Revealed Tillage Decisions and Implications for Agricultural GHG Abatement

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Abstract

Mitigating climate change requires reducing the concentration of greenhouse gases (GHGs) in the atmosphere relative to business-as-usual. Evidence suggests that agricultural soils have a large physical potential to sequester carbon from the atmosphere but with significant heterogeneity across space and time. Less is known about how the variability impacts the economic viability of policies to build soil carbon at large scales. Here, we use revealed crop and practice choices on working cropland to examine the scale of agricultural GHG abatement under a range of carbon prices. Using a discrete choice modeling framework and a spatially explicit model of GHGs, we explore the impact of model specification and distributional assumptions on the estimated supply curve of GHG abatement from corn and soy production in Iowa. We find that the choice of the discrete choice model of crop and practice choice affects estimates of the GHG supply curve but that even the most optimistic case suggests that tillage changes can only provide 263,000 tonnes of abatement per year, equal to 0.004% of US annual emissions. Our results suggest that there is limited potential for GHG abatement from incentivizing changing tillage practices on working agricultural lands.

Introduction

Rising greenhouse gas (GHG) concentrations in the earth's atmosphere cause increasing temperatures and alter the patterns of weather across the planet (IPCC 2013). To avoid extreme costs of this change in climate, the global community has agreed to maintain atmospheric GHG concentrations at a level consistent with significantly less than 2 degrees C of warming[1]. To achieve this goal, individual countries have made voluntary commitments[2] to decrease GHG emissions while increasing efforts to remove carbon dioxide (CO2) from the atmosphere using both chemical processes (Sanz-Perez et al. 2016) and natural solutions (Griscom et al. 2017). Natural solutions include managing forests to store carbon (Sohngen and Mendelsohn 2003), influencing land use change (Stavins 1999), and incentivizing practice changes that store carbon in agricultural soils (Pautsch et al. 2001, Choi and Sohngen 2010) or reduce agricultural emissions (Ogle et al. 2020). Highlighting the desired role for natural solutions on agricultural land, the United States' Nationally Declared Contribution to global climate change mitigation efforts states that "The United States will support scaling of climate smart agricultural practices (including, for example, cover crops)[3]."

Despite the increasing policy attention given to carbon sequestration in agricultural soils, the economic viability of policies incentivizing practice changes remains unclear. Therefore, we use a discrete choice modeling approach to estimate how the probability of adopting crop and tillage practices depends on the expectation and variability of returns. We leverage field level estimates of productivity and soil carbon changes to capture the role of spatial and temporal heterogeneity in physical conditions. Then, we use coefficient estimates to simulate how payments for additional changes in net GHG emissions (considering soil carbon and nitrous oxide (N2O) emissions) affect practice choices and GHGs over time. Finally, we examine how heterogeneity in responses to GHG payments affects the estimated supply curve for GHG abatement from agricultural land. Specifically, we estimate conventional and mixed logit models that make different assumptions about heterogeneity in producer responses to revenues.

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[1] https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement
[2] https://unfccc.int/process-and-meetings/the-paris-agreement/nationally-determined-contributions-ndcs/nationally-determined-contributions-ndcs
[3] https://www4.unfccc.int/sites/ndcstaging/PublishedDocuments/United%20States%20of%20America%20First/United%20States%20NDC%20April%2021%202021%20Final.pdf

An accurate estimate of the scale of GHG abatement as a function of payment amounts can inform existing efforts to incentivize practice change, reduce N2O emissions, and build soil carbon. This includes federal government programs and private sector initiatives such as carbon offset markets facilitated by companies such as Indigo Ag[4] and Nori[5]. How agricultural GHG abatement responds to carbon prices can inform policymakers and buyers in carbon offset markets who are considering what price to pay to achieve different levels of sequestration. It can also reveal the potential for the agricultural sector to contribute to national GHG mitigation goals. While evidence exists that agricultural soils can physically store significant amounts of carbon—enough to offset ~10% of global emissions initially (Paustian et al. 2016)—producers must be willing to implement practices that build soil carbon.

Estimating responses to conservation policies is complicated by heterogeneity in producer decisions related to conservation and soil health. For example, Chouinard et al. (2008) demonstrate that some producers adopt conservation practices at the expense of profitability. This suggests that not all conservation practice use is a result of policy, and that there is likely a benefit to using observed producer decisions related to conservation and practice choice. A reliance on profit/net present value-maximization models can inform qualitative questions about payment design (Antle et al. 2003) but may produce misleading conclusions about the scale of practice change. Pautsch et al. (2001), Wu et al. (2004), and Wang et al. (2015) use observed choices over time to estimate discrete choice models of producer crop and/or practice decisions and to examine the environmental implications of these choices. Claassen et al. (2017) add to this literature by estimating random parameters and endogenously allowing producers to fall into different response classes. They use a latent class, random parameters model to examine how crop insurance subsidies have affected crop choice and environmental outcomes. Uz et al. (2021) demonstrate that ignoring heterogeneity in responses to salinity can lead to significant underestimates of the impacts of salinity.

In addition to variable producer behavior, there exists considerable heterogeneity in the ability of soils to store carbon (Ogle et al. 2019). Factors such as land use history, soil type, and climate determine the physical potential for practice change to sequester carbon. This suggests that

[4] https://www.indigoag.com/
[5] https://nori.com/

understanding the economic viability of carbon sequestration programs at scale requires an appropriate representation of this physical heterogeneity over space and time.

To address heterogeneity in producer behavior and soil carbon changes, we use biophysical modeling (DayCent (Del Grosso et al. 2001)) to capture variability in yields and economic returns across a range of practices and to consider heterogeneity across space and time in the change in soil carbon stocks under alternative practices. We use data points from the US National Resources Inventory (NRI) (NRCS 2018) and account for changes that occur even in the absence of abatement incentives. We also investigate the importance of producer heterogeneity by allowing responses to expected net revenue to vary across producers (Train 2009). When estimating GHG abatement supply responses, we then allow for both physical and behavioral heterogeneity across space and time by simulating responses to field-level predicted changes in soil carbon and N_2O emissions.

We find that the choice of discrete choice model meaningfully affects the estimated abatement supply curve. Specifically, while all the models that we consider show an increase in utility for an increased average profitability and a decrease in utility from the variation in profits, we find that the elasticity of CO2 abatement supply curves is significantly different across different modeling and specification assumptions. Baseline results suggest that GHG abatement on agricultural lands is increasing as a result of changes in tillage practices. Therefore, we focus on a program that pays for additional carbon to demonstrate the gains from cost effective program designs.

Our results knit together the literature using discrete choice models to explore the interaction between producer crop and practice choices (Pautsch et al. 2001, Wu et al. 2004, Wang et al. 2015 Claassen et al. 2017 Uz et al. 2021) with the literature exploring GHG abatement policies using natural solutions (Antle et al. 2003, Klotz 2016). We follow Pautsch et al. (2001) and use discrete choice econometric modeling to investigate the cost of incentivizing tillage practices in Iowa. We update their approach by allowing for heterogeneity in producer behavior while focusing on physical heterogeneity across the state. Whereas they rely on county average yields and profitability, we incorporate field-level heterogeneity in the profitability of alternative crops and practices. When modeling changes in soil carbon, we use the DayCent model to reflect field-level heterogeneity while also considering N2O emissions over time.

We jointly consider the impacts of practice choices on soil carbon and N2O emissions because N2O is a particularly potent GHG, with each tonne emitted equivalent to 298 tonnes of carbon dioxide (CO2). Also, agriculture is the largest source of N2O emissions in the US. Therefore, if policy ignores changes in N2O emissions that accompany changes in soil carbon (Ogle et al. 2020), programs could lead to unintended increases in atmospheric GHG concentrations. We account for multiple pollutants and spatial heterogeneity by using interdisciplinary research methods that integrate biogeochemical process models with observed producer decisions over space and time.

Our results show the potential for (and limitations of) working agricultural lands to contribute to national GHG mitigation efforts. In particular, using observed producer behavior, we find that at the current carbon price of around $15/tonne, we would expect between 1,300 and 42,000 CO2e tonnes of additional abatement. This is between 0.00002% and 0.0006% of annual US emissions. This information is timely because policymakers and private sector actors have begun to commit significant resources to incentivizing GHG abatement in the agricultural sector. Our results suggest that A limited scope for additional abatement from changes in tillage practices on US cropland.

This paper is laid out as follows. The next section describes the data and context that we use to estimate the supply of GHG abatement from working agricultural land. We then describe the behavioral and econometric model that describe the relationship between net revenues and crop and practice choices. This is followed by a description of the simulations that allow us to characterize abatement supply curves. The results section presents econometric estimates and the supply curves associated with each econometric specification. Finally, we discuss results and conclude.

Data and Context

To estimate behavioral models of crop and practice choices, we rely on several data sources. First, we use the US National Greenhouse Gas Inventory dataset (US EPA 2020) to obtain crop and practice choices along with crop yields and changes in soil carbon and N2O emissions from all NRI points in Iowa. We combine this with data on crop prices and input costs from the USDA.

Greenhouse gas inventory data

Data on crop and tillage, as well as other practices such as irrigation, synthetic fertilization and manure amendment practice choices are available at each NRI survey point in Iowa from the US National Greenhouse Gas Inventory dataset (US EPA 2020). Management choices are obtained for each NRI survey point over time from information compiled by the United States Department of Agriculture, such as the National Resources Inventory (NRI) (NRCS 2018b), Agriculture Resource Management Surveys (USDA-ERS 2018), and the Conservation Effects Assessment Project (CEAP) (NRCS 2018a). Using the dataset, we identify NRI survey points every five years for years 1981, 1986,…, 2006, 2011 that produce corn grain (i.e., not silage) or soy over the time period (N = 80,901) and classify the tillage practice at each point and year as full till, reduced till, or no till. We focus on this time period because the National GHG Inventory data for soil carbon are available for this period. While crop choices are available for every year of the period 1979-2015 in the NRI dataset, the tillage practices are only updated every 5 years. Tillage is imputed from 2001-2005, which coincides with the CEAP data on tillage, with imputation classes based on CEAP region, crop group, and soil texture class. For an individual class, tillage systems are assigned by randomly selecting from a sub-population of CEAP donors in the same imputation class as the NRI survey location. Tillage systems for remaining five-year time blocks are imputed forward and backward in time using trending information obtained from a time series from the Conservation Technology and Information Center Data (CTIC 2004), CEAP and ARMS (See US-EPA 2020 for more information). As a result, for the purposes of econometric model estimation, we use data from the years 1981-2011 in 5-year intervals. When simulating changes in GHGs over time, we hold tillage choice constant between years with CEAP observations.

At each NRI survey point and year, we use the DayCent ecosystem model (Parton et al. 1998; Del Grosso et al. 2001, 2011) to estimate the yield per acre of the crop and practice observed at the point. DayCent provides yields in grams of carbon in grain. As a result, to calculate yield in bushels per acre, we convert grams of carbon to harvestable biomass in bushels per acre based on constants that vary by crop. These constants convert carbon to dry matter and dry matter to marketable biomass. We compare county averages of modeled yield to county average yields reported by USDA NASS and apply a scaling factor to ensure that modeled yields match average reported yields in every year of our data. Similarly, DayCent provides an estimate of nitrogen fertilizer use per acre. To obtain estimates of total fertilizer use, we estimate phosphorous and potash use as implied by the nitrogen use in DayCent with nutrient ratios common in the area. We then estimate the total fertilizer cost for each NRI point, and variable profit as the difference between production revenues and fertilizer cost.

For the crop and tillage practices not observed at each point and year (i.e., not selected by the producer at a NRI survey location), we first estimate each individual's average and standard deviation of profitability. Based on these values, we estimate a productivity index for each individual (for both average and standard deviation of profits), which is the ratio of each individual's average profitability to average profitability in Iowa for the previous three years. This index for profitability, θ_{it}^{r}, is used to approximate profitability for crop-practices that were not planted each year. The assumption is that an individual that was more productive in growing corn relative to the average would also be more productive in growing soybeans relative to others. We create a similar index, θ_{it}^{s}, for each individual's standard deviation over three years relative to the standard deviation of profitability across Iowa. This process provides us with estimates of profit mean and standard deviation for all crop and tillage practices for all NRI points in our dataset over time.

To generate estimates of changes in N_2O emissions and soil carbon stock change for Iowa, we used the emissions data from the United States National Greenhouse Gas Inventory (US-EPA 2020), which is estimated with a Tier 3 modeling approach following the IPCC guidelines (Aalde et al. 2006). Specifically, the DayCent ecosystem model (Parton et al. 1998; Del Grosso et al. 2001, 2011) is used to simulate the influence of past land use and management on soil biogeochemical processes. DayCent incorporates critical processes that influence soil carbon stocks and N_2O emissions, including crop production, soil organic matter formation and decomposition, water flows through the crop-soil system, and soil temperature regimes. DayCent also requires input data on soil characteristics, which are based on the United States Department of Agriculture Soil Survey Geographic Database (SSURGO 2019), in addition to data on historical weather patterns, which are derived from the Parameter-elevation Regressions on Independent Slopes Model (Daly et al. 1994; Daly and Bryant 2013).

For each NRI survey point, the DayCent model is applied in three time blocks for the GHG inventory assessment, including a) simulation of native vegetation for 5000 years to initialize the model at steady state conditions, b) simulation of the expansion of agriculture in the United States over a varying amount of time following land use conversion from as early as the 1700s, and c) simulation of recent agricultural management from 1979 through 2015 (see US-EPA (2020) for more detail on the modeling framework). The NRI survey of land use and cropping histories serves as the primary data frame for simulating soil carbon dynamics and N_2O emissions in the latter part of the inventory assessment from 1979 through 2015. We use the output of this recent period to approximate soil carbon stock changes and N_2O emissions from observed crop and practice choices over time. To predict N_2O emissions and changes in soil carbon from the other crop and practices not observed in the data, we estimate (unconditional) average of changes in soil carbon and N_2O emissions for each crop and practice based on historical changes in soil carbon and N_2O emissions across the NRI survey points[6].

We convert changes in soil carbon to tonnes of CO2 by multiplying changes in soil carbon by 44/12. Finally, we use the global warming potential of N2O (298) to convert emissions into CO2 equivalent (CO2e). This facilitates calculation of net emissions changes and allows us to examine practice changes as a function of carbon prices that are paid for changes in emissions of CO2e.

Table 1 provides a summary of revenue, fertilizer costs, N2O emissions, and soil carbon changes by crop and tillage practice. It also presents the proportion of point-year observations that use each crop and practice. Interestingly, full till corn has lower yields and fertilizer use per acre than reduced- or no-till. A similar pattern exists for soy yields and fertilizer use.

[6] In current work, we are modeling changes in emissions as a function of production and other physical characteristics (e.g., soil type)

Crop	Practice	Proportion of crop-years	Average revenue per acre	Average fertilizer cost per acre	Tonnes of soil carbon per acre per year	Tonnes of N2O emissions per acre per year	Soil carbon in CO2e per acre per year	N2O emissions in CO2e per acre per year
Corn	Full till	0.28	384.368	25.792	0.042	0.002	0.154	0.596
	No till	0.15	449.107	29.924	0.171	0.001	0.627	0.298
	Reduced till	0.15	489.808	32.035	0.109	0.001	0.400	0.298
Soy	Full till	0.20	275.8	12.121	0.038	0.002	0.139	0.596
	No till	0.11	308.343	14.583	0.178	0.002	0.653	0.596
	Reduced till	0.11	326.673	15.681	0.106	0.002	0.389	0.596

Table 1: Summary Statistics by Crop and Practice, 1981-2011, every 5 years

Figure 1 shows how tillage choices have evolved over time on average in our study area. The use of full till has declined substantially over time, with the use of reduced and not till increasing. As of 2015, reduced till was the dominant tillage practice on land growing corn and soy in Iowa. Given this, soil carbon stocks are not constant in a no-policy baseline (see Figure 2). In fact, cropland in Iowa accumulated more than 70 million tonnes of soil carbon between 2000 and 2015. Table 2 shows the stability of conversion from full-till to reduced- or no-till by showing the proportion of fields using full till in year t continue to do so in year t+1 (t indexes over years in which we observe practices in the data). It also shows the same for reduced- or no-till. Figure 1 demonstrates that producers are adopting reduced- and no-till over time but Table 2 illustrates that nearly 2% of observations switch from no- or reduced till back to full till.

Figure 1: Number of Acres in Iowa using Full- No- and Reduced-Till (million acres)

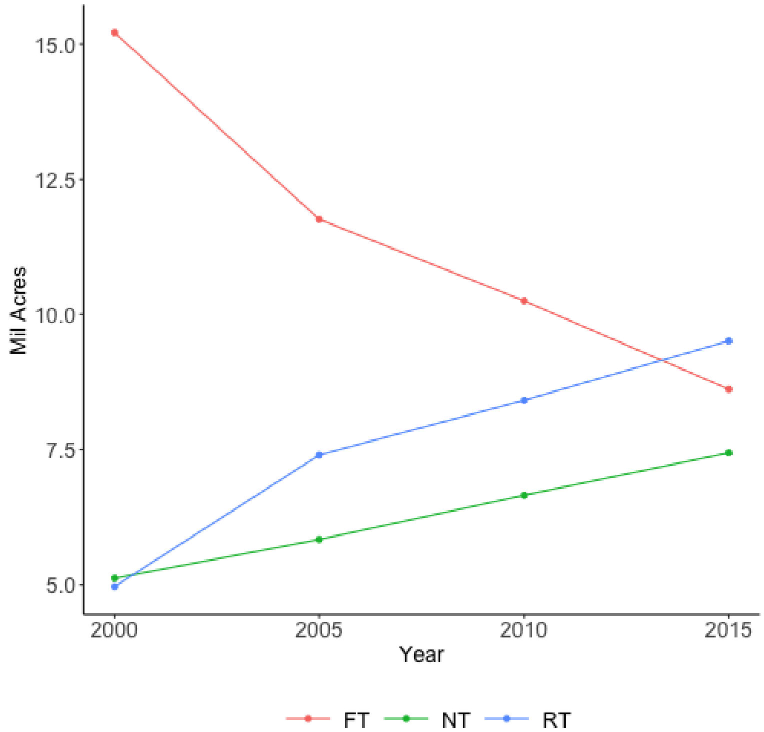
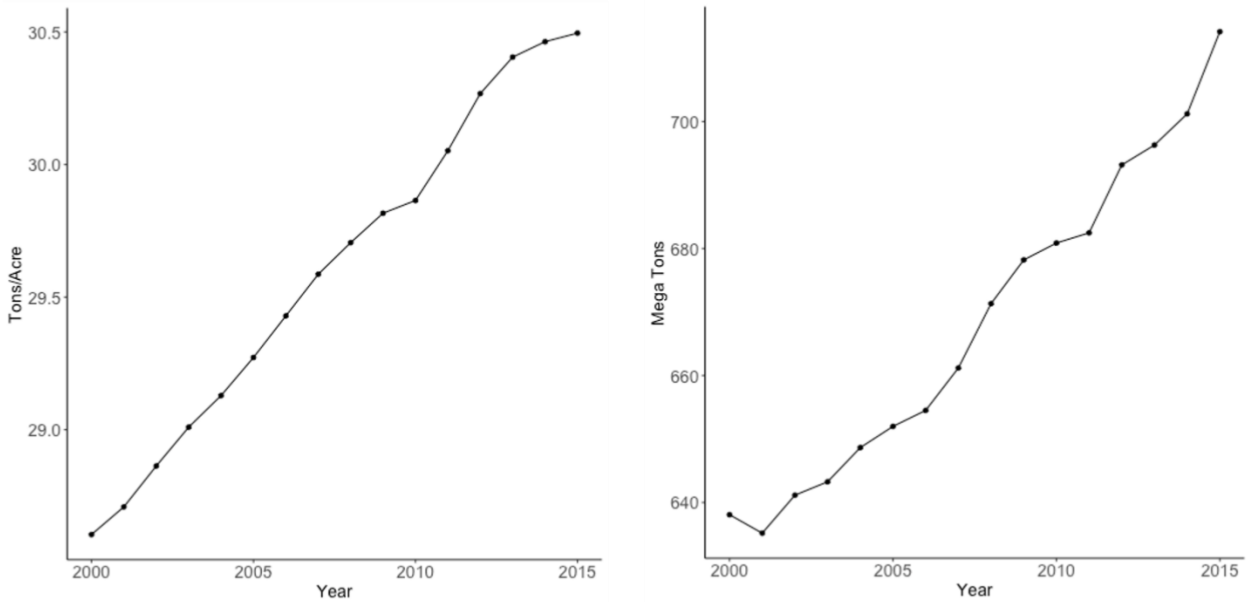


Figure 2: Soil Carbon Changes over Time In Iowa



Left-hand panel shows change in soil carbon (tonnes) per acre and right-hand panel show changes in soil carbon overall (million tonnes)

Table 2: Stability of tillage choice, %

		t+1	
		Full till	Reduced or no till
t	Full till	44.36%	6.24%
	Reduced or no till	1.93%	47.46%

Table indicates the percent of point-years where row practice was done in t, and column practice was done in year t+1. t indexes over CEAP years.

Finally, to facilitate scale-up of model estimates, NRI data contain weights that describe the number of acres represented by each point. In our supply curve analysis, we use these weights to scale our predictions to the state of Iowa.

USDA data

We calculate field level revenue per acre for each crop and tillage practice combination at each NRI survey point in our data by multiplying the output of the DayCent model by state-level output prices provided by USDA NASS. Similarly, we estimate fertilizer costs by multiplying fertilizer use in DayCent by prices provided by USDA ERS. These data include annual prices at the state level for nutrients applied. We create annual fertilizer costs for the state of Iowa by estimating the ratio of nitrogen, phosphorous, and potash because DayCent only reports nitrogen fertilizer application values. We use the average quantities for the year 2018 and calculate the amount of potash and phosphorous based on these ratios. Next, we estimate the annual price of each of these elements based on a fertilizer price index reported by USDA. Finally, we estimate the cost of fertilizer as the sum of the cost of all three elements. There are other costs involved in production besides fertilizer. In the empirical application, we discuss how our modeling assumptions address these other costs. Table 1 summarizes revenue and fertilizer costs by practice in our dataset.

Model and simulation

In this section, we present the structural econometric model used to describe producer behavior related to tillage decisions. We then describe the integration of biogeochemical information and carbon prices to predict changes in practices and GHG emissions over time under a range of carbon price scenarios.

Random utility model

Here, we present a random utility model of the discrete crop and practice choices that producers make. We assume that producer $i = 1, \ldots N$ receives utility U_{ijt} from crop/tillage practice combination $j \in \{soy\ full - till, soy\ reduced - till, soy\ no - till, corn\ full - till, corn\ reduced - till, corn\ no - till\}$ in year $t = 1, \ldots T$. This utility can be described as

$$U_{ijt} = \alpha_j + \beta R_{ijt} + \delta S_{ijt} + \gamma X_{it} + \theta_{jt} + \varepsilon_{ijt} \tag{3}$$

Where α_j is an alternative-specific constant. This controls for time-invariant factors that affect utility from each practice and are common to all producers. For example, this could include labor and capital costs associated with each tillage practice. R_{ijt} is the expected revenue for each crop and practice net of fertilizer costs as of year t. We calculate revenue in each year as output price times yield minus the fertilizer cost implied by DayCent and as described in the previous section. Define this as r_{ijt}. We then calculate $R_{ijt} = \bar{R}_{jt}\theta_{it}^{r}$ where $\bar{R}_{jt}$ is the observed average revenue for crop-practice j in year t. $S_{ijt} = \bar{S}_{jt}\theta_{it}^{s}$ where $\bar{S}_{jt}$ is the standard deviation of r_{ijt} across all i in year t[7].

X_{it} contains a vector of indicators that control for the crop and practice used in $t-1$. As in Claassen et al. (2017), this controls for rotational constraints and transition costs of moving from one crop and practice to another. θ_{jt} is a practice-year fixed effect that controls for other incentives associated with each practice that may vary over time. For example, the Environmental Quality Incentives Program (EQIP) provided cost share for tillage practice changes (among other practice changes).

Finally, ε_{ijt} is a random variable that represents other idiosyncratic factors that influence producer utility. It represents factors that decision-makers know but that we cannot control for in our model specification.

The probability that a producer chooses practice j' is

$$prob\left(U_{ij't} > U_{ijt}\right) \quad \forall\, j \neq j' \tag{4a}$$

$$= prob\left(\varepsilon_{ijt} - \varepsilon_{ij't} < V_{ij't} - V_{ijt}\right) \tag{4b}$$

With $V_{ijt} = \alpha_j + \beta R_{ijt} + \delta S_{ijt} + \gamma X_{it} + \theta_{jt}$.

If we assume that ε_{ijt} is distributed extreme value and that all at independent, then $\varepsilon_{ijt} - \varepsilon_{ij't}$ is distributed logistic, and we can express this probability as:

$$prob\left(U_{ij't} > U_{ijt}\right) = \frac{e^{V_{ij't}}}{\sum_j e^{V_{ijt}}} \tag{5}$$

In our empirical application, we estimate this model using a conditional logit and with a mixed logit that allows β, the response to expected revenue, to be a random variable, with a distribution across the population. In this case, the probability in equation 5 becomes

$$prob\left(U_{ij't} > U_{ijt}\right) = \int \frac{e^{V_{ij't}(\beta)}}{\sum_j e^{V_{ijt}(\beta)}} f(\beta)d\beta. \tag{6}$$

[7] In current work, we also use lagged measure of profitability. Results are qualitatively similar.

We estimate conventional (with and without controls) and mixed logit specifications using maximum likelihood methods. In theory, the marginal utility of net revenue should be positive. Therefore, in mixed logit models, we consider the cases where β is distributed log-normal and truncated normal where the distribution is truncated at 0. In these cases, we estimate the mean and standard deviations of β across our observations.

Simulation of agricultural GHG abatement

To quantitatively explore the scale of GHG abatement from agriculture and to qualitatively examine the importance of modeling assumption and heterogeneity, we simulate practice choices under a no-policy baseline and carbon price scenarios and examine changes in net GHG emissions over a 35-year (1980-2015) simulation period. First, we use estimated parameters to calculate V_{ij1} for each crop and practice in year 1 of the baseline simulation. In the case of the conditional logit, this portion of utility is deterministic. With mixed logit, we make a random draw for each point in our data from the distribution of β.

To calculate $U_{ij1} = V_{ij1} + \varepsilon_{ij1}$, we make a random draw from the distribution of ε_{ijt} (Type 2 extreme value, or Gumbel) and find the crop and tillage practice combination that leads to the highest utility at NRI point i (if there is a tie, we choose arbitrarily). This becomes the crop and practice choice for point i and the process is repeated for all i. Then, in the next time period, we make a random draw from the error distribution for each point, find the crop and practice with the highest utility, and produce the practice choice in year 2 of the baseline simulation[8]. This process repeats annually for 35 years (representing the length of our dataset) and provides an estimate of baseline crop and practice choice, N2O emissions, and changes in soil carbon over the simulation period.

Next, we introduce payments for changes in soil carbon and N2O emissions, relative to the baseline. In this case, a producer receives a payment for increases in soil carbon and decreases in N2O emissions. Importantly, these two changes in GHGs are treated differently by buyers of credit (either private entities or the government under a GHG abatement program). Since an avoided unit of N2O emissions (in CO2e) is identical to reduced emissions of CO2 elsewhere,

[8] In future work, we will update soil carbon levels and allow expected (and standard deviation of) yield to depend on soil carbon levels.

the market would pay up to the carbon price, P, for the avoided emission in CO2e. Carbon stored in the soil, on the other hand, is merely being stored for the time being, and could be released in future time periods (Gramig 2012). In fact, many existing programs that pay farmers for stored carbon generate credits that last a finite number of years. In this case, a buyer does not pay for a full unit of avoided emissions. Instead, it "rents" a credit, which delays a permanent reduction (or future offset rental/purchase) (Parisa et al. 2021). When this is the case, the price paid for temporary soil carbon storage from t to T is $p_t = P_t - \frac{P_T}{(1+\rho)^{T-t}}$, where P_t is the carbon price in year t and ρ is the annual discount rate. In other words, a buyer is willing to pay to delay a permanent reduction because the future cost is discounted. Assuming a constant carbon price, P, the annual rental price becomes $p = P\left(1 - \frac{1}{1+\rho}\right)$. In our main specification, we assume $\rho = .07$, leading the rental price to be $0.0654 * P$. Let q_{ijt} be the increase in soil carbon level relative to baseline and n_{ijt} be the reduction in N2O emissions (both in CO2e). Then, the payment for a change in emissions in a given year is

$$M_{ijt}(P) = P\big(0.0654 * q_{ijt} + n_{ijt}\big) \tag{7}$$

Also, let S_{ijt}^{M} be the standard deviation of crop revenue plus carbon payment across locations in year t. Then, utility from each crop and practice can be expressed as

$$U_{ijt}^{M(P)} = \alpha_j + \beta\left(R_{ijt} + M_{ijt}(P)\right) + \delta S_{ijt}^{M(P)} + \gamma X_{it} + \theta_{jt} + \varepsilon_{ijt} \tag{8}$$

We then simulate crop and practice choices for carbon price $P = 5, 10, \dots 120$. To do this, we calculate $U_{ij1}^{M(P)}$ as the sum of $V_{ij1}^{M(P)}$ and the *same* draw of the error term as in the baseline simulation for each point. For mixed logit simulations, we hold the draw of β and the error term constant across all carbon prices. The crop and practice that produces the highest utility level at point i is then the crop and practice choice at point i. Given the realized choice, we calculate $U_{ij2}^{M(P)}$ and find the crop and practice that maximize utility to determine the crop and practice in year 2. This continues for the 35 years of the simulation.

At the end of each simulation, we compare resulting soil carbon stocks and cumulative N2O emissions to the baseline and calculate a total quantity of GHG abatement at each point. To scale this to the state of Iowa, we multiply each field-level abatement amount by the weight provided in the NRI data to estimate total abatement, $A(P)$. Then, to facilitate comparison with statistics related to annual emissions, we calculate the average annual abatement as $a(P) = \frac{A(P)}{35}$.

Finally, we repeat the simulation process for 100 iterations to account for the uncertainty in specific practice choices. We report average abatement quantities and 95% confidence intervals at each carbon price.

We simulate using random draws to capture the heterogeneity in changes in soil carbon over time, especially because of the temporal dependence in these processes. An alternative approach is to calculate expected changes in GHGs by multiplying predicted probabilities by the change in GHGs that result from each practice at each point. This is the approach taken in Pautsch et al. (2001). In future work, we plan to compare this approach to our simulation approach to examine if there are meaningful gains from accounting for spatial and temporal dependence in soil carbon changes.

Results

In this section, we present coefficient estimates from the discrete choice models and we show the output of simulations describing the scale of GHG abatement from corn and soy producers in Iowa.

Econometric results

Table 3 presents coefficient estimates for our discrete choice model under alternative assumptions about the model specification. For conventional logit, the table presents estimates of β's (average profit and standard deviation of profits) and its standard error for two different specifications. For mixed logit, we report the estimated mean and standard deviation for the distribution of $\beta's$ for two different distributional assumptions for $\beta's$. Column 1 presents a conditional logit that includes alternative specific constant for each crop practice choice. Since we have 6 alternative crop practice choices, there are 5 alternative specific constants that are estimated relative to the omitted full-till corn crop practice choice. The second column is the results of a conditional logit model that also includes year and lagged crop interacted with crop-practice choice. These variables capture (linear) time trends that are specific to each crop and practice and also rotational considerations by producers. Column 3 reports the results of a mixed logit model where both average and standard deviation of profit are normally distributed. This distributional assumption does not impose any restrictions on the sign of the average profitability and the standard deviation of profit. Finally, column 4 reports the results for the mixed logit model where average and standard deviation of profitability are distributed log-normally. We expect an increase in average profit to increase utility and an increase in variability of profit to reduce a producer's utility. As a result, we assume that the coefficient of the average profitability is positive and the coefficient of the standard deviation of profitability is negative. Specification in columns 3 and 4 also include year and lagged crop interacted with crop-practice.

Qualitatively, the results are similar across specifications and follow our intuition. Specifically, an increase in average profitability increases the utility and the probability of planting a crop and using a specific tillage practice while higher standard deviation decreases this probability. Examining alternative-specific constants, we can observe that there is a disutility from moving away from corn production under the full till practice across all modeling assumptions as full till corn is more profitable and is a dominant crop practice in Iowa in the study period.

When comparing the coefficients of average and standard deviation of profits across the models, we see that model specification affects the result quantitatively. Specifically, the coefficients of mean and standard deviation of profit are larger in column 2 relative to column 1, which presents the results of the conditional logit with no controls, showing that considering the rotation and temporal patterns are important. This comparison is reflected in the log-likelihood values. The results are quantitively similar across columns 2, 3 and 4 for profitability. However, columns 3 and 4 show that there is significant heterogeneity across NRI points that is not captured in the conditional logit model.

Table 3. Econometric output

	conditional logit	conditional logit	mixed logit normal	mixed logit log-normal
(Intercept):Corn_NT	−0.606***	−44.114***	−37.841***	−44.148***
	(0.011)	(2.281)	(2.277)	(2.270)
(Intercept):Corn_RT_0	−0.595***	−83.954***	−82.823***	−83.952***
	(0.011)	(2.315)	(2.293)	(2.286)
(Intercept):Soybeans_FT	−0.171***	−56.404***	−71.462***	−56.470***
	(0.014)	(3.216)	(3.689)	(3.390)
(Intercept):Soybeans_NT	−0.788***	−96.050***	−117.248***	−96.101***
	(0.016)	(3.645)	(3.963)	(3.668)
(Intercept):Soybeans_RT	−0.728***	−143.295***	−167.268***	−143.331***
	(0.016)	(3.683)	(3.946)	(3.672)
Average profit	0.0004***	0.002***	0.003***	0.002***
	(0.0001)	(0.0001)	(0.0002)	(0.064)
Standard deviation of profit	−0.008***	−0.011***	−0.012***	−0.010***
	(0.001)	(0.001)	(0.001)	(0.107)
Standard deviation of average profit			0.038***	0.328***
			(0.0004)	(0.108)
Standard deviation of standard deviation of profit			0.037***	0.750***
			(0.001)	(0.098)
Observations	81,760	81,760	81,760	81,760
Controls		year lagged crop	year lagged crop	year lagged crop
Log Likelihood	−142,156.000	−123,120.300	−134,176.800	−123,088.300

Note: *p<0.1; **p<0.05; ***p<0.01

Agricultural GHG abatement supply

Here, we first compare our average simulated baseline practice proportions over time and compare them to actual proportions in each year of the simulation. This comparison ensures that our simulation replicates observed behavior, at least on average. Table 4 presents the number of no-till corn simulations under the baseline for each of the discrete choice modeling assumptions and comapares them with observed data (other crop-practices reveal similar results). This comparison reveals that the models, on average, predict the number of observations that plant corn under no-till practice. Moreover, our models can pick up temporal changes in baseline choices, e.g., the increase in no-till corn in the last two periods. Overall, the table shows that our estimations calibrate well to the base data such that using all models, we successfully recover baseline probabilities, suggesting that all models describe the current data reasonably well.

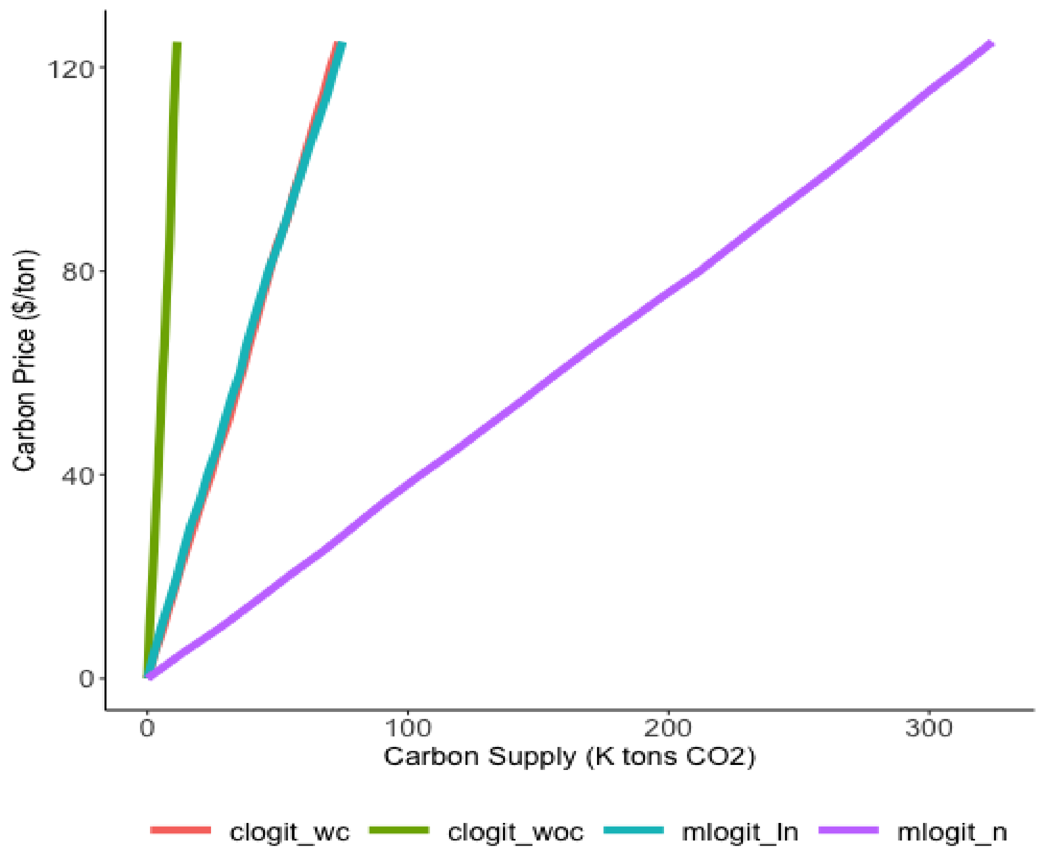
Table 4. Baseline simulation results for the number of no-till corn observations compared to data proportions by year

year	actual	clogit_woc	clogit_wc	mxlogit_n	mxlogit_ln
1981	1,636	1,591	1,554	1,544	1,561
1986	1,741	1,563	1,489	1,530	1,501
1991	1,592	1,674	1,598	1,543	1,632
1996	1,416	1,780	1,761	1,662	1,787
2001	1,568	1,810	1,852	1,851	1,868
2006	1,885	1,713	1,744	1,689	1,746
2011	2,224	1,938	2,032	1,778	2,092

Figure 3 shows the supply curve using four different models presented in Table 3. The x-axis describes the annual predicted abatement $\big(a(P)\big)$ and the y-axis is the carbon price, P, per ton of CO2. Abatement (y-axis) is presented in CO2e and includes changes from the baseline path in N2O emissions and soil carbon stocks. The abatement supply curves for the mixed logit models were estimated based on a random draw for each producer (NRI point) in each year.[9]

Qualitatively, the simulation output makes clear that modeling assumptions can meaningfully affect predictions about the scale of GHG abatement from agricultural lands. Specifically, we can see that the conditional logit model without any controls is very inelastic while the mixed logit model with normally distributed profit coefficients is very elastic with respect to the price of CO2. This occurs despite similar baseline practice choices on average. Therefore, while model choice does not affect baseline simulations, it has a meaningful impact on resulting supply curves created through counterfactual simulation. Interestingly, we find that the conditional logit model that includes the control interactions provides a similar supply curve as the mixed logit model with log-normally distributed profit coefficients while making very different assumptions about producer heterogeneity.

[9] Future work will include confidence intervals based on different coefficient draws and error term.



Quantitatively, simulation output shows that there is limited scope for GHG abatement through incentivizing reduced- and no-till practices. Under the current CO2 price of $15 per tonne of CO2, our simulations predict an abatement of between 1,300 and 42,000 tonnes of CO2e, which is between 0.00002% and 0.0006% of annual US CO2 emissions, which is around 6.6 billion tonnes (EPA). Under the most optimistic case with the mixed logit model and normally distributed profit coefficients, the amount of GHG abetment is around 0.0006% of annual US emission. Even assuming a price of $100 per tonne of CO2, the amount of GHG abetment is 263,000 tonnes per year. This is around 0.004% of annual US emission.

Figure 4 shows the emissions reductions for the mixed logit specification with normally distributed profit coefficients, separated by N2O and soil carbon changes. The figure shows that most of the emissions are coming from the SOC emissions. However, we should point out that while the CO2e of SOC emissions are higher, SOC sequestrations are not necessarily permanent, while reduced N2O emissions are permanent.

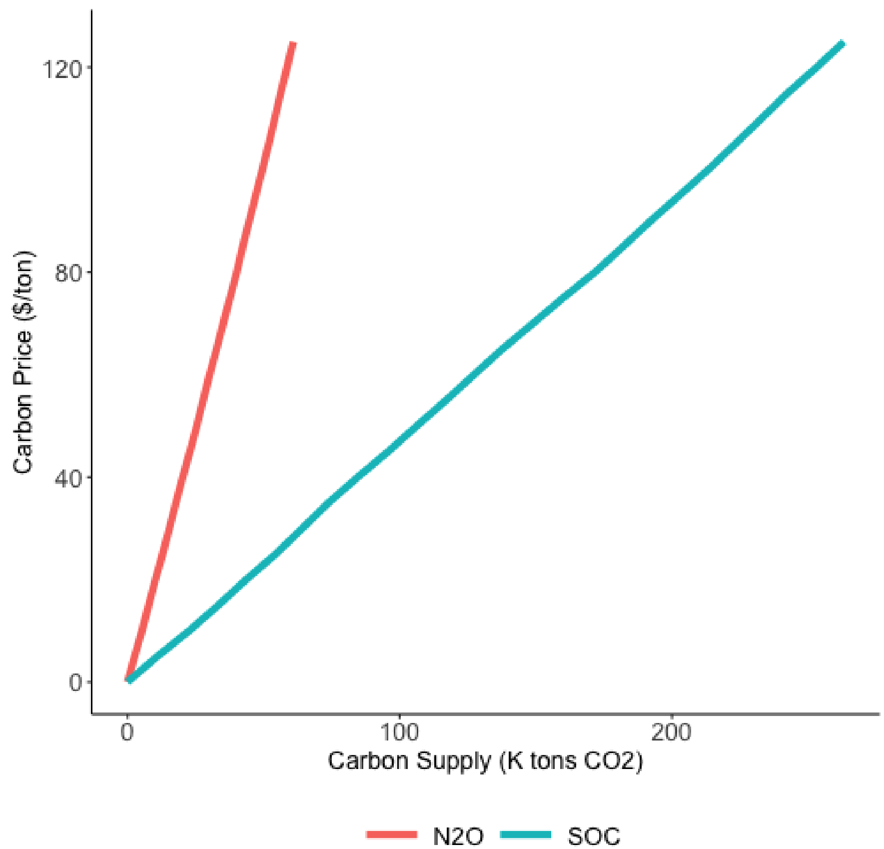


Figure 4. Abatement by emission type for the mixed logit specification with normally distributed profits

Discussion and Conclusion

We use observed tillage decisions on corn and soy acres in Iowa to describe the potential for policy and/or carbon markets to incentivize GHG abatement from working lands. Econometric results are used to examine the agricultural GHG abatement supply curve for the region. Results show the importance of model specification and heterogeneity in predicting changes in practices and GHG emissions. Accounting for heterogeneity by allowing variable responses to net revenue results in more elastic abatement supply curve.

Quantitatively, our results point to the challenges of using policy or carbon markets to increase GHG abatement from the agricultural sector. At least in Iowa, soil carbon is increasing even in the absence of GHG policy. Therefore, paying only for additional abatement leads to relatively small payments compared to differences in profitability by practice and crop. Even at a 100-dollar carbon price, only 263,000 tonnes of CO2e are obtained from acres in soy and corn.

Compared to US annual GHG emissions of 6.6 billion tonnes[10], changes in tillage practices on working croplands in Iowa likely have a limited impact.

Programs to incentivize practice change could be designed in ways that increase payments, practice change, and abatement, but it is unlikely to be cost effective. For example, paying for non-additional changes may cause more producers to change tillage practices but this will include payments for change in GHG emissions that would have occurred anyway, leading to higher program costs per unit of additional abatement. Payments for non-additional changes in GHG emissions do not necessarily mean that an inefficient level of abatement is achieved. If the carbon price is set appropriately the efficient amount of total abatement from agriculture can be achieved. Nevertheless, payments for non-additional carbon are transfers that lead to higher program costs than necessary. If non-additional changes in emissions are included in offset programs, it can change baseline emissions of buyer firms but does not lead to any abatement at the aggregate level.

Our work provides a useful example of integrating physical (biogeochemical) knowledge into behavioral models to examine how the natural environment interacts with human decisions to affect policy outcomes. This approach can be useful in other environmental and resource economics settings when it is costly to observe individual environmental conditions or impacts. For example, other settings such as non-point source pollution regulation may benefit from the ability to model heterogeneity in emissions, emissions damages, and policy impacts.

In current and future work, we hope to improve and apply our modeling infrastructure in a number of ways. First, we plan to update our dataset using the most recent GHG Inventory. This will include additional remotely sensed observations of practice choices at NRI points and years without CEAP information. We also plan to include cover crops in our analysis. Cover crops are much less common in our data, suggesting that there is a larger potential for additional changes in soil carbon from expanding their use. The lack of adoption also suggests that it may be more costly to incentivize at scale.

Once finalized with the updated dataset, we will be well-placed to examine the cost effectiveness and efficiency implications of alternative payment designs. For example, what is the impact of

[10] https://www.epa.gov/climate-indicators/climate-change-indicators-us-greenhouse-gas-emissions

ignoring N2O, non-additional payments, or payment for practice instead of payment for service? We also hope to further examine the gains of using biogeochemical models by comparing our results to models estimated using county averages and point-level controls that can be accessed publicly (e.g., soil type, weather, slope, etc.). Finally, we are currently working to allow δ (the impact of net revenue variance) to be random as well (and correlated with β).

Taken together, our approach suggests that producers have economically important incentives to invest in soil health by reducing tillage, but that well-designed incentives can increase the adoption of reduced- or no-till methods. While the scope for contributing additional abatement to climate change mitigation efforts is limited, these changes can lead to reduced runoff, drought resilience, and reduced input costs. Therefore, investments in soil health may be justified by concerns for climate change adaptation, food security concerns, or local environmental challenges (Grosnell et al. 2020). Future work should examine how policy can be designed to simultaneously reduce the climate change impacts of agriculture while furthering other social and environmental goals.

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