Marginal Cost of Carbon Sequestration through Forest Afforestation of Agricultural Land in the Southeastern US*

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*This work was supported by a cooperative agreement with the USDA Forest Service, Agreement #17-JV-11242309-115. We would like to thank Grant Domke at the USDA Forest Service for compiling the estimates of forest carbon sequestration used in this paper. We would also like to thank Bob Haight at the USDA Forest Service for his help in acquiring the data and for seminar participants at University of Wisconsin, University of Nebraska, and the AAEA annual meeting for their helpful comments.

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Abstract

One tool to mitigate climate change is to sequester carbon through changes in land use. The purpose of this study is to analyze the cost–effectiveness of carbon sequestration through afforestation of cropland via the Conservation Reserve Program (CRP) in the United States. We use the correlated random effects (CRE) probit model to estimate the impact of an increase in the Conservation Reserve Program (CRP) rental payments on land use transitions between cropland and forest. Our estimates are used to simulate land use change and carbon sequestration supply curves over different time horizons. Increasing the CRP rent to reflect the social cost of carbon of $154/tonne of carbon increases annual carbon sequestered by 7.42 million tonnes, 23.58 million tonnes, and 34.96 million tonnes over 1, 5, and 10-year horizons.

Keywords: Afforestation, Carbon Sequestration, Climate change
JEL codes: Q15, Q23, Q24, Q54

Introduction

Increasing concentrations of greenhouse gases in the atmosphere pose potentially large costs to society through climate change. Mitigating climate change can be achieved by either reducing emissions or sequestering carbon. Afforestation is one of the primary mechanisms available to sequester carbon (EPA, 2018b; Bastin et al., 2019; Pan et al., 2011; Quiggin, 2010; Carraro, 2016). For example, forests sequester roughly 11 percent of the total carbon emissions in the United States (EPA, 2018b). To understand the cost-effectiveness of afforestation as a climate mitigation tool requires an estimate of the supply curve for carbon sequestration at different carbon prices.

The United States (US) does not currently have a large-scale program solely devoted to the purpose of carbon sequestration. However, the Conservation Reserve Program (CRP), authorized by the Farm Bill, pays farmers to retire land from crop production and plant trees for a broad array of environmental services. Although most of the land enrolled in CRP is a grassland cover, about 2 million acres were enrolled as a tree land cover in 2012. Farmers that enroll in CRP enter into a 10-15 year contract with a fixed rental payment provided by the government for the change in land use.

In this paper, we estimate the supply curve for carbon sequestration through CRP in the Southeastern United States. We estimate a correlated random effects (CRE) probit model of land use transitions between cropland and CRP with tree cover using repeated point-level data on land use from the National Resources Inventory (NRI). We estimate land use transitions as a function of the CRP rental rate, returns to crop production, and land quality while accounting for the fact that farmers can only enroll in signup years and can only exit when the CRP contract expires. We then simulate the impact of changes in the CRP rental rate to estimate the change in CRP acres and the corresponding change in carbon sequestration over 1, 5, and 10-year horizons.

Overall, our results indicate that afforestation can be a cost-effective method to sequester carbon. At the historical average CRP rental rate of $50.41 per acre, the program sequesters

1.96 million tonnes of carbon annually at a marginal cost of about \$35.98 per tonne of carbon—equivalent to carbon emissions from 1,559,981 passenger vehicles on the road each year.[1] At the historical average CRP rental rate of \$50.41 per acre—equivalent to \$35.98 per tonne of carbon, this represents 0.11% of the total U.S. greenhouse gas emissions in 2019 (EPA, 2021). The number would increase to 1.95% if the average CRP rent is increased to \$239.44 per acre to reflect the social cost of carbon of \$154/tonne of carbon (i.e., the social cost of carbon assuming a 3 percent discount rate). Our simulation indicates that an increase in average CRP rent by 30 percent increases the amount of carbon sequestered by 9.64 percent after 10 years. Increasing the average CRP rent to reflect a price of carbon of \$154/tonne increases carbon sequestration by 34.96 million tonnes after 10 years—equivalent to removing carbon emissions generated by roughly 27.9 million additional passenger vehicles from the road each year. We also simulate the effect of changes in crop prices and find that a 50 percent increase in crop prices decreases the annual amount of carbon sequestered by 5.32 percent after 5 years and 9.36 percent after 10 years.

Previous research has estimated the supply curve for carbon sequestration using mathematical programming models (Richards et al., 1993; Parks and Hardie, 1995; Adams et al., 1993; Bamière et al., 2021; Schneider and McCarl, 2006; Beach et al., 2008; Frey et al., 2013), econometric models (Stavins, 1999; Plantinga et al., 1999; Newell and Stavins, 2000; Plantinga and Wu, 2003; Lubowski et al., 2006), or a mix of programming and econometric models (Antle et al., 2003). Some of the previous work depend on stated preference on how landowners would respond to a hypothetical policy (Richards et al., 1993; Parks and Hardie, 1995; Adams et al., 1993; Van Kooten et al., 2002). Our work is also related to several previous studies that estimate the determinants of land use using the point-level NRI data (Lubowski et al., 2008; Polyakov and Zhang, 2008; Rashford et al., 2011; Lawler et al., 2014; Langpap and Wu, 2011; Claassen et al., 2017; Beaudry et al., 2013; Wu et al., 2004; Lewis and Plantinga, 2007; Schatzki, 2003; Van Kooten et al., 2002).

[1] Note that these estimates reflect the carbon sequestration potential of CRP with tree cover in the Southeastern United States—the sequestration from all forests or all CRP is much larger.

Our paper makes several significant contributions to this literature. First, our work is different than previous studies because we analyze how changes in payment rates affect carbon sequestration in an existing program that pays for land retirement (i.e., CRP). Our use of econometric analysis makes our results more realistic than previous studies that use mathematical programming models or stated preferences. Our estimates are also more realistic than previous studies that estimate econometric models of how changes in forest returns could affect carbon sequestration. These other studies implicitly assume that landowners will respond the same to market returns and a government policy incentive, which may not be valid.

Second, we control for cross-sectional unobserved heterogeneity using a correlated random effects probit model. The CRE model controls for time-invariant variables by including the individual mean of each right-hand side variable as additional controls (Wooldridge, 2010). Intuitively, this allows us to exploit the variation in CRP rent and cropland returns over time instead of the pure cross-sectional variation. The cross-sectional variation in returns is likely subject to endogeneity concerns—more land is likely to transition to CRP in areas with lower CRP rent because CRP rent is lower in areas with lower quality land, but farmers are more likely to enroll in CRP in areas with lower quality land. One exception is Bigelow et al. (2017) who use a CRE model to estimate transitions from agriculture to urban development. Failing to adequately control for land quality biases the estimates and is likely a reason for estimates of a negative impact of CRP rental rates on enrollment in the literature (Goodwin et al., 2004; Fleming, 2004; Chang and Boisvert, 2009). Previous studies use logit, nested logit, or random parameters logit models that do not control for unobserved heterogeneity (Lubowski et al., 2006; Polyakov and Zhang, 2008; Rashford et al., 2011; Lawler et al., 2014; Claassen et al., 2017; Lewis and Plantinga, 2007). Random parameters and random effects model the unobserved heterogeneity, but impose an assumption that the heterogeneity is independent of the right-hand side variables (Wooldridge, 2010). Jang and Du (2018) use a structural model to back out the unobserved productivity using farm-level data from the

Census of Agriculture. We exploit the panel nature of our data to control for unobserved heterogeneity using the correlated random effects framework.

The third contribution of our paper is that our modeling explicitly accounts for the CRP contract. We only estimate the econometric model for transitions from cropland to CRP in years with general signup for CRP. Similarly, we only estimate the model of transitions from CRP to cropland when there are potential exits from CRP for the respective CRP signup number of the parcel. A key feature of our dataset is that we know the CRP signup number for a given NRI point that provides information on which years the parcel could exit CRP. No previous studies account for signups or contract expiration in their analysis.

Our fourth contribution is that we estimate how the CRP rental rate affects land use transitions. One reason that we can estimate the impact of CRP rental rates is that we have data on the CRP rental rate of newly enrolled contracts in each county each year. We obtain the data through a Freedom of Information Act (FOIA) request. These data are different than the average rental rate posted online by the Farm Service Agency (FSA) because the average rental rate posted online gives the average rent across all contracts currently enrolled—including some contracts that enrolled nearly 10 years prior—rather than the rental rate affecting farmers' decision to enroll in the current year. Lubowski et al. (2006) include land quality as an explanatory variable for CRP but not the rental rate. Jang and Du (2018) include the farm-level average CRP rent received as a key explanatory variable, but this does not reflect the rental rate affecting a farmer's decision in the current year. Claassen et al. (2017) is one exception in the literature that does include CRP rental rates in the analysis.

Data

We restrict the study area to Land Resource Regions N (East and Central Farming and Forest Region), O (Mississippi Delta Cotton and Feed Grains Region), and P (South Atlantic and Gulf Slope Cash Crops, Forest, and Livestock Region) which cover many states in the

Southeastern region of the United States. While only 4.9 percent of all CRP acres across the United States are used for tree-planting, more than 78 percent of the CRP acres in tree-planting are located in Land Resource Regions (LRRs) N, O, and P (figure 1). Within this region, more than 55 percent of CRP acres are used for tree-planting.

We obtain the land use transition data at the point level from the National Resources Inventory (NRI). The Natural Resources Conservation Service (NRCS) in the United States Department of Agriculture (USDA) collects the NRI data at a sample of representative points across the United States. The land use at each point is classified manually, and administrative records from the Farm Service Agency are used to determine if a point is enrolled in CRP, the signup number of the CRP contract, and the type of CRP cover practice (e.g., grass or trees). The point-level NRI data do not record the GIS coordinates of the point but identify the county in which the point belongs. The NRI data also provide information on the land quality of the point. The NRI was only available every 5 years beginning in 1982 but started to be recorded annually in 2000. We exploit the annual point-level data between 2000 and 2012 and combine it with county-level estimates of annual net returns per acre for six major crops and the CRP rental rate.

CRP enrollment is through either general or continuous signups. General signups only occur in certain years determined by administrators and landowners submit bids for parcels to be enrolled in the program. Each offer has an Environmental Benefits Index (EBI) score that is based on the parcel-specific characteristics, the practices offered, and the bid price. Administrators determine an EBI score cutoff and all parcels with a score above the cutoff are accepted. Continuous signups occur regularly and target land with high environmental benefits. There is no bidding mechanism with continuous signup—parcels are accepted if they meet the criteria. Parcels that enroll in CRP enter a contract for a 10–15 year period (Hellerstein, 2017).

The NRI CRP land use classification only includes CRP in the general signup—parcels enrolled in continuous CRP are classified as pasture, forest, etc. Our model estimates transitions between cropland and general CRP, but we cannot capture enrollment in continuous CRP. Continuous CRP has increased in importance over time, but in 2012 only 14 percent of CRP acres with tree cover were enrolled through continuous (USDA-FSA, 2012). Therefore, our model captures the majority of CRP transitions with tree cover.

We obtain the CRP rental rate data through a Freedom of Information Act (FOIA) request. The CRP rental rate that we use is the county-level average rental rate for the newly enrolled contracts. The CRP rental rate data through the FOIA differs from the CRP rental rate available online as the online data represent the average rental rate across all enrolled contracts—including the rental rate of contracts enrolled nearly 10 years prior. The rental rate that we use captures the rent that landowners received in the current year when the enrollment decision was made. In some cases, the rental rate for a county for newly enrolled contracts was missing in the data obtained through the FOIA, but the average rent was non-missing in the publicly available data. We interpolate the missing rent data by using the predicted value from a regression of rent of newly enrolled contracts on average rent of all enrolled contracts, where we estimate a separate regression for each year. Therefore, the variation over time is entirely driven by the data on newly enrolled contracts. A map of the average CRP rental rates in LRRs O, N, and P is shown in figure 2.

We construct the cropland return (R_{ct}) as an acre-weighted county gross revenue less variable cost of soybeans, cotton, rice, corn, wheat, and sorghum in equation 1.

$$R_{ct} = \sum_{m=1}^{M} w_{ct}^{m} \Big(price_{t}^{m} \times yield_{ct}^{m} - cost_{rt}^{m} \Big), \tag{1}$$

where r denotes a Farm Resource Region. The expected revenue is a product of future expected price ($price_t$) from the Chicago Mercantile Exchange (CME) contract and county-specific trend yield ($yield_{ct}$). For corn, we use the average of the daily settled price between January and February for the December corn contract. For wheat, the expected price is the average daily settled price between August and September of the previous year for the July contract. For soybeans and rice, we use the average settled price between January and

March for the November contract. Cotton revenues include revenue from cotton lint and cottonseed. For cotton lint, we use the average settled price between January and March for the October contract. For cottonseed, we use the state-level marketing year price. We use the state-level marketing year price as the price for sorghum. We estimate the trend yields from county-specific linear trend regressions using the National Agricultural Statistics Service (NASS) data from 1980 to 2012. We calculate the yield for cottonseed as 1.62 times the trend yield for cotton lint.

We derive the acreage weight (w^m_{ct}) for crop m in county c at time t by using the rolling average of county acreage in the four most recent years. The use of a rolling average reduces the impact of short-run changes in cropping mixes due to changes in relative prices (Claassen et al., 2017). We obtain the variable cost information ($cost_{rt}$) from the Economic Research Service (ERS) cost estimates at the Farm Resource Region level. We include the cost of seed, fertilizer, chemicals, and custom operation expenses for each crop. Figure 3 shows a map of average cropland returns in our region of analysis.

We use the land capability class (LCC) from the NRI data to create dummy variables that measure soil suitability to produce a crop. LCC is time–invariant and ranges between 1 and 8. We divide the LCC into two categories: classes 1–2, and classes 3–8. Land in LCC classes 1 and 2 have few limitations for crop production, while land in classes 3 to 8 have some limitations for crop production.

Conceptual Model

We assume that a profit-maximizing landowner has a choice of allocating parcel i between either crop production or CRP with tree cover. Let j denote the original use of the land and k denote the next use of the land where j and $k \in \{crop, CRP, Forest\}$. The landowner chooses to transition from land use j to land use k at time t according to the condition

(Lubowski et al., 2006)

$$\arg\max_k (R_{it}^k - rC_i^{jk}) \geqslant R_{it}^j,$$

where R_{it}^k represents the expected net return to parcel i at time t of land use k, r is the interest rate, and C_i^{jk} is the one-time expected conversion cost of transitioning from land use j to k. We assume that the conversion costs do not change over time. The conversion cost of transitioning is zero if the land use stays the same. The decision to convert to CRP with tree cover depends not only on current returns but expected returns in the future. One advantage with modeling CRP is that the rental rate stays constant during the 10-15 year contract period so the current rental rate reflects the expected returns of CRP in the near future.

We assume that the utility of choosing land use k for a parcel initially in land use j can be represented as the linear function

$$U_{it}^{jk} = \boldsymbol{\theta}^{jk}\mathbf{X}_{it}^{jk} + \varepsilon_{it}^{jk}, \tag{2}$$

where $\mathbf{X}_{it}^{jk}$ is a vector of returns, conversion costs, and parcel-specific factors that affect land use and ε_{it}^{jk} is an unobserved idiosyncratic error component (Train, 2009). A landowner transitions parcel i from land use j to land use k if the utility of transitioning is greater than the utility of maintaining the same land use (i.e., $U_{it}^{jk} > U_{it}^{jj}$). The probability that a landowner will transition from j to k is

$$Pr_{it}^{jk} = P(\boldsymbol{\theta}^{jk}\mathbf{X}_{it}^{jk} - \boldsymbol{\theta}^{jj}\mathbf{X}_{it}^{jj} > \varepsilon_{it}^{jj} - \varepsilon_{it}^{jk}). \tag{3}$$

Econometric Model

If ε_{it}^{jk} is normally distributed, the probability can be estimated using a probit model. Let $\Phi(\cdot)$ denote the cumulative normal distribution. The transition probability is defined as

$$Pr_{it}^{jk} = \Phi\big(\beta^k R_{ct}^k + \beta^j R_{ct}^j + \gamma^k LCC_i^{12} R_{ct}^k + \gamma^j LCC_i^{12} R_{ct}^j + \alpha + \mu LCC_i^{12} + \delta_i\big), \tag{4}$$

where R_{ct}^k is the county-level return for land use k in county c and LCC^{12} is a binary variable equal to 1 if the LCC is 1–2 (i.e., high-quality land).[2] We use land with LCC 3–8 as the base category. We interact the LCC variable with CRP rent and cropland returns to capture the possibility that high-quality land may respond differently to changes in returns.

We use the terms $\alpha + \mu LCC_i^{12}$ to capture the conversion costs of switching from land use j to k. Our model allows the conversion costs to differ depending on the initial land use (i.e., there are different models for each initial land use). The term μLCC_i^{12} allows the conversion cost to differ by land quality similar to Lubowski et al. (2008). The term δ_i captures other time-invariant factors specific to the parcel—such as conversion costs or other factors that affect the probability of land use transition—that are unobserved by the econometricians.

Equation 4 represents an unobserved effects probit model. A simple pooled probit model that ignores the unobserved heterogeneity is consistent under the assumption that the unobserved heterogeneity is independent of the right-hand side variables (Wooldridge, 2010). In our context, a pooled probit is consistent assuming that parcel-specific factors that affect transitions are independent of the spatial variation in CRP rent and cropland returns. This assumption is likely to be violated. For example, parcels that are in counties with low CRP rental rates may be more likely to transition from cropland to CRP because they also tend to have a larger EBI score or due to other reasons not captured by the observed measure of county cropland returns. Another option is to estimate a random effects probit estimator, but the consistency of this estimator also requires that unobserved heterogeneity is inde-

[2]Pischke (2007) notes that including aggregate measures of variables on the right-hand side does not induce any bias.

pendent of CRP rent and cropland returns (Wooldridge, 2010). Another option is to treat δ_i as parameters to estimate (i.e., fixed effects), but this leads to the well-known incidental parameters problem in nonlinear models (Wooldridge, 2010).

Our approach is to instead estimate a correlated random effects (CRE) probit model. We allow for correlation between the unobserved heterogeneity and CRP rent and cropland returns by assuming that the unobserved heterogeneity is a linear function of the mean right-hand side variable (Mundlak, 1978):

$$\delta_i = \rho^k \overline{R}_c^k + \rho^j \overline{R}_c^j + \xi^k LCC_i^{12} \overline{R}_c^k + \xi^j LCC_i^{12} \overline{R}_c^j + \zeta_i, \tag{5}$$

where $\overline{R}_c^k = \frac{1}{T}\sum_{t=1}^{T} R_{ct}^k$. Assuming unobserved factors that are uncorrelated with mean rent and returns (i.e., ζ_i) are independent of CRP rent and cropland returns (i.e., R_{ct}^k), we can consistently estimate β, γ, and the respective average partial effects (APEs) by simply adding the means shown in equation 5 as additional controls in the probit model (Chamberlain, 1980; Wooldridge, 2010). Assuming that ζ_i is independent of R_{ct}^k for consistency of the CRE model is much less restrictive than either a pooled or random effects probit that assume δ_i is independent of R_{ct}^k.

We estimate the probability of transitioning from cropland to CRP with tree cover (i.e., enrolling in CRP) as

$$\begin{aligned} Pr_{it}^{crop,CRP} = \Phi\big(&\beta_0^{CRP} R_{ct}^{CRP} + \beta_0^{crop} R_{ct}^{crop} + \gamma_0^{CRP} LCC_i^{12} R_{ct}^{CRP} + \gamma_0^{crop} LCC_i^{12} R_{ct}^{crop} + \alpha_0 + \mu_0 LCC_i^{12} \\ &+ \rho_0^{CRP} \overline{R}_c^{CRP} + \rho_0^{crop} \overline{R}_c^{crop} + \xi_0^{CRP} LCC_i^{12} \overline{R}_c^{CRP} + \xi_0^{crop} LCC_i^{12} \overline{R}_c^{crop}\big) \\ &\text{if } lu_{i,t-1} = crop \text{ and there is a general signup in year } t, \end{aligned} \tag{6}$$

where the last line in equation (6) indicates that the model for enrolling in CRP is only estimated for parcels whose previous land use ($lu_{i,t-1}$) was cropland and in years when there was a general signup. General signups occurred in the years 2001, 2004–2007, and 2011–

2012.[3] The coefficients β_0^{CRP} and β_0^{crop} indicate the effect of changes in rent and returns for parcels with relatively poorer land quality (i.e., LCC between 3 and 8). The coefficients γ_0^{CRP} and γ_0^{crop} indicate how the coefficients on rent and returns differ for land with relatively good quality (i.e., LCC between 1 and 2). The parameters ρ and ξ are nuisance parameters and should not be interpreted as causal parameters because they are included to control for unobserved heterogeneity.

Similarly, we estimate the probability of transitioning from CRP with tree cover to cropland (i.e., exiting CRP) as

$$
\begin{aligned}
Pr_{it}^{CRP,crop} = \Phi\big(&\beta_1^{CRP} R_{ct}^{CRP} + \beta_1^{crop} R_{ct}^{crop} + \gamma_1^{CRP} LCC_i^{12} R_{ct}^{CRP} + \gamma_1^{crop} LCC_i^{12} R_{ct}^{crop} + \alpha_1 + \mu_1 LCC_i^{12} \\
&+ \rho_1^{CRP} \overline{R}_c^{CRP} + \rho_1^{crop} \overline{R}_c^{crop} + \xi_1^{CRP} LCC_i^{12} \overline{R}_c^{CRP} + \xi_1^{crop} LCC_i^{12} \overline{R}_c^{crop}\big) \\
&\text{if } lu_{i,t-1} = CRP \text{ and the contract on parcel } i \text{ expires in year } t. \quad (7)
\end{aligned}
$$

The last line in equation (7) indicates that the model for exiting CRP is only estimated for parcels whose previous land use was CRP and when the contract for the respective parcel is potentially expiring. If a CRP contract is not renewed by the government, then often parcels that exit CRP with tree cover transition to forest rather than cropland. To account for this option in the model, we include observations where the land use in period t was forest when we estimate equation (7). Since forest is included in the estimation sample, $1 - Pr_{it}^{CRP,crop}$ is the probability that a parcel previously in CRP is either staying in CRP with tree cover or transitions to forest. While we have information on the signup number for each parcel, it is difficult to know exactly when the contract expired. One reason that it is difficult to know the exact expiration year is that, USDA offered re-enrollment and extension contracts for 2 to 5 years in 2006 (Stubbs, 2016). Nevertheless, the signup number provides valuable information on years when the contract could exit. We tabulate how often land exited CRP for each respective signup year in the NRI to determine the years that account for 92 percent

[3]General signup numbers corresponding with these years are as follows: 2001 (signup 20), 2004 and 2005 (signup 26), 2006 (signup 29), 2007 (signup 33), 2011 (signup 39), and 2012 (signup 41) (USDA-FSA, 2012).

of exits for each signup. Then we only estimate the probability of a parcel exiting CRP in the years with significant exits for the respective signup.

We estimate equations (6) and (7) using a pooled probit estimator with standard errors clustered by parcel. Alternatively, we considered a random effects estimator, but it failed to converge. Wooldridge (2010) notes that the pooled probit and random effects probit are both consistent under the assumptions of the CRE model, but the random effects estimator is more efficient. Clustering standard errors by parcel accounts for the remaining parcel-specific unobserved heterogeneity (ζ_i). The probit models that we estimate are weighted by the area represented by the NRI point.

Intuitively, we are concerned that omitted variables are correlated with the spatial variation in our measure of county-level CRP rent and cropland returns. Including the mean CRP rent and cropland returns as controls in equations (6) and (7) alleviates this concern and allows us to instead exploit the variation over time. The variation in CRP rent and cropland returns over time are likely exogenous because changes in CRP rent are driven by administrative policy and changes in cropland returns are driven by demand and weather shocks that affect futures prices.[4]

One potential concern with our model is that the variation in CRP rental rates over time could be endogenous because landowners submit bids for the rental rate. However, Hellerstein (2017) shows that CRP bids tend to be close to the bid caps that are set by administrative policy. Bids on lower-quality land are usually equal to the bid cap, but bids on even the highest-quality land were more than 90 percent or 94 percent of the bid cap in the 2004 and 2012 signups. Therefore, changes in the CRP rental rate over time are driven primarily by the bid cap set by administrators rather than landowners. Before 2008, bid caps were determined by land value surveys administered by the Farm Service Agency. After 2008 the bid caps were determined by National Agricultural Statistics Service (NASS) surveys of cash rental rates. However, state offices can submit alternative rates and an Office of Inspector General (OIG)

[4]Hendricks et al. (2015) find no need for instrumental variables in models that regress growing area on futures prices before planting.

report found that most of these alternative rates were accepted by the national office without sufficient evidence for the alternative rate (USDA-OIG, 2012). Each state could determine the bid cap in different ways. The state director for FSA in Iowa stated in a recent interview that Iowa calculates the bid cap using a three-year historical average of NASS rental rates (Farm Progress, 2016). Therefore, bid caps will not directly correspond to expected market returns for cropland due to the use of historical averages and sometimes ad hoc procedures to construct the bid caps.

Simulation Methods

We use the econometric estimates to simulate carbon sequestered or emitted under different scenarios of CRP rental rates or crop prices. When simulating a change in CRP rental rate, we assume a uniform percent increase or decrease across counties. We simulate land use changes for changes in CRP rent between -30 percent to +400 percent. An increase in the CRP rent causes more land to be enrolled in CRP and less land to exit CRP and, we account for the carbon benefits from both types of changes in transitions. Our research is different from Lubowski et al. (2006) and Stavins (1999) that simulated a subsidy to parcels newly entering forestry and tax on parcels exiting forestry. We also simulate carbon sequestered on CRP by increasing crop prices between 10 percent and 100 percent. We calculate cropland returns with the new simulated prices and then use the simulated cropland returns to estimate CRP transitions. This provides insights on the impact of crop price changes on carbon sequestration.

We calculate the 1, 5, and 10-year probabilities of CRP for each simulation scenario. The 5 and 10-year probabilities account for the idea that a persistent increase in CRP rent results in a greater probability of CRP over time due to adjustment costs. Let the transition probability matrix be denoted as

$$\mathbf{T}_s = \begin{bmatrix} 1 - \hat{Pr}_s^{crop,CRP} & \hat{Pr}_s^{crop,CRP} \\ \hat{Pr}_s^{CRP,crop} & 1 - \hat{Pr}_s^{CRP,crop} \end{bmatrix}, \tag{8}$$

where $\hat{Pr}_s^{crop,CRP}$ is the average predicted probability from eq. (6), $\hat{Pr}_s^{CRP,crop}$ is the average predicted probability from eq. (7), and the subscript s denotes the simulated scenario. The probability of enrolling in CRP ($\hat{Pr}_s^{crop,CRP}$) is the weighted average predicted probability across every NRI point that was previously cropland, where the weights correspond to the area represented by the NRI point. The probability of exiting CRP to cropland ($\hat{Pr}_s^{CRP,crop}$) is the weighted average predicted probability for every point that was previously CRP, but we assume that only 25.3 percent of the land has the option of exiting in a given year based on the proportion of observations in our sample period that were classified as potentially expiring contracts.[5]

We calculate the 1-year state probabilities as

$$\mathbf{\Pi}_{s,1} = \mathbf{\Pi}_0 \mathbf{T}_s, \tag{9}$$

where $\mathbf{\Pi}$ is 2×1 vector with the probability of cropland as the first element and the probability of CRP as the second element. We denote the historic average probabilities as $\mathbf{\Pi}_0$ and the probabilities in scenario s in one year as $\mathbf{\Pi}_{s,1}$. The five-year state probabilities are $\mathbf{\Pi}_{s,5} = \mathbf{\Pi}_0 \mathbf{T}_s^5$ and, the ten-year state probabilities are $\mathbf{\Pi}_{s,10} = \mathbf{\Pi}_0 \mathbf{T}_s^{10}$. We calculate the acres of cropland and CRP in scenario s as $\mathbf{\Pi}_s Acres$, where $Acres$ is a scalar that denotes the total acres of cropland or CRP in the region.

[5] In other words, we calculate the predicted probability for every parcel previously in CRP and multiply the weighted average predicted probability times 0.253. A contract can only exit in a year when it is expiring. Although this is typically once every 10 years, we do not know the precise year a parcel expires so sometimes we allowed multiple potential exit years for a given contract. Offers of short-term contract extensions also made it more frequent that a contract could exit than 1/10 years. To make our simulation consistent with our econometric model, we assume the same frequency of exiting years in the future as in the historical data to estimate the model.

The amount of carbon sequestered differs for each type of land use transition. Therefore, to estimate the amount of carbon sequestered in each scenario, we calculate the probability of each type of transition. For example, the one-year probability of transitioning from cropland to CRP is calculated as

$$\Psi_{s,1}^{crop,CRP} = \Pi_0^{crop} \hat{Pr}_s^{crop,CRP}, \tag{10}$$

where Π_0^{crop} is the first element of $\mathbf{\Pi}_0$. The five-year probability of transitioning from cropland to CRP is $\Psi_{s,5}^{crop,CRP} = \Pi_{s,4}^{crop} \hat{Pr}_s^{crop,CRP}$, where $\Pi_{s,4}^{crop}$ is the first element of $\mathbf{\Pi}_{s,4}$.

The one-year net carbon sequestered by the CRP program is calculated as

$$\begin{aligned} \text{Net Carbon} = \Big[&\left(\Psi_{s,1}^{crop,crop} - \Pi_0^{crop}\right) \mathcal{C}^{crop,crop} + \Psi_{s,1}^{crop,CRP} \mathcal{C}^{crop,CRP} + \Psi_{s,1}^{CRP,crop} \mathcal{C}^{CRP,crop} \\ &+ \Psi_{s,1}^{CRP,Tree} \mathcal{C}^{CRP,CRP} \Big] Acres, \end{aligned} \tag{11}$$

where $\mathcal{C}$ is the net carbon sequestered for the respective land use transition. We subtract the baseline probability of cropland in the first term in brackets (i.e., Π_0^{crop}) so our estimates represent net carbon sequestered by the CRP program and do not include carbon sequestered or emitted on cropland that always stays cropland in the region. We take into account the historical role of crop rotation and the carbon-storage level of a parcel transitioning to CRP or abandoning tree–planting for cropland when calculating the net carbon sequestered. We obtained data on the average annual gross carbon sequestered in aboveground biomass for softwood and hardwood trees by county from the USDA Forest Service (2020). We then use the acres of softwood and hardwood acres within each county from USDA-FSA (2017) to create a weighted average carbon sequestration of forest land within each county that we use as our estimate of $\mathcal{C}^{CRP,CRP}$.[6]

To calculate the net carbon sequestration or emissions of cropland, we assume that corn, wheat and sorghum sequester 1.00, 0.49, 0.73 tons of carbon per acre while rice, cotton, and

[6] If county level data on the acres of softwood and hardwood were missing, then we use the state level average for that county.

soybeans emit 4.92, 0.71 and 0.01 tons of carbon per acre based on Popp et al. (2011). We calculate an average emission of 0.22 tons per acre for cropland that remains cropland (i.e., $\mathcal{C}^{crop,crop} = -0.22$). Net carbon sequestered for transitions from cropland to CRP were calculated as the county-specific forest carbon sequestration rate minus the average sequestration for cropland of parcels that transitioned from cropland to CRP. Net carbon sequestered for transitions from CRP to cropland were calculated as the average sequestration of cropland for parcels that transitioned from CRP to cropland minus the county-specific forest carbon sequestration rate. These calculations account for the fact that parcels that transition between cropland and CRP may have systematically different cropping patterns than average cropland and account for the fact that forest carbon sequestration varies across counties. On average across counties, we calculate $\mathcal{C}^{crop,CRP} = 0.89$ tons per acre and $\mathcal{C}^{CRP,crop} = -1.74$ tons per acre. Importantly, these estimates account for the decrease in cropland emissions when cropland transitions to CRP and the increase in cropland emissions when land transitions from CRP to cropland. We calculate the marginal cost of carbon sequestered for a given scenario as the cost of CRP payments—the simulated CRP payment rate times acres in CRP—divided by the net amount of carbon sequestered by CRP.

Results and Discussion

First, we report the results of the estimates from Equations (6) and (7) in tables 1 and 2. Table 1 shows the parameters for land use transition from cropland to CRP, while table 2 shows the parameter estimates of land use transitions from CRP to cropland. Next, we report the results from our simulations for changes in CRP rent and crop prices.

Marginal Effects of the Preferred Model

Table 1 shows the result for land use transitions from cropland to tree–planting under CRP. First, we focus on the average partial effects of our preferred specification in column (1).

The coefficients on CRP rent and crop returns are statistically significant with the expected sign. Even though the average partial effects look small, the number of acres transitioning is small—the average transition probability is only 0.08 percent—and returns have a significant impact on the number of transitions. An increase of the CRP rent by $10 per acre increases the probability of cropland transitioning to tree-planting by 0.016 percentage points for parcels with poor land quality (i.e., LCC of 3 or more). An increase of cropland returns by $10 per acre decreases the probability of a cropland parcel transitioning to CRP by 0.001 percentage points for parcels with poor land quality. The coefficient on the indicator of good land quality (i.e., LCC 1 or 2) is not statistically significant. Most of the variation in land quality between counties is likely captured by the coefficient on average county CRP rent and cropland returns, so the variable for good land quality mostly captures within-county variation. The interaction terms between good land quality and returns are also not statistically significant.

Table 2 shows the result for land use transitions from CRP with tree–planting to cropland. Again, the probability of transitioning is small but larger for transitions from CRP to cropland (0.7 percent) than from cropland to CRP. The coefficient on CRP rent and its average partial effect although with the correct sign is not statistically significant. The probability that a parcel transitions from CRP to cropland increases as cropland returns increase and is significant at the 1 percent level. A $10 increase in cropland returns increases the probability of a parcel exiting CRP by 0.05 percentage points for poor-quality land. The interaction between good quality land and cropland returns indicates that changes in cropland returns have a smaller impact on the probability of exiting CRP for high-quality land than for poor-quality land.

Next, we compare the parameter estimates from the CRE model, a fixed effects linear probability model (FE-LPM) and a pooled probit model.[7] The CRE model controls for

[7]

$$Pr_{it}^{transition} = \beta_0^{CRP} R_{ct}^{CRP} + \beta_0^{crop} R_{ct}^{crop} + \gamma_0^{CRP} LCC_i^{12} R_{ct}^{CRP} + \gamma_0^{crop} LCC_i^{12} R_{ct}^{crop} + \alpha_0 + \mu_0 LCC_i^{12}$$

unobserved heterogeneity and avoids the incidental parameters problem of the fixed effects model in nonlinear settings. The statistical significance of the coefficients on average returns (i.e., $\overline{R}_c^k$) in the CRE model is statistical evidence that ignoring the unobserved heterogeneity results in biased coefficients (tables 1 and 2). The coefficients on average CRP rent and cropland returns in table 1 indicate that parcels in counties with larger CRP rent and larger cropland returns are less likely to enroll in CRP. Counties with more productive land and larger CRP rents are less likely to enroll in CRP and this cross–sectional variation is not the type of variation that we want to exploit to estimate the causal impact of changes in returns. Similarly, the results in table 2 indicate that counties with larger CRP rent are more likely to exit CRP, and counties with larger cropland returns are less likely to exit CRP.

The marginal effects of the FE-LPM have the same sign and are similar in magnitude to the average partial effects (APEs) from the CRE model. Using the pooled probit, the APEs for CRP rent in tables 1 and 2 are statistically significant but the wrong signs. The coefficients on cropland returns for the pooled probit have the correct signs, but in table 2 the APE is biased towards zero. These results highlight the importance of controlling for cross-sectional unobserved heterogeneity in models of land use change.

Simulation Results

Using the transition probabilities estimated in tables 1 and 2, we simulate the additional land gained by the CRP tree–planting program by increasing the CRP rental rate. We simulate the changes in CRP with different time horizons. Panel A of figure 4 shows the number of acres that enroll in CRP for different CRP rental rates. The 5-year result represents the number of newly enrolled acres (i.e., transitions from cropland to CRP) in 5 years if the CRP rental rate is maintained at the simulated level for 5 years. Note that this does not represent the cumulative acres enrolled over 5 years, but only the newly enrolled acres in year 5. Panel B of figure 4 shows the number of acres that remain in CRP. The 5-year result represents the

, where transition can either be from crop to CRP or vice versa.

acres that transition from CRP to CRP in 5 years at the simulated rental rate. Panel C of figure 4 represents the total acres of CRP, which is the sum of the acres in panels A and B.

At the average CRP rental rate of \$50.41 per acre, the number of acres enrolled in CRP is 24,789 acres with 1,515,132 acres remaining in CRP. In the short-run, increasing the average CRP rental rate by 10 percent to \$55.45 per acre increases the acres enrolled by 16.09 percent (3,991 acres) while the number of acres remaining in CRP increases by 0.01 percent (143 acres). The total number of CRP acres increases by 0.27 percent (4,134 acres) (Panel C of figure 4). Increasing the average CRP rental rate to \$55.45 over 5 years increases enrollment by 16.04 percent (3,964 acres), land remaining in CRP by 1.04 percent (16,597 acres), and the total land in CRP by 1.26 percent (20,561 acres). Over a 10-year horizon, the supply of CRP is even more elastic—increasing the CRP rent rate to \$55.45 increases the total land in CRP by 2.35 percent (40,852 acres). Conversely, reducing the CRP rent by 10 percent to an average rent of \$47.89 decreases total land in CRP by 0.23 percent (3,506 acres) with a 1-year horizon, 1.07 percent (17,445 acres) with a 5-year horizon, and 2.0 percent (34,678 acres) with a 10-year horizon. The elasticity of new CRP enrollment does change substantially for different time horizons, but the elasticity of land remaining in CRP is much more elastic with longer time horizons because the cumulative enrollment of land in CRP increases over time, and less land exits CRP.

Figure 5 shows the carbon sequestration supply curve calculated using eq. (11).[8] Carbon flow increases as the CRP rent increases, and the supply function is more elastic at higher carbon prices. At an average CRP rental rate of \$50.41, 1.96 million tonnes of carbon are sequestered at a marginal cost of \$35.98/tonne per year under a 1-year horizon. With 5 and 10-year horizons, 2.09 and 2.25 million tonnes of carbon are sequestered. Increasing the payment for carbon sequestration by 10 percent to about \$39.56/tonne increases the amount of carbon sequestered by 0.32 percent(0.01 million tonnes), 1.46 percent (0.03 million tonnes), and 2.68 percent (0.06 million tonnes) per year under 1, 5 and 10-year horizons.

[8]We consider a smaller range of marginal costs of abatement in our simulations than Stavins (1999) and Lubowski et al. (2006), who both consider a range of roughly \$0/ton to \$250/ton of carbon.

Next, we compare our supply curve for carbon sequestration to estimates of the social cost of carbon in the literature. A recent social cost of carbon estimate that is commonly cited is $154/tonne of carbon. This estimate of the social cost of carbon assumes a discount rate of 3 percent for emissions in the year 2020 (Auffhammer, 2018; Interagency Working Group on Social Cost of Carbon, 2013).[9] Cai and Lontzek (2019) estimate an average social cost of carbon of $87/tonne of carbon, but note that the cost can be much higher depending on model assumptions. A social cost of carbon of $154/tonne of carbon is 4.3 times greater than the marginal cost of carbon at current average CRP rental rates of about $35.98/tonne (i.e., $50.41/acre). Increasing the current rental rate to reflect a social cost of carbon of $154/tonne of carbon would increase carbon sequestered by 7.42 million tonnes, 23.58 million tonnes, and 34.96 million tonnes over 1, 5, and 10-year horizons. In addition, this comparison ignores the additional benefits from improved water quality and wildlife habitat from CRP so fully accounting for the most common social cost of carbon estimate in CRP would increase CRP rental rates from their current levels in the Southeastern US.

We also compare the amount of carbon sequestered to the equivalent emissions from an average passenger travel car. A typical passenger vehicle emits about 4.6 tonnes of carbon dioxide per year (EPA, 2018a).[10] The amount of carbon sequestered at the average CRP rental rate is equivalent to emissions from 1,559,981 typical passenger vehicles per year. Increasing the average CRP rent to reflect $154/tonne offsets emissions from an additional 5,918,523, 18,180,000, or 27,900,000 cars with 1, 5, and 10-year horizons.

Figure 6 shows the results of simulations for increasing crop prices up to 100 percent. Higher crop prices reduce the acres that enroll in CRP and also increase the acres that exit CRP and return to cropland. At baseline crop prices, 24,789 acres enrolled in CRP and 1,515,132 acres remain in CRP in the short run. A 50 percent increase in crop prices decreases

[9]Note that 12/44 tonne of carbon is equivalent to 1 tonne of carbon dioxide, and $154/tonne of carbon is equivalent to $42/tonne of carbon dioxide.

[10]This assumes the average gasoline vehicle on the road today has a fuel economy of about 22.0 miles per gallon and drives around 11,500 miles per year. Every gallon of gasoline burned creates about 8,887 grams of CO_2 (EPA, 2018a). 4.6 tonnes of carbon dioxide per year 1.2

acres enrolling in CRP by about 15 percent for all time horizons (Panel A of Figure 6), while decreasing the acres remaining in CRP by 0.64 percent (9,293 acres), 3.95 percent (61,239 acres) and 7.64 percent (126,622 acres) with 1, 5 and 10-year horizons (Panel B of figure 6). A 50 percent increase in crop prices decreases the total acres in CRP by 0.86 percent (12,960 acres), 4.11 percent (64,820 acres) and 7.74 percent (130,1465 acres) with 1, 5 and 10-year probabilities and decreases the amount of carbon sequestered annually by 1.64 percent (0.04 million tonnes), 5.32 percent (0.13 million tonnes) and 9.36 percent (0.24 million tonnes) (Panel D of figure 6). Our results indicate an inelastic response to changes in crop prices for the Southeastern US. One reason for the inelastic response is that converting CRP with tree cover to crop production requires a substantial conversion cost.

Conclusion

In this study, we estimate the marginal cost of sequestering CO_2 through forest afforestation using the Conservation Reserve Program in the Southeastern United States. We use a correlated random effects probit model that controls for unobserved heterogeneity that is spatially correlated with land use returns. Our model finds that the probability of switching to cropland when the land was already enrolled in CRP with tree cover is very small and this is likely due to the large costs of removing tree cover. At the historical CRP rental rate of $50.41 per acre, 1.96 million tonnes of carbon are sequestered annually at a marginal cost of roughly $35.98/tonne. The current marginal cost of carbon for CRP is comparable to the most commonly cited social cost of carbon (Auffhammer, 2018). However, this does not account for other environmental benefits of CRP and the social cost of carbon increases over time and differs depending on the assumed discount rate. Increasing the CRP rental rate to reflect a payment of $154/tonne of carbon increases annual carbon sequestration by 7.42 million tonnes, 23.58 million tonnes, and 34.96 million tonnes over 1, 5, and 10-year horizons. The 10-year impact of this increase in CRP rental rate is comparable to the impact of removing roughly 27.9 million additional passenger cars from the road. We also simulate the impact of increases in crop prices on carbon sequestration. A 50 percent increase in crop prices reduces the amount of carbon sequestered by 1.64 percent, 5.32 percent, and 9.36 percent over 1, 5, and 10-year horizons.

There are several limitations to our work that are worth noting. First, apart from carbon sequestration, reforestation of CRP land has the potential of reducing soil erosion and improving water quality, and we do not directly account for these co-benefits of CRP (Plantinga and Wu, 2003). Second, our paper estimates additional carbon sequestration that could be achieved with CRP by increasing the rental rate but holding other aspects of the program the same. Restructuring the Environmental Benefits Index (EBI) to give greater weight to carbon sequestration could increase sequestration, and changing the bidding mechanism could reduce the rental rates paid to retire land (Kirwan et al., 2005). Third, one of the limitations of this study is that we do not have the individual landowner characteristics of the producers. Fourth, we do not account for potential leakages due to changes in international prices.

Our paper makes several contributions to the literature that estimates the drivers of land use change and has important implications for policymakers. We utilize revealed preferences from changes in payment rates for an actual program that retires land from crop production rather than simulating a hypothetical policy. We show that estimation without controlling for unobserved heterogeneity produces biased estimates. Our modeling framework also demonstrates how to account for the CRP contract when estimating land use transitions. More broadly, our results provide further evidence that afforestation through the Conservation Reserve Program is a cost-effective method of sequestering carbon.

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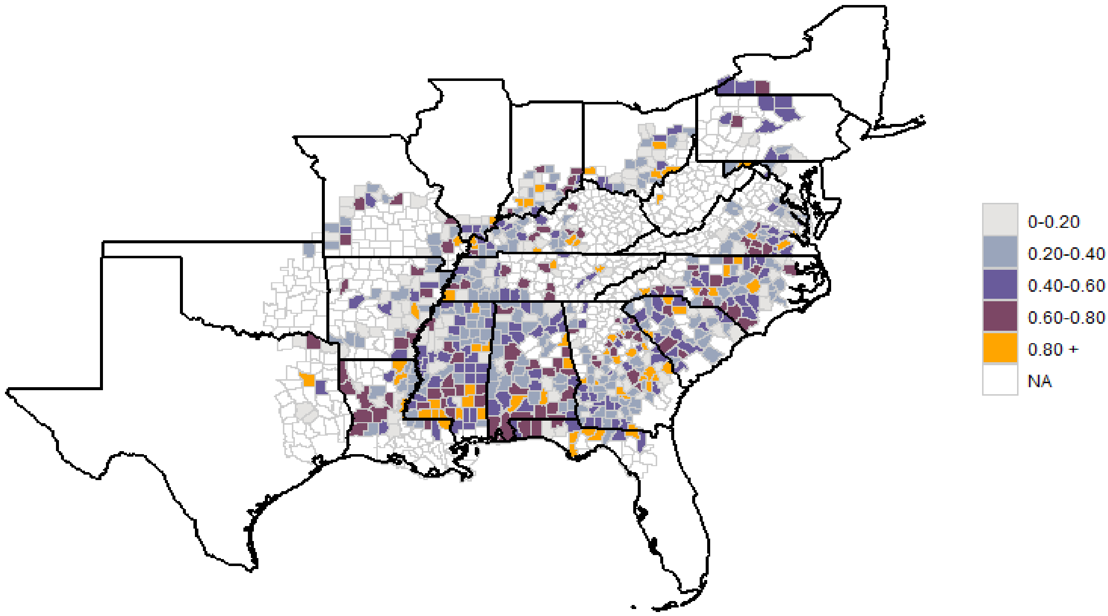

Figure 1: Share of the CRP that is afforested per county in 2017. Data source: USDA-FSA (2017)

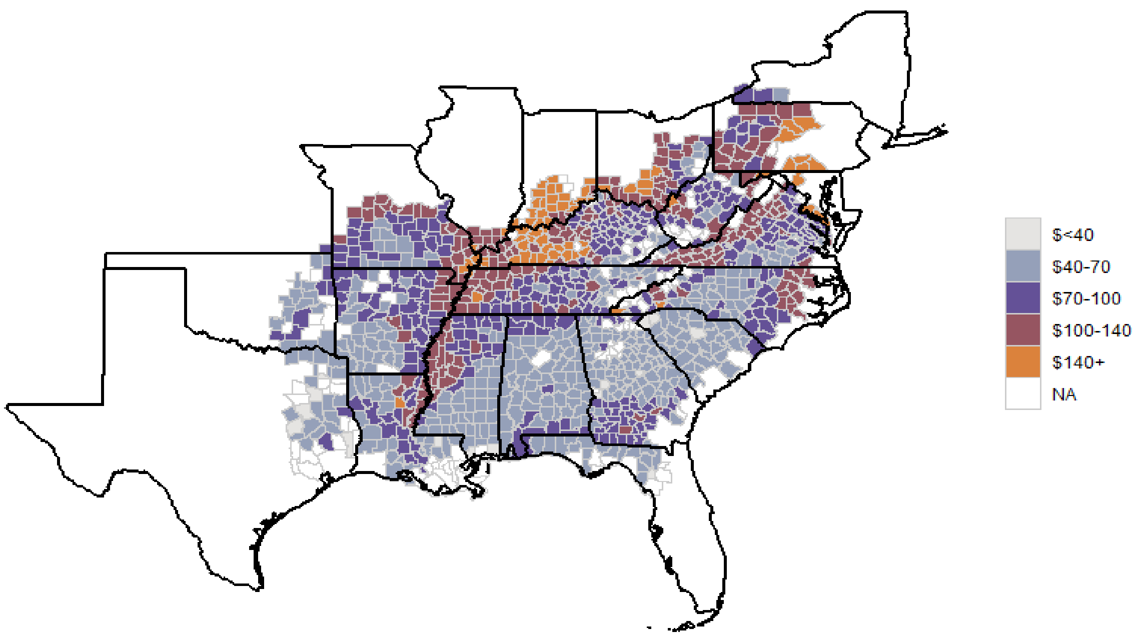

Figure 2: Average CRP Rent per County in LRRs O, N, P (2000–2012)

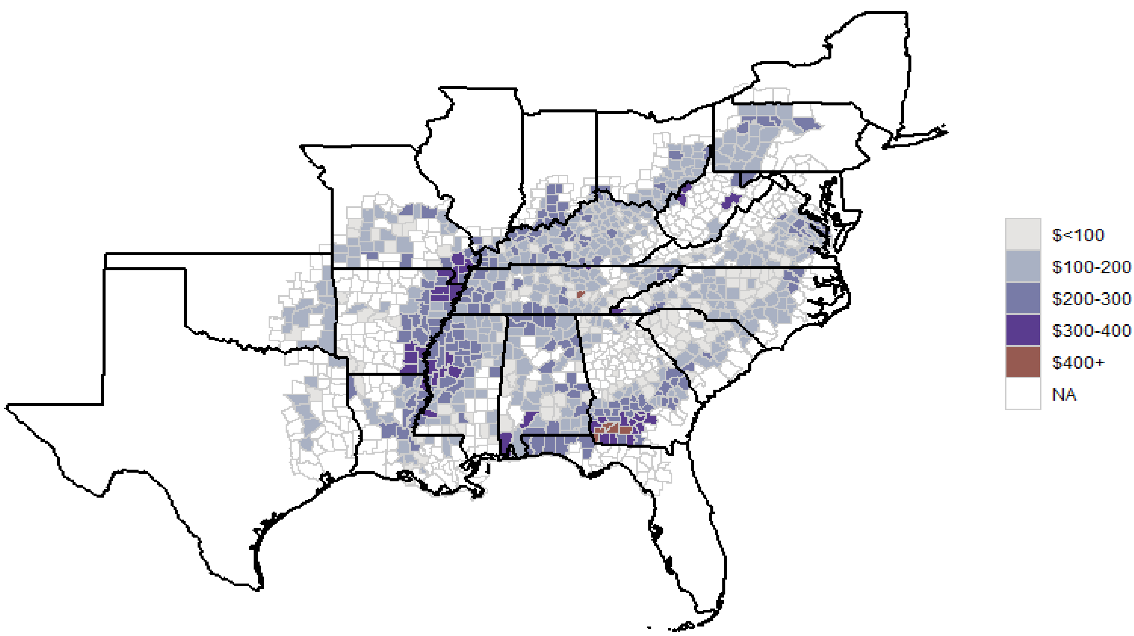

Figure 3: Average Cropland Return per County in LRRs O, N, P (2000–2012)

Table 1: Parameter Estimates for Land use Transition from Cropland to CRP Tree

Estimation Methods	(1) Chamberlain's CRE Probit Pooled MLE		(2) Linear Fixed Effects	(3) Probit Pooled MLE	
Variables	Coefficient	APE	Coefficient	Coefficient	APE
R_{ct}^{CRP}	0.006436***	0.000016***	0.000011**	-0.005185**	-0.000014**
	(0.001926)	(0.000005)	(0.000004)	(0.002108)	(0.000006)
R_{ct}^{crop}	-0.000529**	-0.000001**	-0.000001**	-0.001238***	-0.000003***
	(0.000243)	(0.000001)	(0.000000)	(0.000205)	(0.000001)
$LCC_i^{12} R_{ct}^{CRP}$	0.002108	0.000005	0.000009	0.003320	0.000009
	(0.002859)	(0.000007)	(0.000010)	(0.003190)	(0.000009)
$LCC_i^{12} R_{ct}^{crop}$	0.000470	0.000001	0.000000	-0.000194	-0.000001
	(0.000360)	(0.000001)	(0.000001)	(0.000463)	(0.000001)
α_0	-1.973291***		-0.000075	-2.555371***	
	(0.156982)		(0.000267)	(0.156171)	
LCC_i^{12}	-0.019304	-0.000049		-0.133119	-0.000355
	(0.206669)	(0.000529)		(0.200855)	(0.000545)
$\overline{R}_c^{CRP}$	-0.014243***	-0.000036***			
	(0.003491)	(0.000010)			
$\overline{R}_c^{crop}$	-0.002305***	-0.000006***			
	(0.000603)	(0.000002)			
$LCC_i^{12} \overline{R}_c^{CRP}$	0.001043	0.000003			
	(0.004721)	(0.000012)			
$LCC_i^{12} \overline{R}_c^{crop}$	-0.001538**	-0.000004**			
	(0.000751)	(0.000002)			
N	130,849		130,849	130,849	
$\tilde{\chi}^2$	278.6			78.52	

Note: . *, ** and *** indicate significance at 10, 5, and 1 percent levels.

Table 2: Parameter Estimates for Land use Transition from CRP Tree to Cropland

Estimation Methods	(1) Chamberlain's CRE Probit Pooled MLE		(2) Linear Fixed Effects	(3) Probit Pooled MLE	
Variables	Coefficient	APE	Coefficient	Coefficient	APE
R_{ct}^{CRP}	-0.005481	-0.000090	-0.000160	0.006328***	0.000109***
	(0.003906)	(0.000069)	(0.000139)	(0.001266)	(0.000023)
R_{ct}^{crop}	0.002860***	0.000047***	0.000063**	0.000515***	0.000009***
	(0.000672)	(0.000017)	(0.000030)	(0.000168)	(0.000003)
$LCC_i^{12}R_{ct}^{CRP}$	0.005386	0.000088	0.000171	-0.000542	-0.000009
	(0.005220)	(0.000087)	(0.000144)	(0.002562)	(0.000044)
$LCC_i^{12}R_{ct}^{crop}$	-0.002330***	-0.000038**	-0.000058*	-0.000801***	-0.000014***
	(0.000739)	(0.000016)	(0.000030)	(0.000303)	(0.000005)
α_0	-3.003893***		0.001481	-2.924630***	
	(0.354156)		(0.003233)	(0.084547)	
LCC_i^{12}	0.104067	0.001709		-0.008375	-0.000145
	(0.794221)	(0.013152)		(0.158817)	(0.002743)
$\overline{R}_c^{CRP}$	0.022730***	0.000373**			
	(0.006193)	(0.000154)			
$\overline{R}_c^{crop}$	-0.004876***	-0.000080**			
	(0.001222)	(0.000032)			
$LCC_i^{12}\overline{R}_c^{CRP}$	-0.014177	-0.000233			
	(0.012044)	(0.000219)			
$LCC_i^{12}\overline{R}_c^{crop}$	0.003260**	0.000054*			
	(0.001601)	(0.000030)			
N	1,971		1,971	1,971	
$\tilde{\chi}^2$	38.88			107.2	

Note: . *, ** and *** indicate significance at 10, 5, and 1 percent levels.

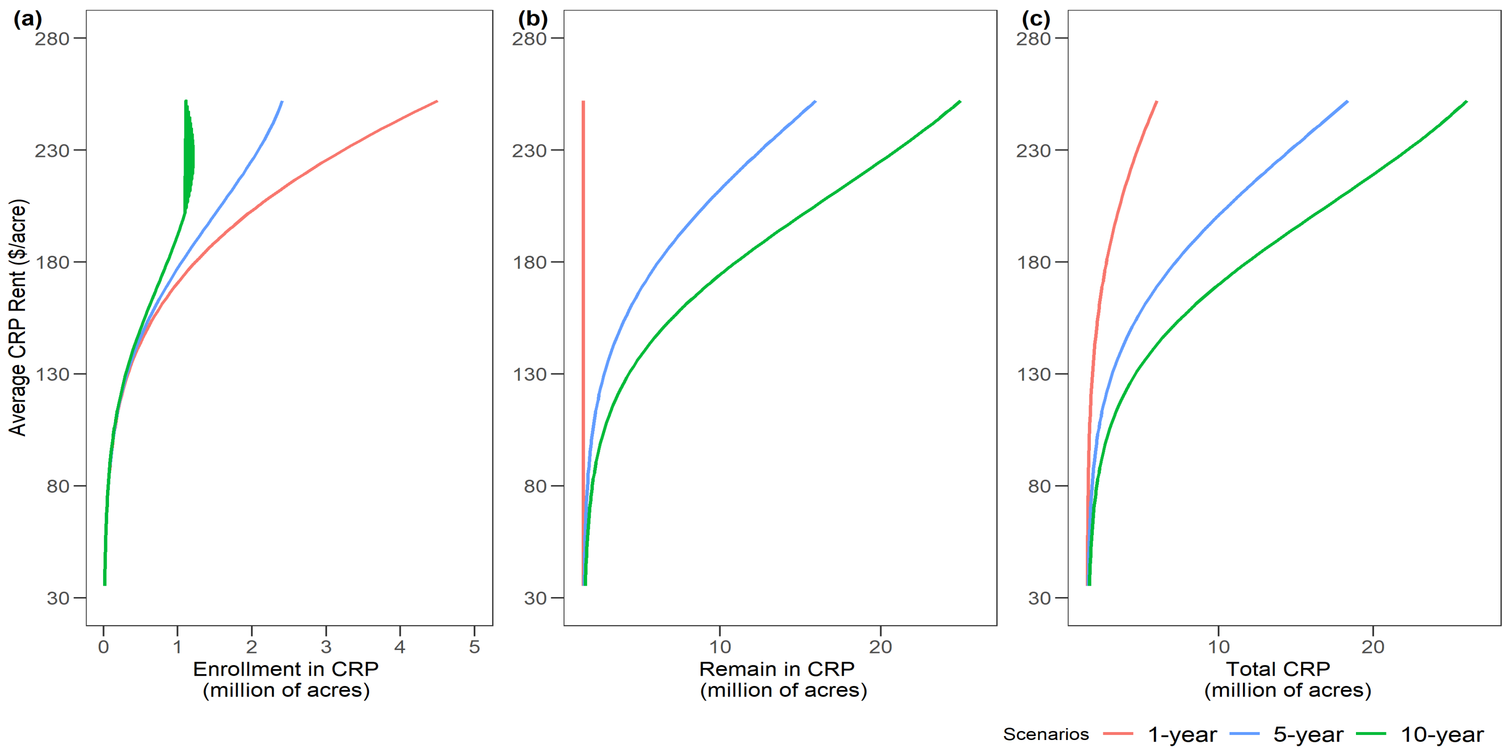

Figure 4: CRP supply curve

Note: Panel A shows the acres of land that transition from cropland to CRP. Panel B shows the acres of land that transition from CRP and remain in CRP. Panel C shows the total acres enrolled in CRP. The CRP rental rate is the average rent across all parcels and simulations assume proportional changes in rents across counties.

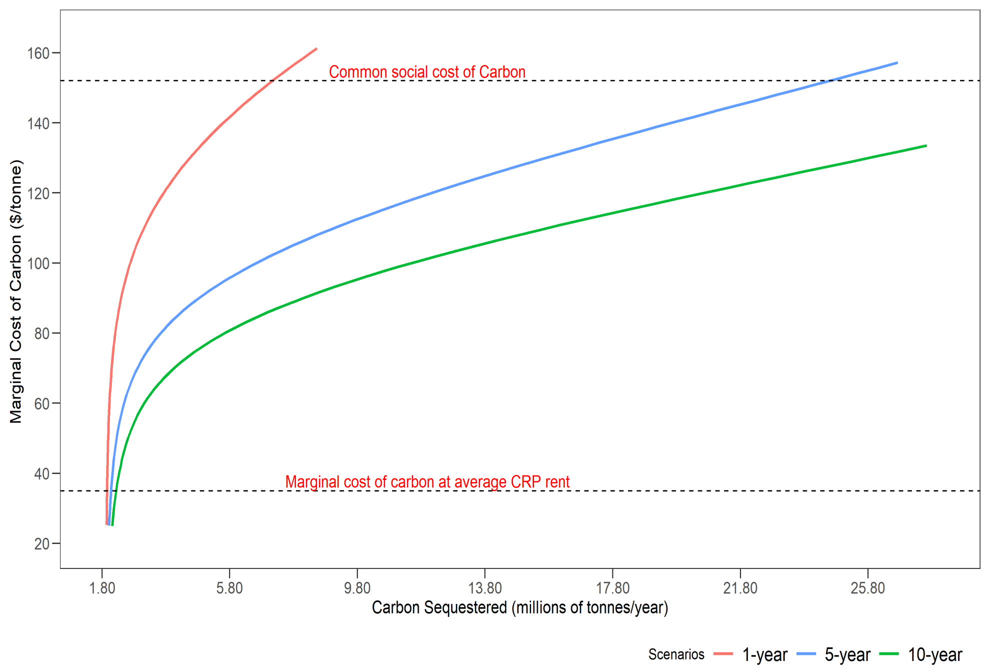

Figure 5: Carbon sequestration supply curve

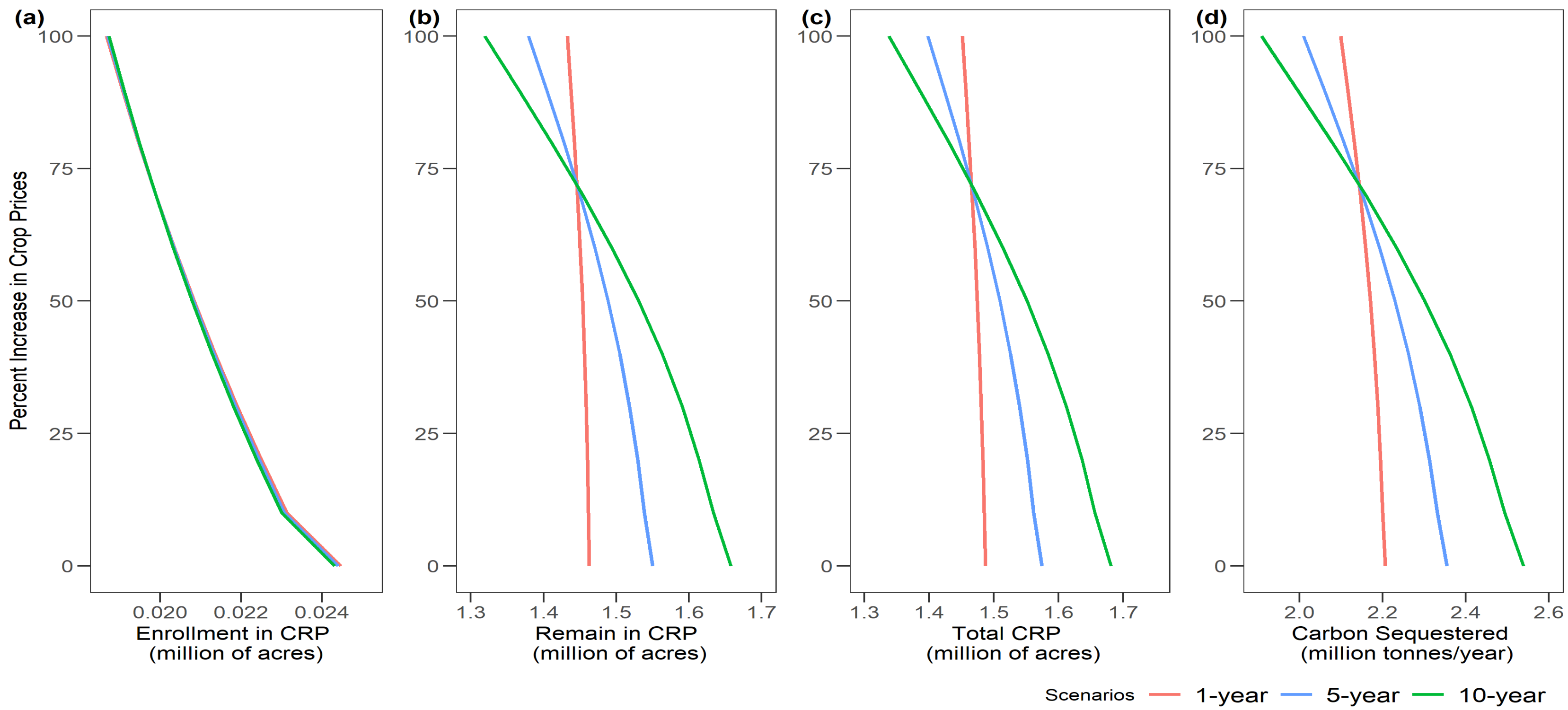

Figure 6: The effect of increases in crop prices on CRP and carbon sequestration

Note: Panel A shows the acres of land that transition from cropland to CRP. Panel B shows the acres of land that transition from CRP and remain in CRP. Panel C shows the total acres enrolled in CRP. Panel D shows the amount of carbon sequestered by CRP for different increases in crop prices.