VIII is the least productive land. Missing LCC for initial rural uses are replaced by the integer of weighted average LCC for each specific land use type based on county clusters. In this study, we create a dummy variable for LCC to measure land quality. LCC dummy equals 1 for LCC I to IV, 0 otherwise.

County-level economic return data are used as a proxy for plot-level data. Data for different land use alternatives are taken from Lubowski (2002), Lubowski et al. (2006).

Crop net returns are annual county-level weighted average of the gross returns per acre from different varieties of crops from 1982 to 1997 plus the value of direct government payments per acre (excluding payments to the CRP) less seed, fertilizer and petroleum product costs, farm labor expenses, and other related costs. Annual net returns to land under pasture are calculated based on the county-level average of pasture yields for different soil types weighted by soil type acreage less pasture management costs in each county. Forestry returns are weighted county-level net present values of sawtimber revenue from different forest types. Net returns to developed use are proxy for county-level annual measure of developed lot prices, back calculated from county-level data on single-family home prices, which includes the value of both the house and the land.

Property tax data for different land uses are obtained from the Georgia Department of Revenue and tax assessors of various counties. The original data include land areas of each land use category, assessed land values for taxed purpose, and millage rates of corresponding taxation sectors, such as state tax, school tax, city tax, and so on. We create a per-acre county tax variable using the ratio of aggregated taxes to land areas. The aggregated tax is the sum of each tax sector, which is the product of assessed land value for taxed purpose in thousand dollars and the corresponding millage rate. Historical records of property tax only date back to 1990. Tax value for a specific year is calculated as the mean of the previous 5 years data. Property taxes for 1987 are extrapolated using data for 1992 and 1997. Rural tax data provided by the Georgia Department of Revenue is the sum of crop, pasture and forest taxes. Individual County Tax Assessors Offices provided information on property value of open lands and woodlands, where open lands are comprised of cropland and pastureland, while woodlands are equivalent to forests. To obtain forest property tax, we use the proportion of woodland property value to multiply rural tax. All values are deflated using 1987 consumer price index (CPI) as the base (i.e., CPI1987=100).

Population density, the ratio of population to total land area of a county is used as a demographic effect on land use change. Increases of population raise the demand of lands on developed purposes. Total population for each county is taken from the Regional Economic Information System (REIS) of the Bureau of Economic analysis (BEA).

Table 1 presents the summary statistics for these explanatory variables. NRI land use data from 1987 to 1997 are pooled together. Missing values for each variable are replaced by county-average data. After merging county-level data with NRI plot level data, 39,981 plots are generated for use in this study.

Estimation results

Our dependent variable is the choice of land use in period t at each NRI point. Explanatory variables are values for period $t-1$. We model the transition between five major land use categories (crop, pasture, forestry, CRP, and developed use) simultaneously, and consider land use transition terms α_{ij} with three initial land uses i (crop, pasture and forestry) and five final uses j. DC models are estimated using Nlogit 4.0. Scaled NRI expansion factors are created as weights to obtain correct values of standard error, where the sum of scaled NRI expansion factors equals the total number of actual observations used in the model (Greene 2007).

The conditional logit (CL) model is estimated by maximum likelihood method, and the random parameter logit (RPL) model is estimated using maximum simulated log-likelihood. The coefficients of returns and property taxes are specified as random parameters in the

Table 1 Description of explanatory variables

	Number of observations	Mean	Std. Dev.	Minimum	Maximum
Plot-level Variables					
Plot in Land Capability Class 1–4	39981	0.33	0.47	0.00	1.00
NRI Sampling Weight	39981	1.51	0.83	0.10	10.20
County-level Variables					
$\text{Return}_{\text{Crop}}$	318	7.30	43.89	−291.64	127.10
$\text{Return}_{\text{Pasture}}$	318	−10.42	4.64	−21.36	−4.51
$\text{Return}_{\text{Forest}}$	318	13.13	4.49	3.90	26.04
$\text{Return}_{\text{Dev.}}$	318	1321.06	967.67	612.86	4695.27
Tax_{Crop}, Tax_{past}	318	4.65	6.61	−36.46	34.64
$\text{Tax}_{\text{Forest}}$	318	3.73	2.72	−0.56	26.29
$\text{Tax}_{\text{Developed}}$	318	24.98	57.09	−425.79	227.18
Population Density	318	128.92	206.94	13.70	1620.76

RPL model to account for the variation among parcels since county-level returns and property taxes are used as proxies for parcel-level values. They are specified as log-normal distributions, as Hensher et al. (2005) has recommended, and 1,000 Halton draws instead of random draws are performed to provide better estimates.

Table 2 reports the complete set of parameter estimates for the CL and RPL models. The estimated parameters are generally highly significant with expected signs. Likelihood ratio tests in both models reject the hypothesis that all of the coefficients are simultaneously equal to zero at the 0.01 level, which means that the models perform well compared with the corresponding models in which all parameters are zero (Train 2003). Rejection of null hypothesis from likelihood ratio tests between the CL and RPL models proved that the RPL model is preferred over the CL model (the value of likelihood ratio statistic is 9.83, with 99% critical value of $\chi_2^2 = 9.21$). The coefficients and standard errors for fixed parameters in the CL and RPL models are similar, and the statistically significant standard error of property tax derived from the RPL model indicates that the influence of property tax varies across plots.

The conversion-specific constants α_{ij} are statistically significant at the 0.01 level with expected negative signs. Since lands remaining in their initial rural uses α_{ii} account for high transition probabilities, restricting α_{ii} to zeros leads to negative estimates of land transition terms. Estimates of α_{ij} determine land use transition probabilities in the first-order Markov transition matrix. A high value of α_{ij} indicates a high transition probability from use i to use j. Among the twelve transition constants, conversion from forestry to CRP has the lowest value (−10.0233) and conversion from crop to forest has the highest value (−1.6693), implying that lands converted from forestry to CRP are less likely to happen, and lands converted from crop to forest are more likely to happen. Comparing three conversion-to-CRP terms, conversion from croplands has the highest value, which means CRP lands most likely came from croplands. This is consistent with land quality statistics in NRI records, and consistent with the CRP enrollment policy that lands under CRP must be croplands first.

To examine how land quality influences landowner's final land use decision, we create a series of dummy variables by interacting land quality dummy and land use alternatives. The signs of the corresponding coefficients indicate the effects of land quality on the probability of choosing a certain type of land use from any other potential land use alternatives, and the magnitude of the coefficient can be used to compare the propensity of land use transitions

Table 2 Regression results of conditional logit and random parameter logit models

		Conditional logit	Random parameter logit
Transition Specific Constants (α_{ij})			
Crop→Pasture		−2.3240[a] (0.1480)	−2.3259[a] (0.1507)
Crop→Forest		−1.6698[a] (0.1342)	−1.6693[a] (0.1335)
Crop→CRP		−5.2333[a] (0.4904)	−5.2370[a] (0.5175)
Crop→Developed		−4.2224[a] (0.1853)	−4.2035[a] (0.1880)
Pasture→Crop		−3.3402[a] (0.1510)	−3.3389[a] (0.1542)
Pasture→Forest		−1.9749[a] (0.1114)	−1.9734[a] (0.1122)
Pasture→CRP		−7.3834[a] (0.5337)	−7.3854[a] (0.5942)
Pasture→Developed		−4.6123[a] (0.1710)	−4.5985[a] (0.1752)
Forest→Crop		−6.2270[a] (0.1405)	−6.2279[a] (0.1340)
Forest→Pasture		−5.5655[a] (0.1146)	−5.5677[a] (0.1176)
Forest→CRP		−10.0191[a] (0.5142)	−10.0233[a] (0.5721)
Forest→Developed		−5.1970[a] (0.1020)	−5.1855[a] (0.1038)
Fixed Time Effects (τ_{ij})			
Crop	1987–1992	0.2401[b] (0.1009)	0.3242[a] (0.1057)
Pasture	1987–1992	0.4871[a] (0.1027)	0.5741[a] (0.1072)
Forest	1987–1992	0.2212[a] (0.0834)	0.3072[a] (0.0893)
CRP	1987–1992	1.8542[a] (0.2020)	1.9415[a] (0.2259)
Attributes of Land Uses (β)			
Return	Mean of Coefficient	0.0007[a] (0.0000)	0.0007
	Mean of ln(coefficient)		−7.2427[a] (0.1286)
	Std.Dev. of ln(coefficient)		0.0381 (1.0596)
Property Taxes	Mean of Coefficient	0.0021[a] (0.0005)	0.0035
	Mean of ln(coefficient)		−7.6752[a] (0.7889)
	Std.Dev. of ln(coefficient)		1.9793[a] (0.5124)
Attributes of Plots (γ_j)			
Crop	X Population density	0.0001 (0.0002)	0.0001 (0.0002)
	X Land quality	0.7663[a] (0.1421)	0.7564[a](0.1434)
Pasture	X Population density	−0.0002 (0.0002)	−0.0002 (0.0002)
	X Land quality	0.1602 (0.1219)	0.1499 (0.1261)
Forest	X Population density	−0.0006[a] (0.0001)	−0.0006[a] (0.0002)
	X Land quality	−0.3149[a] (0.0818)	−0.3271[a] (0.0845)
CRP	X Population density	−0.0005 (0.0005)	−0.0006 (0.0005)
	X Land quality	1.5082[a] (0.4685)	1.4977[a] (0.4770)
McFadden R^2		0.8277	0.8279
Log Likelihood		−11081.5300	−11071.7000

Numbers in parentheses are standard deviations

[a] is significant at the 1% level

[b] is significant at the 5% level

to that type use. As we have chosen developed lands as reference land use, and CRP is largely influenced by government budget, we are interested in the remaining coefficients of interactions of land quality dummy and land use alternatives. They can be ranked as crop—

developed—pasture—forest. This means that high quality land is likely to be converted, in a declining order, to croplands, developed use, and pasture, and least likely to be converted to forests from any initial use.

Population growth usually precipitates land use transited to non-rural use. Interactions between population density and land use alternatives are expected to yield low land transition probabilities for rural use. The statistically insignificant estimated parameters on crop and pasture and the negative and significant parameter on forests in the RPL model indicate that human disturbance or population growth does not motivate private landowners to change agricultural land uses, but does reduce forest land use.

Following Hensher et al. (2005), we reverse the sign of property tax values in the RPL model to avoid the problem of non convergence or convergence with unacceptably large mean estimates. The means of the coefficients of returns and property taxes in the RPL model are calculated from the estimated means and standard errors of log-normal distributed returns and property taxes using the formula $\beta_i = \exp\left(b_i + \frac{s_i^2}{2}\right)$. To be able to compare estimates in both models, we use negative property tax values in the CL model as well. Net returns and property taxes in the CL model have significant positive impacts on land use transition probabilities, such that higher economic returns and lower property taxes on a certain use could motivate landowners to either remain in or convert lands to this use. This confirms the classical land rent theory. The mean of the coefficient of property tax is greater in the RPL than in the CL model while there is no difference for the mean of the coefficient of return between the two models.

The estimated means of natural logarithm of return and property tax for RPL are both highly significant at the 0.01 level, while the standard error for tax is highly significant and that of return is not, implying that the influence of property taxes varies among plots while the influence of return does not. Note that there is a good chance of correlation between the random component of utility and the tax variable, since the tax variable will be positively correlated with the higher returns to land, and returns to land are measured somewhat crudely with county-averages values. Therefore, we perform another log likelihood ratio test to see if we can combine the return and tax as one variable. The value of likelihood ratio statistic is 12.62 with 99% critical value of $\chi_1^2 = 6.635$, which indicates that separating returns and property taxes is more appropriate in the model. This could not help us avoid the potential correlation problem; but it at least provides some evidence that if the return and property tax are highly correlated, one combined variable should capture some of its effect, but two separate variables do better.

Since the DC models cannot provide any intuitive behavioral indications beyond the direct role of each interested variable on the probabilities of land use transitions through the sign of estimated parameters, we provide additional results based on the results from the RPL model. Table 3 shows estimates of predicted probabilities and their associated elasticities with respect to property tax. Each initial land use type can potentially impact 25 land use transition elasticities. The diagonal elements of the elasticity sub-table in Table 3 represent own-elasticities, indicating the percentage change in probability of converting from a certain land use when its property tax changes by 1%. The off-diagonal elements are cross-elasticities, showing the probability of converting to a certain land use type from another when its property tax increases by 1%. For example, a 1% increase in property tax on forestry will decrease the probability of land use conversion to forestry by 0.013%, 0.011% and 0.001% from lands initially used for crop, pasture and forestry, respectively, as shown in the diagonal elements under Forest. The same level of property tax change on forestry will cause the probability of transition from crop to pasture to increase by 0.001%, as shown by the entry corresponding to Crop→Pasture under Forest. The small values of elasticity imply inelastic land use transitions such that a change in property tax for one kind

Table 3 Land use transtion probabilites and elasticities of probabilities with respect to property tax

Transition / Retention	Predicted probabilities	Elasticities of transition probabilities with respect to property tax per acre on				
		Crop	Pasture	Forest	CRP	Developed
Crop→Crop	0.854	**−0.003**	0.012	0.011	0.019	0.034
Crop→Pasture	0.051	0.001	**−0.014**	0.001	0.001	0.002
Crop→Forest	0.053	0.001	0.001	**−0.013**	0.001	0.002
Crop→CRP	0.028	0.000	0.000	0.001	**−0.009**	0.001
Crop→Developed	0.015	0.004	0.004	0.004	0.007	**−0.247**
Pasture→Crop	0.048	**−0.051**	0.001	0.009	0.131	0.016
Pasture→Pasture	0.844	0.014	**−0.001**	0.001	0.009	0.001
Pasture→Forest	0.068	0.013	0.000	**−0.011**	0.008	0.001
Pasture→CRP	0.005	0.005	0.000	0.000	**−0.069**	0.000
Pasture→Developed	0.035	0.057	0.000	0.003	0.038	**−0.093**
Forest→Crop	0.004	**−0.521**	0.108	0.001	0.986	0.018
Forest→Pasture	0.006	0.144	**−0.127**	0.000	0.066	0.001
Forest→Forest	0.960	0.134	0.007	**−0.001**	0.061	0.001
Forest→CRP	0.001	0.055	0.003	0.000	**−0.518**	0.000
Forest→Developed	0.030	0.598	0.030	0.000	0.298	**−0.106**

of land use has a minor impact on landowners' decisions to convert lands to a different type. The RPL model fully relaxes the IID assumption as shown by the variation of cross-elasticity among land use alternatives from each initial use.

To check the accuracy of RPL model on predictions, we did a factual simulation to see the deviation between actual and simulated land acreages. Based on the simulation results presented in the first three rows in Table 4, the RPL model accurately predicts aggregated land use acreages since all factual simulated and actual land use comparisons have nearly zero percentage deviations except for CRP and developed lands. There is a 0.42% underestimation of lands in CRP and a 0.87% underestimation of lands in developed use in 1997.

The remaining rows of Table 4 show the impacts of property tax on aggregated land use changes. It is more intuitive to tell how much lands decrease or increase in terms of the change of a land use type. Keeping all other variables constant in their 1992–1997 values, we use the observed property taxes in 2007 to simulate land use change situations by comparing the land use projected results with factual simulation results in 1997. There were actual increases of 185.56% in per acre crop and pasture taxes, 134.72% in per acre forest taxes, and 158.72% in per acre developed taxes. Assuming taxes of each type of land are changed separately, then under the observed historical property taxes, crop, pasture, forestry and developed lands will switch their initial use to the other four types by 13.25, 13.64, 22.97, and 27.48 thousand acres, respectively. Despite more than double of the tax in all cases, these changes are small in absolute terms, reflecting again, the inelastic nature of land use change to property tax variations.

Conclusions and future work

This study presents an econometric analysis of the effects of property taxes on land use transitions in five major land uses in Georgia between 1987 and 1997. A panel RPL model is

Table 4 Aggregated land use change with property tax changes under 2007 observed property tax values

Simulation scenarios[a]	Actual changes for property tax	Crop	Pasture	Forest	CRP	Developed
Actual Area in 1997 (in 1,000 acres)		4719.80	2819.30	21379.10	56.70	810.50
(1) Factual Simulated Area in 1997[b]		4720.53	2820.38	21384.61	56.46	803.42
		0.02%	0.04%	0.03%	−0.42%	−0.87%
(2) Property tax changed on crop[c]	185.56% increase	−13.25[d]	4.33	0.32	1.67	6.92
		−0.28%	0.15%	0.00%	2.97%	0.86%
(3) Property tax changed on pasture	185.56% increase	4.50	−13.64	0.95	1.00	7.19
		0.10%	−0.48%	0.00%	1.76%	0.89%
(4) Property tax changed on forest	134.72% increase	5.13	5.28	−22.97	0.29	12.27
		0.11%	0.19%	−0.11%	0.51%	1.53%
(5) Property tax changed on Dev.	158.72% increase	2.75	3.50	20.50	0.72	−27.48
		0.06%	0.12%	0.10%	1.28%	−3.42%
(6) Changed for all lands	Combine all	1.55	2.18	15.37	2.05	−21.16
		0.03%	0.08%	0.07%	3.64%	−2.63%

[a] Simulations are based on coefficient estimates of random parameter logit (RPL) model reported in Table 2

[b] Percentage change is the difference between factual simulated area and actual area divided by the actual area, which is used to check the accuracy of the RPL model on predictions

[c] Simulation 2–6 holds the property tax variable on their average of 2002–2007 values, and all the other variables in the model constant at the average of 1992–1997 annual values

[d] Values of change are the difference between simulation under 2–6 and the factual simulation. The percentage change is the difference between simulation under 2–6 and the factual simulation divided by the factual simulation. Positive (negative) values indicate that under the corresponding change of property tax to a specific land use alternative, how much lands increase (decrease) compare to the factual simulation, or how much lands change due to the change of that property tax

used to analyze NRI plot-level land use and land quality information merged with aggregated county-level economic returns and property taxes data. This approach is preferred due to the ability to capture individual impacts from the aggregated county-level socioeconomic factors, and to mitigate the broad variance in local economic returns and taxes caused by applying county-wide returns and taxes to the individual parcels. It also relaxes the IIA assumption of multiple choice models, and accounts for temporal correlation between observations of the same sample points and heterogeneity of marginal utility of property taxes among landowners.

The result of the model estimation confirms the classical land rent theory that land use patterns are determined by the rents of alternative uses and land quality. High economic returns to a particular land use could increase the probability of land remaining or converting to this use, and decrease the probability of switching to other uses. Land quality significantly influences land use decisions. Lands in high quality are most likely to be converted to croplands, and least likely to be converted to forests from any initial use. Property taxes negatively affect land use transition decisions, indicating that the greater the property taxes on a particular land use, the lower the probability of lands converting to or remaining in this use, and the effects vary among land parcels. Consistent with Polyakov and Zhang (2008), the elasticities of probabilities of land use transition with respect to property taxes are fairly inelastic.

The main policy implication for this study is that property tax can be used to help curb rapid loss of rural lands in Georgia and perhaps elsewhere. But its impact, in terms of acreage saved, could be rather small. Georgia, as other states, has preferred property tax rates for rural land uses. Because we have used county-level tax data, we have not been able to find the effectiveness of such a policy at parcel level, which will be a future project. Also, we need to find a way to separate property taxes for cropland and pasture, which could lead to more accurate estimates of elasticity for lands in agricultural uses.

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