Equilibrium Land Use Model

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1 Introduction

Currently human use directly affects more than 70 percent of global ice-free land area (Mbow et al. 2017). How this land is used has profound consequences for a variety of ecosystem services, including carbon storage, water quantity and quality, biodiversity, air quality, and more. Yet individual land owners frequently do not have explicit incentives to manage land in ways that maximize its social benefits. For example, while as much as one-third of the climate mitigation needed by 2030 to stabilize global warming to 2 degrees C could be provided cost-effectively through land management actions Griscom et al. (2017), land owners typically do not consider these social benefits of their land management.

Policy can be used to encourage land owners to manage land in socially beneficial ways, but in order to design policy effectively, policymakers need to understand how land owners will respond to policy incentives. For example, programs can be implemented that tax or subsidize forest conversion. To understand how effective a subsidy program will be, it is critical to understand how responsive land conversion is to changes in the returns from various land uses, and the degree to which policies alter land use decisions or merely reward choices that would have been made despite the policy.

Within the U.S., some of the best evidence regarding the potential effects of land use policy comes from studies that use of the National Resource Inventory (NRI), a survey of land use and natural resource conditions on non-federal lands throughout the contiguous U.S. Lubowski et al. (2006) use the NRI, combined with a national dataset describing county-level returns to various land uses, to estimate a series of land-use choice elasticities. They use those elasticities within a policy simulation to predict the costs of a policy to incentivize carbon storage in forest. Other papers have made use of NRI data to assess consequences of federal farm policy (e.g. Claassen et al. 2016), conservation outcomes (e.g. Lewis and

Plantinga 2007,Lewis et al. 2011,Lawler et al. 2014), and the effects of local land use laws on urban development (e.g. Wu and Cho 2007).

Existing studies have found that land use conversion decisions are inelastic with respect to changes in net returns. Elasticity estimates vary across studies and land use type conversion pairs, but Lubowski et al. (2006) estimate, for example, that the probability of converting from forest to cropland increases by 0.30 percentage points when returns to cropland increase by 1 percent.

While Lubowski et al. (2006) and other studies allow for endogenous adjustments in land use returns within policy simulations, they do not typically account for price endogeneity in estimates of land conversion elasticities. As Roberts and Schlenker (2013)show, not accounting for price endogeneity can bias agricultural supply elasticities toward zero. Price endogeneity can arise due to both cross-sectional and variation in unobserved factors affecting land use returns. For example, counties may vary in unobserved ways that affect the suitability of average parcels for particular land uses. Factors that favor a particular land use are expected to be negatively correlated with returns to that land use. Therefore, we expect omitting these unobserved factors should bias elasticity estimates downward. Similarly, unobserved land supply shocks (e.g. due to changes in production technology) over time are expected to be negatively correlated with net returns, driving elasticity estimates downward. Accounting for price endogeneity is particularly important in national land use models that make use of county-level NRI and land use returns data because most of these studies rely on NRI data in which parcels have been anonymized at the county level, which constrains measurement of parcel-level returns. Price endogeneity may explain why Lubowski et al. (2006) found several negative land conversion elasticities, in which more land is converted to a particular use when relative returns from that use decrease. These elasticity estimates drive results from policy simulations, therefore better accounting for price endogeneity may improve the accuracy of predicted policy outcomes.

We build on this body of literature by incorporating features of modern discrete choice methods that account for price endogeneity. First, we will define county-land condition class groups and estimate the share of parcels within each group undergoing each conversion type. Because for some land use conversion types, many counties may not experience any land use conversions in a given year, we use a Poisson regression. We include county-year-conversion type fixed effects and in the second step, we estimate the fixed effects as a function of county-year returns. Because county level returns are endogenous, we will instrument for them using a Hausman instrument.

We expect this work will yield new insights into the potential for climate policy that incorporates the land use sector. Because existing estimates of land conversion elasticities have not taken into account price endogeneity, we expect they may under-estimate the cost-savings associated with mitigating climate change through the land use sector. We next discuss a series of applications for the model.

2 Land Use Transition Choice Model

Landowners maximize net returns by choosing to transition their land to one of six broad land use types in the NRI: crops, pasture, range, forests, urban, and CRP. Owner of parcel i obtains returns V_{ijkt} by choosing to transition its land parcel from use j to use k in year t. Owner of parcel i obtains a net return of V_{ijjt} if it decides to keep the land parcel in use j. Net returns are defined by

$$V_{ijkt} = U_{ijkt} + \varepsilon_{ijkt} = \alpha_{jkt} LCC_{it} + \beta_{jkt} LCC_{it} R_{kct} + \delta_{jkct} + \varepsilon_{ijkt}. \tag{1}$$

The term LCC_{it} represents parcel i's land capability class (LCC) in year t. The lower the class number, the fewer restrictions the land has for crops. The term R_{kct} denotes the revenue from converting a parcel to land use type k in county c in year t. Parameter α_{jkt} measures the average net return of transitioning a land parcel that shares the LCC of parcel i from use j to use k in year t. We expect values of α_{jkt} to be smaller for converting land from crops to forest for land that has a low LCC. Parameter β_{jkt} measures the relationship between revenue and net returns of transitioning a land parcel that shares the LCC of parcel i from use j to use k in year t. We expect values of β_{jkt} to be larger for converting land from crops to forest for land that has more marginal, perhaps in the middle of the range of LCC. The term ε_{ijkt} is parcel i's unobserved net return for converting from use j to use k that is unexplained by the observed attributes.

The term δ_{jkct} measures the average net return from converting a parcel of land in county c from use j to use k in year t. We express this as

$$\delta_{jkct} = \overline{\alpha}_{jkt} + \overline{\beta} R_{kct} + \xi_{jkct}. \tag{2}$$

The term $\overline{\alpha}_{jkt}$ represents the average net return from converting a parcel of land from use j to use k in year t. The term $\overline{\beta}$ represents the average response of net returns to changes in revenues earned by use k in county c and year t. The term ξ_{jkct} includes all unobserved net returns at the county level for converting from use j to use k that is unexplained by the county-level characteristics.

Under the assumption that the error term ε_{ijkt} has a type 1 extreme value distribution, the probability that parcel i in use j is converted to use k in year t is

$$Pr_{ijkt} = \frac{e^{U_{ijkt}}}{\sum_m e^{U_{ijmt}}}. \tag{3}$$

We assign parcels to distinct groups differentiated by LCC, county, and initial land use. We denote a group differentiated by LCC and county by g. For each parcel group, we assign as the outside option the decision to keep the parcel in the same land use, and we normalize the net return from this option to zero, so that $U_{gjjt} = 0$ for all g, j, t. Based on this assumption, Equation (3) can be converted to a linear equation linking observed transition shares and components of net returns:

$$\ln(s_{gjkt}) - \ln(s_{gjjt}) = \alpha_{jkt} LCC_{it} + \beta_{jkt} LCC_{it} R_{kct} + \delta_{jkct}. \tag{4}$$

The left-hand side of Equation (4) is the difference between the log share of parcel group g conversions of initial land use j to use k in year t and the log share of parcel group g initial land use j remaining in land use j in year t.

A concern for estimating the parameters of the model is that the shares could be zero for some of the transition categories. To circumvent this issue, we convert Equation (4) to a Poisson regression. Combining the terms on the left-hand-side, cancelling like terms, and exponentiating both sides yields

$$\frac{COUNT_{gjkt}}{COUNT_{gjjt}} = exp(\alpha_{jkt} LCC_{it} + \beta_{jkt} LCC_{it} R_{kct} + \delta_{jkct}). \tag{5}$$

The $COUNT$ terms represent counts of the conversions. This equation is defined as long as $COUNT_{gjjt}$ is not zero. For our setting, this is likely to be the case since parcel transitions are relatively uncommon. This equation can be estimated with a fixed effects Poisson regression. The fixed effects are δ_{jkct}.

The fixed effects are obtained post-estimation and are used as the dependent variable in a second stage regression:

$$\widehat{\delta}_{jkct} = \overline{\alpha}_{jkst} + \overline{\beta} R_{kct} + \xi_{jkct}. \tag{6}$$

The per-acre revenue variable R_{kct} is equal to the per-acre equivalent equilibrium price, P_{kct},of the commodity associated with each land use category. Prices are endogenously determined in equilibrium by supply and demand of each commodity. We assume that demand is defined as

$$D_{kct} = d_{kt} + \delta(P_{kct}) + \varepsilon^{D}_{kct} \tag{7}$$

The term d_{kt} represents a commodity demand shock common to all counties in year t. This term represents changes in the demand for the commodity over time, such as changes in consumer preferences for meat products or wood furniture. The function δ defines the demand price sensitivity. The third term, ε^{D}_{kct}, is a demand shock that is specific to land category k in county c in year t.

The equilibrium price P_{kct} is defined by the intersection of supply and demand. Given our definitions of demand and supply, we can express equilibrium returns and prices as

$$R_{kct} = P_{kct} = f(\Omega, d_{kt}, \varepsilon^{D}_{kct}, \xi_{jkct}), \tag{8}$$

where Ω contains all supply and demand parameters besides d_{kt} (such as $\overline{\alpha}_{jkt}$ and $\overline{\beta}$). We assume that the functional form for $f()$ is approximated as

$$R_{kct} = P_{kct} = d_{kt} + \widetilde{f}(\Omega) + \varepsilon^{p}_{kct}(\varepsilon^{D}_{kct}, \xi_{jkct}). \tag{9}$$

We assume that the parametrized error term $\varepsilon^{p}_{kct}(\varepsilon^{D}_{kct}, \xi_{jkct})$, which represents shocks to demand or supply, is idependent across counties. From equation (9), we see that returns and the error term, ξ_{jkct}, are correlated. Therefore, estimating equation (6) with ordinary least squares will lead to biased estimates for $\overline{\beta}$. Our assumptions imply that prices for commodity type k in year t are correlated only due to the common demand shock d_{kt}. Therefore, average prices of the same commodity and time period in different counties can be used as an instrument for returns. Formally, we construct an instrument for land use k returns in county c in year t as

$$R^{IV}_{kct} = \frac{1}{N_{cs} - 1} \sum_{c'} R_{kc't}, \tag{10}$$

where N_{cs} is the number of counties in state s where county c is located and where c' denotes counties in state s besides county c.

This identification approach is a well-known strategy in the industrial organization literature for dealing with price endogeniety (Hausman et al. 1994, Hausman 1996, Nevo 2000). It also is well understood that the assumptions underlying this strategy could be violated in some circumstances. For example, suppose there is a national supply shock, such as the discovery of a technology that increases crop yields per unit of input. This discovery would lower production costs per unit of crops, shifting out the crop supply curve in all counties. This would violate the assumption that the error terms ε^p_{kct} are independent across counties. We attempt to control for this possibility by including a rich set of fixed effects, including $\overline{\alpha}_{jkst}$, which absorb all unobserved supply shocks that are common to transitions from land use j to land use k in state m in year t.

3 Commodity Equilibrium Model

We integrate land use transition choices in an equilibrium of commodity supply and demand. We extend the approach taken in Lubowski et al. (2006) by allowing commodity prices to be endogenously determined by supply and demand factors. Following Lubowski et al. (2006) , we convert land use transitions to changes in corresponding commodities. The corresponding commodities include timber from forests, raw, non-meat food inputs from crops, housing from urban, beef, chicken, and pork from range and pasture. In contrast to Lubowski et al., we assume that commodities of all land use types besides CRP have prices that are endogenously determined. We aggregate beef, chicken, and pork into a single meat market. In summary, we model endogenous prices and quantities for timber, non-meat food inputs, meat, and housing.

We calibrate demand curves for each of the commodities. Following Lubowski et al. (2006), we use demand elasticities for seven timber production regions — Pacific Northwest (-0.300), Pacific Southwest (-0.497), Rocky Mountains (-0.054), North Central (-0.141), Northeast (-0.029), South Central (-0.193), Southeast (-0.285). We assume a national market for non-meat food inputs and assume a demand elasticity equal to -0.661. We assume a national market for meat and assume an aggregate elasticity of demand equal to -0.71 (Gallet 2010). We calibrate separate housing demand curves for each county assuming a demand elasticity of -0.8 (Albouy et al. 2016).

With supply and demand for each commodity specified, we are able to solve for equilibrium prices of each commodity and region that equates supply and demand in each region. Since supply and demand are non-linear functions of all commodity prices, we use root-finding methods (such as Newton's method) to obtain an equilibrium.

4 Research Interests

4.1 Subsidy policies and asymmetric information

Reducing greenhouse gas emissions through land use change often involves a subsidy payment to landowners. Carbon offset programs, such as those in the California AB 32 program, the Regional Greenhouse Gas program, and the proposed offset provision as part of the Waxman-Markey federal cap and trade program, are designed in this manner. A common concern with these programs is that the payments are for activities that would have been done without the subsidy. This problem of "additionality" has significant distributional and efficiency implications for policy design (Bento et al. 2015). Additionality arises because of asymmetric information between landowners and policy makers: landowners know more about their future decisions than policy makers. This leads to adverse selection: landowners that would have reduced carbon emissions anyway are more likely to opt in to the voluntary program than landowners that have to experience a costly transition to obtain the subsidy. At worst, a subsidy program could be transferring significant rents from capped to uncapped sectors with little to no emissions reductions taking place.

Our model is well-suited to quantify these issues for carbon mitigation programs in the US. We model the decision of landowners based on observed and unobserved characteristics. The unobserved characteristics, which are represented by landowner-specific error terms, represent asymmetric information (Mason and Plantinga 2013). Therefore, with our model, we will be able to quantify the distribution of additional versus non-additional emissions reductions are being credited by a subsidy program, and how this distribution is affected by changing subsidy amounts and altering other policy design features. With our model, we will be able to quantify the efficiency and distributional costs of alternative policy options that address additionality, including setting stringent baselines, discounting, and limiting the use of offsets.

4.2 Ecosystem services

Land use choices impact a variety of ecosystem services in addition to carbon storage, but the extent of these impacts frequently depend critically upon where within counties conversions take place. To better understand the consequences of county-level land conversion rates on ecosystem services, historical county-level conversions observed within the NRI can be paired with NLCD satellite data to predict portions of counties in which probability of each land conversion type is highest. Using policy simulations to predict county land conversion rates, within-county conversion probabilities can then be used in combination with a spatial ecosystem services model (such as InVEST) to estimate changes to ecosystem services. This approach differs from Lawler et al. 2014 in that it makes use of NLCD data to estimate spatially-explicit within-county conversion probabilities based on overall county-level conversion probabilities.

4.3 Integration with forest sector models

RFF Senior Non-resident Fellow Dave Wear has proposed a line of research improving on models of US forestry sector. Such a model could be integrated with a land use model to provide predictions of how exogenous shocks to forest product demand translate to forest and land use change.

4.4 Policy analysis for states

In addition to the academic value of this research, we believe this research will be of significant interest to the climate policy community. Resources for the Future's connections to this community will help it make an impact. In 2019, Resources for the Future was engaged by US Climate Alliance, a bipartisan coalition of governors in 25 US states, to assess member states' progress in achieving goals of the 2015 Paris Agreement. RFF is now in discussions with the State of New York to assist in policy analysis that would help state agencies meet targets set under New York's Climate Leadership and Community Protection Act, passed in 2019. While these policymakers recognize the importance of the land use and land use change sector in meeting climate goals, they need better projections regarding how land use is expected to change in their states, how this will affect emissions, and how they can craft policy to improve outcomes.

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