

Essays on the adoption and welfare effects of conservation management practices in the u.s.

by

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B.S., Prairie View A&M University, 2018
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AN ABSTRACT OF A DISSERTATION

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Abstract

Analyzing the Use and Intensity of Carbon Farming Practices in the U.S.

The implementation of carbon farming management strategies is an area of ongoing research. Practices such as partial tillage or complete no-till, cover crop production, crop rotation, and land use change (LUC), aid in sequestering carbon from the atmosphere in the soil. These practices can also benefit producers by preserving water quality, soil productivity, and improving resilience to changing climate conditions. Research suggests that maximizing the sequestration potential of these practices requires the joint adoption and use of multiple complementary practices. Though U.S. producers have begun implementing some carbon practices, others face barriers to entry that make joint use difficult. Thus, there is a need to understand the factors that influence the adoption and use of multiple sustainable farming practices.

This study seeks insight into the current landscape of joint carbon practice management decisions by U.S. producers. Using a Multinomial Logit Model (MNL) the likelihood of joint use of four conservation practices: (1) no/reduced tillage, (2) land use change (LUC), (3) cover crops, and (4) crop rotation is evaluated while controlling demographic factors, farm characteristics, weather, climate, and soil/field conditions. The data for this research comes from the United States Department of Agriculture (USDA) Agricultural Resource Management Survey (ARMS) conducted by the Economic Research Service (ERS). Supplemental data includes gSSURGO soil data from the USDA Natural Resource Conservation Service and climate/weather data from the PRISM Climate Group database. The results identify a significant relationship between the likelihood of using complementary practices and control variables. The weather, climate, and soil variable groups greatly influenced jointly used practices. Implications

from these results can aid policymakers in crafting incentives to encourage and support the implementation of sustainable production practices.

Evaluating the Welfare Implications of Carbon Farming Practices in the U.S.

Carbon farming conservation practices, such as reduced-tillage, no-till, land conversion, crop rotation, and cover crops, are critical in ongoing efforts to reduce climate change impacts. However, these practices can require additional inputs from producers, potentially impacting the financial stability of farm operations. Studies argue that producers may benefit financially from carbon farming practices through potential increases in yield and crop quality resulting from improved environmental soil health conditions. However, maximizing the mitigation benefits may require the use of more than one carbon farming practice. Thus, there is a need to understand how carbon farming practices impact the financial well-being of agricultural producers. Further insight into this area can assist policymakers and private sector entities in further developing and improving mechanisms to encourage the use of these practices.

The purpose of this study is to gain insight into the welfare implications of carbon farming practice implementation for producers. The analysis uses a propensity score matching approach to evaluate the financial impact of using one or more carbon farming practices on agricultural operations in the U.S. This research uses data from the USDA's Agricultural Resource Management Survey (ARMS) which provides information on the management practices, input use, and economic well-being of U.S. producers. The results from the analysis suggest that the use of a single carbon farming practice has either a negative or insignificant impact on net farm income when compared to farms that use none. However, the use of multiple practices is shown to have a significantly positive impact on net farm income compared to farm operations that use only one.

Assessing the Impact of Policy Reform on Conservation Management Behaviors in the U.S.

Government policies can be a mechanism to influence the management decisions of agriculture producers in the U.S. in ongoing efforts to mitigate climate change. Through implementing programs and offering financial incentives for using carbon farming practices, farmers in the U.S. may be encouraged to increase the use of these practices and reallocate greater amounts of land toward conservation efforts. The Farm Bill is a key piece of government legislation designed to help ensure the longevity and stability of agricultural production in the U.S. Previous versions sought to address natural resource-related challenges in the nation through the development of programs such as the Conservation Reserve Program (CRP) and the Environmental Quality Incentive Program (EQIP). The programs still receive updates with new revisions of the bill. As policies continue to be developed and revised, research is needed to assess whether these programs have significantly impacted the conservation management decisions of farmers in the U.S.

The purpose of this research is to assess the impact of the 2014 USDA Farm Bill on the conservation behavior of U.S. agriculture producers. The analysis uses a fixed effects model to examine the impact of the revised Farm Bill legislation on conservation behavior using a pseudo-panel approach to identify the impact across time. This research uses data from the USDA's Agricultural Resource Management Survey (ARMS) which provides information on the management practices, input use, and economic well-being of U.S. producers. The results show that after the 2014 revisions, the average amount of conservation practices implemented by farms significantly increased along with the amount of land allocated to conservation activities.

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Approved by:
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Dedication

This work is dedicated to my grandfather, Raymond Post. This year you passed before seeing me complete this academic milestone. And yet in the wake of your passing, I feel no sadness. Only the joy of having a grandfather who was so overwhelmingly proud of the accomplishments of his grandchildren. When asked about my name, I never hesitated to say that I was named after you. This name we share carries so much. The love for family and willingness to provide for them in whatever way possible as well as the virtues of hard work and determination in the face of life's challenges. As I prepare to complete the final step of this chapter of my life, I hope you know that I have always been proud of this name we share and hope that I have carried it with honor and integrity. Thank you for the love and support you always showed me during your time on this earth. I hope you'll keep watching from wherever you are now because the best is yet to come.

Chapter 1 - Introduction

Increasing awareness of climate change and global warming has identified the emissions of CO₂ and other greenhouse gases (GHGs) as possible causes of climate change, causing perilous impacts on humans, economies, and livelihoods (Poolen & Ryszka, 2021). In response to this issue, national and global initiatives such as the Paris Climate Agreement (2016) have been developed to reduce global warming to 1.5 degrees Celsius and achieve a climate-neutral world by the mid-century. Several participating countries have pledged to come up with strategies to reduce GHG emissions (United Nations, 2018). Though agriculture is not the largest contributor to greenhouse gasses, emissions from some agriculture production activities are unavoidable (Anders, 2022). The Intergovernmental Panel on Climate Change (IPCC) (2019) reports that agriculture and other land-use changes are responsible for about 23 percent of net anthropogenic global GHG emissions that comprise 13 percent of CO₂ (carbon dioxide), 44 percent of CH₄ (methane), and 81 percent of N₂O (nitrous oxide) from 2007–2016 (Sharma et al., 2021). According to the United States Department of Agriculture Economic Research Service, the agriculture sector in the United States contributed roughly 11% of all greenhouse gas emissions in 2018 and has been consistent in recent years (UDSA-ERS, 2020).

Trends in greenhouse gases are concerning due to their negative environmental implications and potentially harmful effects on the ability of many sectors to continue to operate efficiently. Agriculture faces three related challenges in the presence of growing climate change awareness which include reducing Green greenhouse gas (GHG) emissions, adapting production practices to changing climate conditions, and meeting an increased global demand for food by a growing population (Anders, 2022). Thus, mitigating and adapting to the impacts of climate change has become a priority for many sectors. However, the agriculture sector is also in a

unique position regarding issues surrounding greenhouse gases as it is the only sector with the ability to offset carbon emissions for itself and other industries.

Through the sequestration of GHG emissions via various management practices, the agriculture sector can potentially offset carbon emissions and reduce the negative impacts of greenhouse gases. As a result, the development of carbon credit systems in agriculture has gained attention worldwide (Shockley & Snell, 2021). These systems aid in achieving climate neutrality and provide agriculture producers the opportunity to earn additional revenue by selling carbon credits to producers and business entities that emit large amounts of GHG and CO₂ (Anders, 2022). By using certain agricultural land-management practices, producers can increase carbon transfer from the air into the soil; thus, agricultural carbon credits from additional carbon sequestration are expected to serve as a significant component in achieving carbon-neutrality goals (Vogt, 2021; Shockley & Snell, 2021). Unfortunately, research exploring carbon credit payments often overlooks the total welfare implications of the producers responsible for implementing sequestration practices.

A majority of the literature exploring GHG-mitigation practices covers three broad categories: reducing emissions, enhancing removals, and avoiding (or displacing) emissions (Smith et al., 2007). Though the implementation of these conservation practices could benefit the environment, producers face management decisions that could have an impact on production through conversion costs, changes in resource allocation, and shifts in land use. The potential benefits of these practices may vary widely by region and crop. Thus, encouraging these management practices requires an understanding of the barriers to use for agriculture producers and gaining insight into the potential welfare implications. Additionally, as policies continue to develop to encourage the use of carbon farming practices, research should also seek to evaluate

whether government programming has achieved its desired impact on farm conservation behaviors.

The objectives of the chapters presented in this dissertation are as follows: 1) to explore the current landscape on the adoption and use of carbon farming practices in agriculture production, 2) to examine the welfare implications for producers using climate mitigation practices, and 3) to evaluate the impact of government policy on farm conservation behavior. The first research study lays the groundwork for understanding why farmers may or may not choose to use conservation/carbon farming practices. The subsequent studies provide policy insights into the factors relevant to the continued adoption and successful implementation of climate-smart agricultural practices while accounting for their impact on producer welfare to maximize total social benefits.

Chapter 2 - Analyzing the Use and Intensity of Carbon Farming Practices in the U.S.

2.1 Introduction

Carbon farming and conservation practices focus on storing carbon in the soil or terrestrial vegetation which removes it from the atmosphere (Cheng et al., 2011; Pendell et al., 2007). Through changes in management practices and land use, soil can act as a source of CO₂, CH₄, and N₂O or as a sink for those same greenhouse gases (GHG) (Bruce et al., 1999). This in turn keeps these GHGs from harming the atmosphere. Previous research has estimated that over 1500 Gt of carbon is stored in the earth globally which is roughly double the amount found in the atmosphere (Corbeels et al., 2006). With this, it is clear to see the potential for carbon sequestration in agriculture. Activities such as partial or complete no-till, cover crop production, crop rotation, land use change (LUC), and others help decrease the amount of carbon released into the atmosphere from agricultural production.

Research has suggested that carbon farming can offer benefits such as improved water quality (Jackson et al., 2005; Pattanayak et al., 2005) and soil health (Feng et al., 2007). From an economic perspective, researchers have attempted to explore the cost, benefits, co-benefits, and environmental impacts associated with different carbon farming practices. Each practice varies in implementation and has unique benefits associated. Conservation tillage and no-till for example, has shown to be able to reduce CO₂ emission from soil and increase carbon sequestration (Lal et al., 2003; Luo et al., 2010; Peter R. Grace et al., 2010). Other practices such as rotational cropping have been shown to decrease carbon oxidation and increase stability and the concentration of soil carbon (Blair & Crocker, 2000).

According to the Carbon Cycle Institute (2021), there are roughly thirty-two on-farm practices recognized by the Natural Resource Conservation Service (NRCS). These practices are known to improve soil health and sequester carbon, while also producing co-benefits: increased water retention, hydrological function, biodiversity, and resilience. These practices have been adopted by farmers to varying degrees. There are ongoing efforts by both the public and private sectors to incentivize producers to adopt carbon farming through subsidies or direct payments and other benefits. However, research has found that even in the presence of policy incentives not all farmers will be willing to adopt mitigation activities (Miller et al., 2014). Thus, there is a need to understand the specific farmer and farm characteristics that influence the adoption of sustainable farming practices

While some farmers in the U.S. have begun using these carbon farming practices, others face barriers to entry such as technology or capital constraints, increased production costs, and other issues that make transitioning to carbon farming practices a challenge. Additionally, intensity is also impacted by a producer's ability and willingness to use multiple practices. Thus, the research question of this research is as follows: *What factors encourage the use of carbon farming practices in the U.S.?* The specific objectives of this research are: (1) *to identify major carbon farming practices in the U.S.*, (2) *to identify farmer and farm characteristics that influence use*, and (3) *to identify environmental factors that influence use intensity*. By understanding the factors that contribute to the use and intensity of these practices, policymakers can craft incentives to better support producers to implement sustainable practices that can benefit agriculture and the environment. This study seeks to contribute to the research on sustainable agriculture practices by gaining insight into the current landscape of joint use decisions by U.S. producers.

2.2 Literature Review:

Carbon farming practices have been an area of research interest for decades. Much of the literature focuses on identifying factors that influence the adoption of individual practices (e.g., Wade & Claassen 2017; Lee & McCann, 2019). Previous research on the no-till practices has noted that the benefits from such a practice are only fully realized through continuous use as the soil sequesters carbon slowly over time. However, gains can be undone by a single tillage operation (Johnson et al., 2005). Additional soil health benefits are largely a function of organic matter accumulation that only occurs if no-till is practiced continuously (Economic Research Service et al., 2015). However, the potential of no-till farming to sequester carbon in soils has been questioned within the last decade (Powlson et al., 2014; VandenBygaart, 2016; White, Kathryn E. et al., 2019).

A discrepancy commonly argued around the effectiveness of no-till practices is overestimation due to shallow testing depths for soil organic carbon (SOC). Research suggests that no-till practices do not store significantly more carbon than conventional or reduced tillage practices within the first 20 cm of the soil surface (Blanco-Canqui et al., 2021). Thus, testing conditions can lead to incorrect assumptions about the true impact that no-till or reduced tillage practice can have on sequestering carbon. Eliminating tillage alone is not enough to capture large quantities of carbon (Powlson et al., 2014; Blanco-Canqui et al., 2021). To fully realize the potential of no-till practices for carbon sequestration, no-till practices must be jointly adopted with an aggressive biological strategy to boost the potential of carbon sequestration (Blanco-Canqui, 2021). Based on the current literature, it is clear that changes in tillage practices may not enough to significantly reduce atmospheric carbon stocks.

Increasing the rate of carbon sequestration in agricultural soils requires the use of multiple conservation practices simultaneously. Combining no-till or conservation tillage with other practices such as cover crops or crop rotation yields more aggressive biological strategies that boost no-till performance in reducing carbon (Blanco-Canqui, 2021). Studies have shown that cover crops potentially sequester $<0.56 \text{ Mg ha}^{-1} \text{ yr}^{-1}$ of SOC in the upper 30 cm soil depth on average (Jian et al., 2020; Poeplau & Don, 2015; Ruis & Blanco-Canqui, 2017). Though considered a relatively small amount, applying aggressive strategies with tillage practices can increase the overall rate of sequestration. These would include increasing the area of cropland under cover cropping production strategies or consistently increasing the SOC accumulation rate through biomass. Such strategies are especially effective when applied to environmentally sensitive soils (e.g., sandy, sloping, or eroded soils) with low initial carbon that has a higher potential for sequestration (Blanco-Canqui, 2021). Crop rotation can also aid in storing carbon; however, this largely depends on the type of crop used in the production cycle. Research has shown rotations with perennial grasses or forage crops such as alfalfa and legumes can sequester more carbon than typical corn and soybean mixes (Follett et al., 2012; Powlson et al., 2016). In addition, multi-year perennials can sequester as much as 50 % of SOC at deeper depths in the soil compared to row crops due to their deep and extended root systems (Follett et al., 2012). Complex no-till row crops with multi-year perennial forage or biofuel crops can also enhance the overall resilience and soil ecosystem services from no-till rotations (Blanco-Canqui, 2021).

Land use change (LUC) use also has notable potential for carbon sequestration. Previous carbon cycle analysis showed that within the first decade of the 21st century, roughly one-quarter of the total annual CO₂ emissions produced were accumulated (Le Quéré et al., 2015). This suggests that shifts in land use could greatly enhance efforts to reduce atmospheric carbon levels.

Conversions of primary forest to agricultural land led to the depletion of SOC while the reverse can serve as a means to restore carbon stocks (Maia et al., 2010). Taking land out of agricultural production, less productive land, can aid in carbon absorption through increases in terrestrial vegetation. Wang et al. found that in Florida wetlands, pastures, forests, rangeland, and pineland all contained high levels of SOC and significantly impacted accumulation between the periods 1965–1996 and 2008–2009. When grasses and trees are allowed to grow on these types of land the accumulation of biomass can lead to reductions in atmospheric carbon. However, the potential reversibility of carbon storage has led to apprehension about the reliability of land use, land use change, and forestry projects. As an example, if one ton of fossil CO₂ emissions are sequestered by woodland trees, those trees could release those stocks back into the atmosphere during an event such as a wildfire, adding more carbon than what was originally stored (Levasseur et al., 2012). However, temporary sequestration can be an impactful tool in climate mitigation since the carbon stored during that period would have had an impact on global warming (Pedersen et al., 2022).

The decision to adopt any conservation practice inevitably requires financial investment from producers. This may come in the form of direct costs for seeds, and equipment, or indirect costs such as losses in revenue. The requirements for cost implication for adoption vary across practices depending on intensity. Williams et al. (2012) estimated the overall cost of reduced and no-till practices for farmers to be roughly \$154.17/acre and \$156.43/acre for winter wheat cropping systems with corn and soybean costs ranging from +/- \$50 from that point. This accounted for the cost of equipment and potential input changes. They also found that the per-acre yield differences for these conservation tillage practices were low implying minimal losses in revenue for farmers. Unless new seeding equipment is required for no-till, the cost of adoption

is likely low. In some cases, farmers with more diverse cropping systems may already possess the necessary equipment to incorporate certain practices (Lee & McCann, 2019). With LUC, the cost of adoption comes primarily from the loss in revenue from taking land out of production. This loss may be negligible if the land converted was already low quality in terms of productivity and returns. The cost of LUC could increase for producers if implementation includes grass planting or afforestation. Research has estimated that the average cost for active afforestation in the U.S. can range from \$1.50 to \$581 per metric ton of carbon sequestered (Elberg Nielsen et al., 2014). However, increased demand for forest products and policy incentive programs that encourage afforestation might serve as mechanisms to offset the cost associated with LUC (Cai et al., 2018).

Cover cropping involves planting a secondary crop alongside a staple crop on the same land. Costs associated with cover cropping systems typically include seed inputs, planting, termination, and any losses in primary crop revenue. Bergtold et al. (2019) estimated that the per-acre cost of cover cropping rye and oats in Kansas ranges from \$59.40–119.70 and \$54.90–108 respectively. While this may not seem much compared to no-till practices, losses in potential revenue from staple crops can serve as a major point of apprehension for risk-averse farmers considering adoption. Economic analysis of agronomic benefits and soil improvements suggest positive mean returns, but the chance of loss ranges from 0% to 77% depending on the cover crop in question (Pratt et al., 2014). Cost sharing is a strategy available to producers to help mitigate revenue loss that has both seen increased implementation and led to increased cover cropping area in the U.S. (Seifert et al., 2019). However, forage cover crop usage faces possible restrictions due to cost-sharing regulations which present a tradeoff between flexible management and reduced risk (Bergtold et al., 2017).

Conservation crop rotation consists of growing different crops in the same field over a given rotation cycle or period (USDA-NRCS, 2015). Much like cover crops, costs can include seed inputs and planting costs. The cost-effectiveness of rotation plans depends largely on the crops chosen for the cycle. Christianson and Yuan (2021) found that for Iowa, including perennial legumes in three or more years of a ten-year corn rotation could result in net returns of \$36.00 per hectare per year (roughly \$14.57 per acre). This still yielded significant reductions in nitrate (N) losses and improvements in water quality and did not account for possible returns from tax benefit programs or government subsidies. However, rotations including alfalfa were suspected to yield annual losses ranging from \$80.51-202.66 per hectare per year. Thus, depending on the crop in rotation, farmers may require additional private or federal incentives before adoption. Table 2.1 summarizes the implications for potential sequestration and cost for the conservation practices identified in this study.

Table 2.1 Conservation Practice: Summary of Implications

Practice	Description	Sequestration Impact	Cost to Producers
No-till/Conservation Till	Leaving the soil undisturbed to prevent the release of carbon into the atmosphere	<u>Low</u> Depending on SOC depth sequestration potential may vary	<u>Low- Medium</u> May require the purchase of new seeding equipment
Land Use Change (LUC)	The temporary or permanent removal of farmland from production into pasture or woodland status	<u>Medium – High</u> Adds vegetation to aid in carbon absorption and prevents carbon release from production	<u>Medium - High</u> May require the additional inputs of seeds or seedlings to cover the land removed from production

Conservation Crop Rotation	Planting various crops sequentially on the same land plot to improve soil health	<u>Medium – High</u> Adds vegetation to aid in carbon absorption, returns nutrients to the soil, adds biodiversity	<u>Medium – High</u> Requires the use of additional inputs such as water, seeds, fertilizer, etc.
Cover Cropping	Planting crops to cover the soil and then incorporating them into the latter to improve SOC levels	<u>Medium – High</u> Adds vegetation to aid in carbon absorption, manages soil erosion, adds biodiversity	<u>Medium – High</u> Requires the use of additional inputs such as water, seeds, fertilizer, etc.

When analyzing the likelihood of adoption for conservation practices, a popular motivating framework is random utility maximization proposed by Train (2003). This framework suggests that farmers adopt a practice if the expected utility from adoption, subject to preferences and constraints, is maximized. Factors that influence adoption fall into five broad categories; (1) demographic factors, (2) farm characteristics, (3) adoption of related management practices, (4) environmental attitudes, and (5) climate (Lee & McCann 2019). These categories served to identify explanatory variables used to estimate the likelihood of adoption in typical discrete choice analysis with probit or logit regression models (Wade & Claassen 2017; Lee & McCann 2019). However, evaluating the probability of multiple practice adoption requires developing a joint adoption framework. This allows researchers to capture the effects of interrelated or complementary management practices. Further studies (e.g., Kassie et al. 2015; Teklewold, Kassie, and Shiferaw 2013) have suggested that farmers consider an array of sustainable agricultural practices implying that adoption decisions are inherently multivariate (Mengistu & Assefa, 2019). This has motivated researchers to employ multivariate models, such as

multivariate probit and multinomial logit, in an attempt to estimate the likelihood that specified bundles of conservation practices would be adopted (Gong et al., 2021; Mengistu & Assefa, 2019).

Research has shown that farm characteristics (e.g., erodibility classification, drainage, or farm size) and climate can significantly impact the decision to adopt no-till production practices (Wade and Claassen 2017). Cover cropping and similar practices often require additional labor and management requirements during busy times of the growing season which can be a significant barrier to the adoption (Lee & McCann, 2019). However, additional labor can effectively boost the likelihood of adoption. Incentives are also a key factor in the likelihood of use. Monetary compensation via government programs or market opportunities can directly affect farmer utility. Program participation has been seen to have a substantial impact on the probability of adoption (Gong et al., 2021). This is especially significant when the bundled adoption of multiple practices is required for program eligibility. Though multiple practice adoption is still largely dependent on the characteristics of the farm which may lead to constraints (Bergtold and Molnar 2010) the further development of less complicated and less time-consuming technologies may mitigate barriers related to these characteristics (Lee & McCann, 2019). Farmer demographics such as ethnicity also have precedent in the literature for impacting the likelihood of adoption (Bergtold and Molnar 2010). This may indicate a level of historical disenfranchisement, or advantages that exist and affect the probability of adoption for certain ethnic groups. However, it could be that certain groups of farmers lack the knowledge or training to implement certain practices. This reasoning is plausible given that research has shown that access to extension services and training positively impacts the likelihood of adoption (Mengistu & Assefa, 2019).

2.3 Methods and Data

1.3.1 Conceptual Framework

The conceptual framework in the literature on conservation practice use is typically presented as a utility maximization problem that examines the conditional joint adoption of related practices. Suppose that farmer i can choose to use conservation management practice k where the total number of available practices is given by $k = 1, \dots, K$. Farmer i can choose between using none, one, or some combination of management practices creating $j = 1, \dots, J$ potential adoption bundles given by $J = 2^K$. Let the indicator for using a given practice be denoted by Y_k where $k = 1$ if the k^{th} practice is part of bundle j . A generalized utility-maximizing problem is written to express the use of practices by assuming that farmer i will select bundle j seeking to gain utility u_{ij} given personal unique attributes and environmental factors. The utility maximization problem can be seen outlined in equation 1:

$$u_{ij} = \max(\prod_{k=1}^K u_{ik}) \quad (1)$$

Here the utility from the bundle chosen (u_{ij}) is found by maximizing the total amount of utility derived from each of the practices present in the bundle given by (u_{ik}). The utility of a practice may be observed as both direct and indirect impacts on profit to the operation. Thus, the motivation to adopt a practice within a bundle is conditioned on variables related to expected returns (i.e., revenue and input costs), demographic characteristics (age, education, experience, etc.), and other observed and unobservable factors. The utility of an individual practice k can thus be written as a function of expected returns, farmer/farm characteristics, and environmental factors seen presented in equation 2:

$$u_{ik} = f_k(E[\pi_{ik}; \delta_{ik}] | X_i, Z_i, \varepsilon_i) \quad (2)$$

The total expected returns from practice k can be expressed as the expected direct monetary returns (π_{ik}) and indirect non-monetary benefits (δ_{ik}) from adoption conditional upon the observed and unobserved features of the individual and environment. Where X_i is a vector of demographic variables, Z_i is a set of other observable variables related to the production environment or conditions, and ε_i represents the unobservable factors that influence use. By substituting equation 2 into equation 1, the utility function for bundle j can be expressed as the total collective utility gained from all practices present within a bundle conditioned upon the observed and unobserved characteristics of an individual and environment. This can be seen outlined below in equation 3:

$$u_{ij} = V_{ij}(\prod_{k=1}^K u_{ik} \{f_k(E[\pi_{ik}; \delta_{ik}] | X_i, Z_i, \varepsilon_i)\}) \quad (3)$$

The derivative of the utility function for bundle j for a given practice k should provide the marginal utility for each practice within the bundle on an individual level. As noted by Mengistu & Assefa (2019) adoption decisions that are multivariate could lead to the marginal utilities between complementary practices being related in some way.

1.3.2 Empirical Framework

This research follows a similar empirical framework to the ones presented in the literature that focuses on adopting multiple practices (Bergtold and Molnar 2010; Mengistu and Assefa 2019; Gong, Bergtold, and Yeager 2021). The analysis uses a Multinomial Logit Model (MNL) to estimate the joint use of four conservation practices: (1) no/reduced tillage, (2) land

use change (LUC), (3) cover crops, and (4) crop rotation. A typical mathematical specification of the MNL can be seen outlined in equation 4:

$$\Pr(Y_i = k) = \frac{e^{x_i\beta_k + Z_i\beta_z + e^{(\pi_{ik}; \delta_{ik})}}}{1 + \sum_{j=1}^{J-1} e^{x_i\beta_j + Z_i\beta_z + e^{(\pi_{ij}; \delta_{ij})}}}, \quad k = 1, \dots, 4 \quad (4)$$

The probability of use Y_i for each farmer is given if $Y_i = k$ and zero otherwise. The vector x_i captures relevant farm and farmer characteristics that influence adoption with the vector Z_i capturing other external variables and $(\pi_{ik}; \delta_{ik})$ which capture expected net benefits from adoption. Here β_k is the parameter vector to be estimated for every joint combination of practices. In this model, specific implications on the change in the likelihood of adoption given certain observed characteristics can be found by deriving the marginal effects. Equation 5 gives the mathematical derivation for the marginal effects in the MNL model:

$$\frac{\partial p_{ik}}{\partial x_{ij}} = p_{ik}(\hat{\beta}_{kj} - \bar{\hat{\beta}}_{kj}) \quad (5)$$

The marginal effect of a change in variable j on the probability of farmer i using practice k is given. Where p_{ik} is the probability of farmer i using practice k , x_{ij} is the value of the variables for individual i that adopts bundle j , and $\hat{\beta}_{kj}$ is the estimated coefficient of variable j for choice k with $\bar{\hat{\beta}}_{kj} = \sum_k p_{ik} \hat{\beta}_{kj}$ as the probability-weighted average (average over choice l for each farmer i). As the marginal effect changes with i , the average marginal effect of variable j on the probability of choosing each practice can be calculated. From here the MNL regression model is specified to incorporate the relevant farmer demographics, farm characteristics, climate/weather, and soil variables of interest. This can be seen outlined in equation 6:

$$Y_{ik}^* = \beta_0 + \sum_{k=1}^J \beta_k X_i + \beta_k Z_i + \varepsilon_{ik} \quad (6)$$

Where $i = 1 \dots N$ (farmers)

$k = 1 \dots 12$ (bundles)

$Y_{ik} = 1$ if $Y_{ik}^* > 0$ and 0 if not

Here Y_{ik}^* captures the unobserved preferences associated with the choice of using a practice, Y_{ik} is a binary variable that indicates the use of a particular combination of practices, X_i is a linear combination of observed farm and farmer characteristics along with climate and soil controls with β_k given as a vector of parameters to be estimated. Additionally, k represents the carbon farming practice bundles farmers can use. The conservation practices identified in this analysis include no-till, conservation tillage, land use change (LUC), crop rotation, and cover cropping with conventional tillage used as a base decision outcome for comparison. The practices were grouped to create 12 possible conservation bundles. Lastly, Z_i captures external factors that impact management decisions such as climate conditions experienced by each farmer such as precipitation, temperature, and soil characteristics.

Conservation Bundles, Demographic Variables, and Farm Characteristics

The primary data source is the United States Department of Agriculture (USDA) Agricultural Resource Management Survey (ARMS) conducted by the Economic Research Service (ERS). This data serves as the U.S. Department of Agriculture's primary source of information on the production practices, resource use, and economic well-being of farms and ranches in the county. The results of this survey give farmers, ranchers, and many other institutions factual insights into many aspects of farming, ranching, and conditions in agricultural communities. This study specifically uses data from the ARMS Phases 2 and 3 surveys

containing information on farm inputs, management practices, farm, and household characteristics. The Phase 2 data was used to identify the conservation practices currently in use in a field as reported by the producers being surveyed for a given crop in a year. This study uses repeated cross-sectional data from farmers surveyed between 2002 and 2019. The practices of crop rotation, LUC, and covered cropping were all paired with a tillage practice creating 9 bundles containing at least two practices with the remaining 3 only containing the tillage options used as a base to compare. Due to cover cropping data only being present for certain years (2010, 2015 – 2019) two separate regression models were used. First, all available years were included to estimate the model for bundles including LUC and crop rotation options within the bundle. The next model only included bundles containing cover cropping and was restricted to the years cover cropping data was present. While this does mean that the second model contained fewer observations this allowed for model 1 to remain unrestricted and preserved the variability in the data for the other practices.

Phase 3 data was used to identify the relevant demographic and farm information for producers and farm characteristics that impact the likelihood of conservation practice use. Age is a common control variable when comparing the behavior of farmers. Race was included as a binary control variable to compare non-white farmers to the Caucasian majority. The ethnic groups of farmers in the non-white category include African American, Asian-Pacific Islander, Hispanic, and Native American. Household size accounted for additional labor family members that may not require direct compensation payments. The final two farmer demographics used as controls in this analysis were education and years of farming. Education is a binary variable to distinguish between producers with and without a college degree while years of farming were calculated based on the year a farmer had reported they began their operation. This provided a

way in which actual farming experience could be distinguished from education which is often used as a proxy for experience. The farm characteristic control variables used in this study were the farm size normalized by taking the natural log, the percentage of the total land owned by the farmer, the percentage of the farmland used for crops, and the number of cattle present on the farm operation.

Climate and Weather Variables

Relevant climate and weather data comes from the PRISM Weather Database Developed by Oregon State University. This dataset provides monthly, yearly, and single-event gridded data for mean temperature and precipitation as well as max/min temperature thresholds for the U.S. Degree days above a certain threshold are used to measure the cumulative temperature exposure. Research has demonstrated that temperatures above critical thresholds harm crop yields with said threshold varying by crop (Schlenker & Roberts, 2009). Protecting yield levels when faced with increasingly extreme climate conditions could serve as motivation to implement carbon farming practices that can enhance growing conditions. Temperature also impacts the amount of water retained in the soil through evaporation which can affect the amount of water irrigation needed for production. The temperature variables presented in this study closely follow the specifications presented by Schlenker and Roberts (2009). In their construction of temperature variables, the established threshold for growing degree days (GGD) was between 8° and 29°C with temperatures above that range identified as extreme degree days (EDD). This study modifies this specification by setting the lower and upper bound for growing degree days to be 0° and 30°C respectively. It is typical for degree days within the growing season to be used when accounting for climate impacts. However, practices such as rotational cropping may involve the production of crops outside the normal growing season along with the regular production of

staple crops such as winter wheat. Thus, the temperature variables in this study will account for the entire year.

Continued research on climate impacts has argued that temperature alone is not a sufficient weather control variable as the relationship between temperatures and plant growth is not linear (Schlenker and Roberts 2009). To address this concern, precipitation is included as an additional weather control variable to account for climate impacts. Precipitation is given as the total aggregate rainfall at the county level measured in inches. The squared term of precipitation is also added in the model specification to capture the non-linear impacts of precipitation that may arise in the presence of flooding and waterlogging due to excess rainfall. When considering the impact of climate and weather conditions, many studies do not clearly distinguish between the two. However, long-run climate conditions and short-run weather impacts influence producer management strategies in different ways and thus a distinction might provide additional insight into the choice to adopt certain practices. To distinguish between deviations in long-term climate conditions and short-term weather the differences in GDD, EDD, and precipitation were calculated by subtracting the yearly averages.

Soil Variables

The soil data for this study comes from the gSSURGO database created by the NRCS which provides data on soil characteristics for the entire United States aggregated at the county level. The adoption of carbon farming practices is likely to be influenced by the characteristics, conditions, and productivity of the soil. A common soil control when estimating the likelihood of adoption is erodibility (e.g. Lee and McCann 2019). The model includes a binary variable to identify highly erodible soils in the field survey as well as the erodibility index for the entire county. Other soil characteristics beyond erodibility likely influence management strategies and

adoption decisions. Field slope is included as a control variable since, similar to erodibility, the slope of the land could impact a farmer's ability to effectively benefit from a given practice. Soil productivity is included using the USDA Natural Resources and Conservation Service National Commodity Crop Productivity Index (NCCPI). This index measures the productivity of agricultural land for growing dryland crops. Agricultural land is given a score ranging from 0 to 100 to identify the least and most productive soils, respectively. In addition, soil organic matter was also included as a control to account for soil productivity. Soil electro-conductivity measures the soil's ability to transmit electrical currents and is an indicator of available nutrients and salinity, with higher levels found in poorer soil conditions (Zhang & Wienhold, 2002).

Table 2.2 Descriptive Statistics

Variable Description	Mean	Std Dev.
Age (in years)	55.01	12.07
College Degree (1: yes / 0: no)	27.72	0.43
Race (1: non-white/ 0: Caucasian)	18.96	0.39
Household Size (number of individuals)	2.8	1.45
Farm Size (in acres)	1042.13	3.26
Percent Cropland	83.51	0.21
Percent Owned	46.61	0.70
Heads of Cattle	80.24	1928.34
Normal Growing Degree Days (Norm GDD)	242.21	22.70
Normal Extreme Degree Days (Norm EDD)	17.15	14.22
Normal Precipitation (inches)	708.81	270.38
Deviation Growing Degree Days (Dev GDD)	44.92	10.88
Deviation Extreme Degree Days (Dev EDD)	4.70	7.62
Deviations Precipitation (inches)	180.57	185.55
Highly Erodible Fields (1: highly erodible / 0: otherwise)	15.08	0.36
Wetland Fields (1: if wetland / 0: otherwise)	3.05	0.17
NCCPI Score (0 – 1: least to most productive)	0.50	0.20
Organic Matter (w.% in mm)	2.75	2.82
Percent Slope	4.05	4.20
County Erosion	4.48	0.53
Soil Conductivity	12.68	13.48

Table 2.2 shows the summary statistics for the ARMS data used in the analysis. The average age of the farmers included in this study was 55 with 28% of farmers having a college degree and 19% identifying as non-white ethnicities. The average household size was 2.8 individuals per home. The average farm size was 1042.13 acres with an average of 84% of the land devoted to crop products, 47% being owned, and 80 heads of cattle on the operation. On average, farms were exposed to 242.21 normal GDD, 17.51 normal EDD, and 708.81 inches of rain annually. The annual deviations in climate conditions each year on average were 44.92 GDD, 4.70 EDD, and 180.57 inches of rain on average. 15.08% of fields in the study were classified as highly erodible and 3.05% were classified as wetlands.

Table 2.3 Percentage of Carbon Farming Use by Bundle

Conservation Bundles	<u>Model 1</u>	<u>Model 2</u>
CT	19.68%	37.09%
RT	13.08%	26.03%
NT	15.34%	25.24%
LUC + CT	2.76%	-
LUC + RT	2.47%	-
LUC + NT	3.75%	-
CR + CT	21.95%	-
CR + RT	10.07%	-
CR + NT	10.90%	-
CC + CT	-	3.04%
CC + RT	-	3.11%

Foot Note: Acronyms for carbon farming practices include Conventional Tillage (CT), Reduced Tillage (RT), No-till (NT), Land Use Change (LUC), Crop Rotation (CR), Cover Crops (CC)

Table 2.3 provides a breakdown of the percentage of farmers that used each conservation bundle in either model. In both models, individual tillage practices accounted for the largest proportion of use. Note that in bundles that include conventional tillage, the additional practice is the first carbon farming technique to be adopted. Examining bundles that included more than one conservation practice shows that in model 1 the largest proportion of joint use came from combination no-till and crop rotation. In model 2 the largest proportion came from a combination of no-till and cover crop. Due to the small number of observations in the analysis (<30) farmers that used three or more practices were excluded from the model specification.

Figure 2.1 Tillage Practice Use Through Time

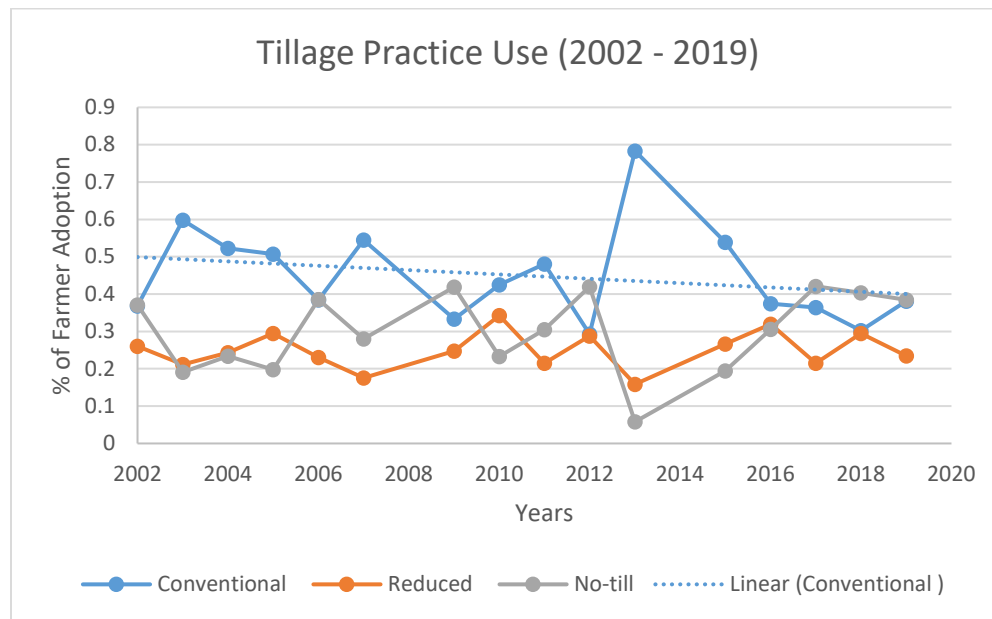


Figure 2.1. shows the trend in tillage practices between the years 2002 -2019. The graph shows a steady decline in the percentage of farmers that continue to implement conventional tillage practices on the farm operation. There is also a slight increase in the percentage of farmers

implementing reduced and no-till management strategies. This suggests that conservation tillage practice use was trending upward over time.

Figure 2.2 Tillage Practice Use by Crop

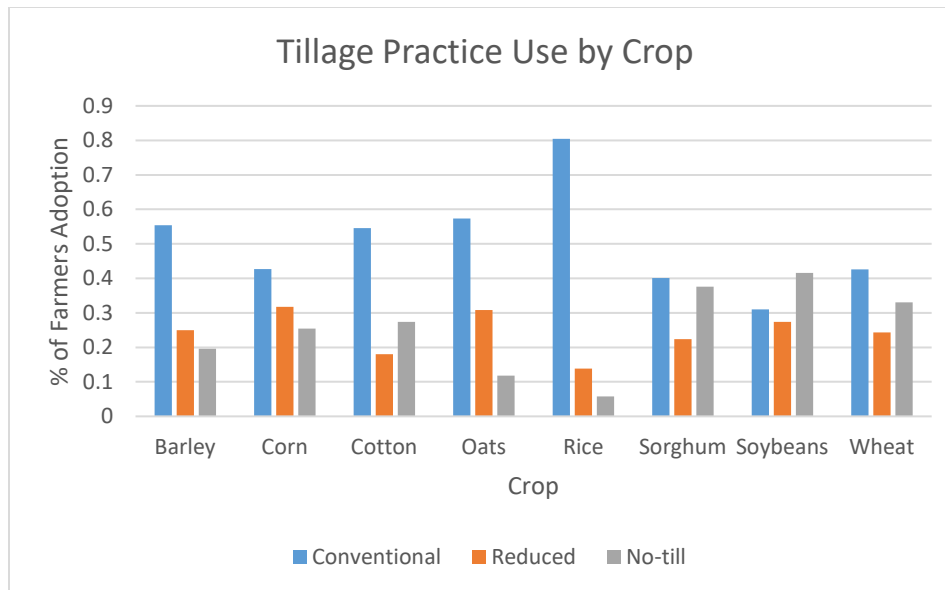


Figure 2.2 displays the distribution of tillage practice used by crop specialty. The bar graph shows that conventional tillage practices are still the most commonly used management strategies across most of the crops in the dataset. Soybean production is the only crop specialty where the proportion of farmers that practice no-till management has exceeded conventional tillage practices. For corn, sorghum, and wheat production, the combined proportion of reduced and no-till users does exceed the percentage of conventional tillage operations. This further demonstrates the steady transition to conservation tillage practices by farmers in the U.S. particularly among row crop producers.

Figure 2.3 Carbon Farming Practice Use by Crop

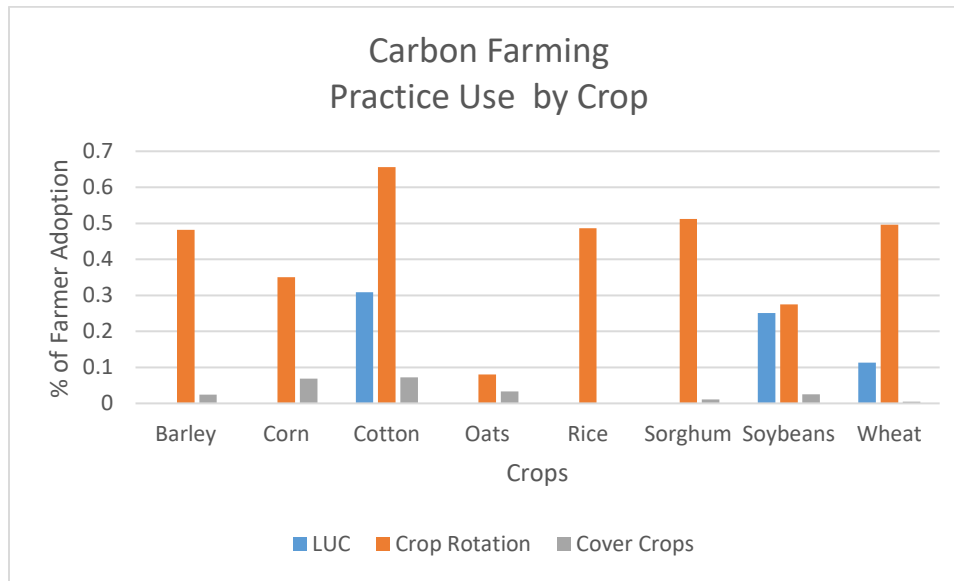


Figure 2.3. show the distribution of LUC, crop rotation, and cover crop practices used by farmers across crops. The graph shows that over 20% of producers of most crop specialties have implemented some crop rotation management strategies. Cover cropping strategies have been used by barley, corn, cotton, oats, and rice producers in the dataset though this accounts for less than 10% of each crop. LUC strategies have only been used by cotton, soybean, and wheat producers. Cotton and soybean production are the only crop specialties where all three carbon farming practices were used in some capacity. Conversely, rice producers have only incorporated crop rotation strategies in production.

2.4 Results and Discussion

Table 2.4 Joint Use Multinomial Logistic Regression Marginal Effects Model 1

Variable	<u>Land Conversion</u>			<u>Crop Rotation</u>		
	<u>Conventional</u>	<u>Reduced</u>	<u>No-till</u>	Conventional	Reduced	No-till
	<u>Tillage</u>	<u>Tillage</u>		Tillage	Tillage	
Age	0.000*	0.000	0.000	-0.001**	-0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education	0.001	-0.001	-0.000	0.003	0.002	-0.005**
	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)
Race	0.006	0.039***	0.006	-0.010	0.001	0.010
	(0.006)	(0.007)	(0.006)	(0.008)	(0.006)	(0.007)
Household Size	0.000	-0.001	-0.000	0.004**	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Years Farming	0.000***	-0.000	0.000***	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Farm Size	-0.001	-0.001	0.003**	-0.015***	-0.002	0.025***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)
% Cropland Acres	0.001	0.002	-0.002	0.036***	-0.004	0.039***
	(0.009)	(0.008)	(0.008)	(0.013)	(0.010)	(0.012)
% Owned	-0.003	0.000	-0.002	-0.003	-0.003	0.016**
	(0.003)	(0.002)	(0.003)	(0.006)	(0.005)	(0.005)

Cattle	-0.000*** (0.000)	0.000** (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Normal GDD	-0.003*** (0.000)	-0.002*** (0.000)	0.002*** (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.002*** (0.000)
Normal EDD	0.000 (0.000)	-0.001 (0.000)	-0.002 (0.000)	0.004 (0.000)	0.001 (0.000)	-0.003 (0.000)
Normal Percip	0.000*** (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.001*** (0.000)	-0.000*** (0.000)	0.000*** (0.000)
Normal Percip ²	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000*** (0.000)	0.000*** (0.000)	-0.000*** (0.000)
Diff GDD	0.005*** (0.000)	0.004*** (0.000)	0.005*** (0.000)	0.006*** (0.000)	0.004*** (0.000)	0.005*** (0.000)
Diff EDD	0.006*** (0.000)	0.006*** (0.000)	0.008*** (0.000)	-0.008*** (0.000)	-0.004*** (0.000)	-0.002*** (0.000)
Diff Percip	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	0.000** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
Diff Percip ²	0.000*** (0.000)	0.000*** (0.000)	0.000* (0.000)	-0.000*** (0.000)	-0.000* (0.000)	-0.000 (0.000)
Highly Erodible Field	-0.025*** (0.006)	-0.009** (0.005)	0.012*** (0.004)	-0.027*** (0.008)	0.006 (0.006)	0.040*** (0.006)

Field	0.003	0.004	0.007	0.042***	0.008	-0.005
Wetland Status	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NCCPI	-0.051***	-0.021*	-0.028*	-0.154***	0.069***	-0.032
	(0.012)	(0.012)	(0.013)	(0.024)	(0.019)	(0.021)
Organic Matter	0.002***	-0.000	-0.001	0.009***	0.000	-0.013***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Slope	-0.005***	-0.002**	0.004***	0.003***	0.004***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
County Erosion Level	-0.003	0.009*	-0.000	-0.000	0.008*	0.007
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)
Soil Conductivity	0.000	-0.000	0.000**	-0.001***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.490***	-9.794***	-29.06***	-6.311*	-9.290***	-18.123***
	(1.999)	(2.244)	(2.011)	(0.789)	(1.034)	(1.043)
Observations	15,529					
Log-Likelihood	-21788.37					
Pseudo - R ²	0.2989					
Akaike Information Criterion	43976.75					

Note: Statistical significance at the 99% (***), 95% (**), and 90% (*) confidence levels. Robust standard errors are given in parentheses.

Table 2.4 gives the marginal effects multinomial logistic model that included bundles containing LUC and crop rotation practices. Examining the marginal effects for the farmer demographics shows that farmer age was significant with a small impact on use for three bundles. The sign on the coefficients suggests age is positively associated with using LUC and conventional tillage practices while negatively associated with using crop rotation with conventional tillage and no-till. This implies that older farmers are slightly less likely to use crop rotation in addition to tillage practices but slightly more likely to convert land out of production while continuing with traditional tillage operations. This could suggest that land conversion is a more appealing gateway carbon farming practice for older farmers who may be more reluctant to adopt more intensive practices. Interestingly the marginal effects of years of farming on LUC for farmers practicing conventional and no-till are also significantly positive which may further support this observation.

The marginal effect for education is significant for no-till farmers and crop rotation with the negative sign suggesting that no-till farmers who are college-educated are slightly less likely to use crop rotation in addition to their tillage practice. This is interesting as educated farmers are thought to be more receptive to conservation practices. The marginal effect of household size was significant and positive for conventional tillage and crop rotation suggesting that conventional tillage farms with larger households are slightly more likely to adopt crop rotation. Lee and McCann 2019 found that additional labor had a positive impact on the likelihood of adopting cover crops. The presence of additional family labor appears to have a similar effect on the joint use of certain practices. The final demographic variable for race is shown to be significant and positive for reduced tillage farms and LUC suggesting that non-white farmers are slightly more likely to convert land out of production as an additional conservation practice. The

barriers to implementing LUC may also be small enough to increase the likelihood of use for limited-resource ethnic farmers.

The impact of farm size has presented varying implications in previous studies. Wade & Claassen (2017) found that farm size positively impacted the likelihood of adoption for no-till practices. Conversely, Lee & McCann (2019) found that farm size hurt the probability of adoption since it is expected that converting management practices on larger amounts of land could result in greater upfront costs and time constraints. The marginal effects for farm size in this analysis suggest that larger farms are more likely to use LUC and crop rotation practices in addition to no-till production while less likely to use crop rotation when practicing conventional tillage management. It could be that larger farms are more willing to remove land from production rather than incorporate growing additional crops outside of their production specialty. Cycling less productive land out of use might have less impact on revenue than the input requirements for crops outside of their production specialty. The effect of economies of scale could also make incorporating more practices less challenging for larger operations. However, this may depend on the amount of farm acreage the operation has dedicated to crop production. The marginal effect for the percent of cropland acres on crop rotation designated as cropland is shown to be significant and positive for conventional and no-till farms. This suggests that farms with a higher percentage of cropland may be more willing to explore producing additional crops outside their specialty. The marginal effects for cattle were small but significant and negative for conventional tillage farms practicing while positive reduced tillage farms and LUC. The implications of this result are unclear but may suggest that mixed crop and livestock operations may be flexible with removing land from crop production since it can be converted to pastureland that benefits livestock.

A key interest in this study is distinguishing between the effects of long-run climate conditions and short-run deviations from climate (i.e. weather) on the likelihood of use. The marginal effects of normal GDD (Norm GDD) were significant in four conservation bundles in this model. The signs of the coefficients suggest that when climate conditions are relatively normal no-till farms are more likely to adopt additional LUC and crop rotation practices. Conversely, conventional and reduced tillage farmers appear less likely to incorporate additional land use change strategies. This may suggest that when climate conditions are consistently normal certain farms may be more willing to explore adopting additional carbon farming practices since the risk of production loss from extreme climate conditions is less prevalent. This idea may be supported by the marginal effects for deviations in normal temperatures (Dev GDD) which are significant and positive across all conservation bundles.

Exploring the impacts of normal and deviated extreme temperatures (Norm EDD and Dev EDD) offers insight into farmer behavior in extreme climate and weather conditions. The marginal effects of Norm EDD are shown to be significant across almost every conservation bundle. Based on the signs of the coefficients, this impact is positive for conventional and reduced tillage farmers practicing crop rotation but negative for no-till farms implementing LUC and crop rotation as well as reduced tillage operations. This may suggest that certain carbon farming practices are perceived as a more efficient adaptation to expected extreme temperatures. Furthermore, the marginal effects of Dev EDD are shown to be significant across all of the conservation bundles that include LUC displaying positive signs while bundles including crop rotation showed a negative sign. This suggests that when faced with increasingly extreme temperature deviations, farmers may be more likely to transition land out of production than they would incorporate the production of additional crops outside their staple commodity. This

rationale could be explained by the idea that farmers focus inputs into highly productive fields and less on alternative production strategies as growing conditions become harsher for staple crops.

The magnitudes for the marginal impacts of precipitation are notably small but still provide insight into how farmers may respond to additional rainfall. The marginal effects for both normal precipitation and its squared term are shown to be significant across all bundles that include crop rotation. The relationship of the signs suggests that for conventional and reduced tillage farmers, the likelihood of using crop rotation in production increases with additional precipitation. The opposite is the case for no-till farms using crop rotation. This result suggests that conventional and reduced tillage farms that experience increased rainfall can more efficiently incorporate the production of alternative crops in their management strategies. In contrast, no-till farms appear less likely to use crop rotation strategies. This could be because no-till strategies are less effective at mitigating flooding in the fields. This speculation is further supported when inspecting the marginal impacts of deviations in normal rainfall. The standard and squared terms for deviations in precipitation are significant for nearly every conservation bundle. The signs suggest that LUC is slightly more likely to be adopted along with any tillage practice in the face of excess rain than crop rotation strategies. This supports the idea that certain practices may limit a farmer's ability to control flooding in fields in the presence of additional rainfall.

The soil variable results further support the notion that productivity influences the type of carbon farming practice farms are likely to use. The marginal effects of the NCCPI index were significant across five of the six conservation bundles. The signs indicate that higher productivity ratings decrease the likelihood of using LUC with any tillage practice and crop rotation on

conventional tillage operations. Conversely, reduced tillage is suggested to be more likely to use crop rotation as the productivity rating increases. A similar result is found in the marginal effects for organic matter as it reduced the likelihood of implementing crop rotation on no-till farms but slightly increased the likelihood of LUC and crop rotation on conventional tillage farms. This trend in the signs of these results suggests that highly productive fields are less likely to have multiple carbon farming practices in most cases. The magnitudes of the marginal effects were small on soil electro-conductivity but were still shown to be significant for two bundles. The signs suggest that more conductive fields increase the likelihood of using LUC and no-till practices but decrease the likelihood of cover crop usage with conventional tillage practices. Greater soil conductivity is associated with highly productive fields which further supports the idea that farmers could be less willing to apply alternative production practices on land that is anticipated to have high yields.

Evaluating the marginal effects of the soil conditions shows that the highly erodible field indicator is significant across almost every bundle. The signs indicate that highly erodible fields are less likely to have additional LUC and crop rotation practices implemented alongside conventional and reduced tillage practices yet more likely when no-till practices are in use. No-till practices are often used to mitigate soil erosion which could explain this result. Interestingly, the erosion level of the county is also shown to increase the likelihood of using LUC and crop rotation used along with reduced tillage practices. The soil slope was shown to be a significant variable across all of the conservation bundles. The signs indicate that soil slope decreases the likelihood of LUC practices being used alongside conventional and reduced tillage practices but increases use with no-till management. The opposite is the case for crop rotation as the signs show that the likelihood of use decreases for no-till while increasing for conventional and

reduced tillage fields. This would suggest that certain practices are more challenging to implement together depending on the slope of the land and the field in use. Finally, the sign for the marginal effect of the wetland indicator was significant, increasing the likelihood of using cover crops on wetland fields. This may indicate that wetland conditions provide an environment for certain cover crops to thrive, and an opportunity may exist to encourage use in wetland fields as a transitional conservation practice.

Table 2.5 Joint Use Multinomial Logistic Regression Marginal Effects Model 2

Variable Coeff (Std Err.)	<u>Cover Crops</u>		
	Conventional Tillage	Reduced Tillage	No-till
Age	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)
Education	-0.004 (0.007)	-0.006 (0.007)	-0.006 (0.007)
Race	0.008 (0.012)	-0.018** (0.008)	0.012 (0.012)
Household Size	0.003*** (0.001)	0.000 (0.002)	0.000 (0.002)
Years Farming	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Farm Size	-0.007*** (0.003)	-0.000 (0.003)	0.012* (0.003)

% Cropland Acres	0.009 (0.017)	-0.016 (0.013)	0.001 (0.016)
% Owned	-0.004 (0.009)	0.005 (0.004)	0.009 (0.006)
Cattle	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
Normal GDD	0.001* (0.000)	0.001*** (0.000)	0.003*** (0.000)
Normal EDD	-0.000 (0.000)	0.000 (0.000)	-0.003*** (0.001)
Normal Percip	0.000*** (0.000)	0.000 (0.000)	0.000 (0.000)
Normal Percip ²	-0.000* (0.000)	-0.000 (0.000)	0.000 (0.000)
Diff GDD	0.001** (0.000)	0.001** (0.000)	0.002*** (0.000)
Diff EDD	-0.003*** (0.001)	-0.000 (0.001)	0.000 (0.001)
Diff Percip	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Diff Percip ²	-0.000	-0.000	-0.000

	(0.000)	(0.000)	(0.000)
Highly Erodible Field	0.006 (0.002)	0.025*** (0.008)	0.013 (0.002)
Field Wetland Status	-0.029 (0.033)	-0.000 (0.021)	0.002 (0.027)
NCCPI	-0.090*** (0.028)	-0.013 (0.029)	-0.001 (0.037)
Organic Matter	0.000 (0.001)	0.002* (0.001)	-0.013*** (0.004)
Slope	0.000 (0.001)	0.002* (0.001)	0.004*** (0.001)
County Erosion Level	-0.003 (0.007)	0.010 (0.007)	-0.012* (0.007)
Soil Conductivity	0.000** (0.000)	0.000*** (0.000)	0.001*** (0.000)
Constant	-14.300*** (3.182)	-23.55*** (3.512)	-27.225*** (3.237)
Observation		3,939	
Pseudo - R ²		0.1237	
Log-Likelihood		-4836.4613	
Akaike Information Criterion		9922.923	

Note: Statistical significance at the 99% (***), 95% (**), and 90% (*) confidence levels. Robust standard errors are given in parentheses.

Table 2.5 displays the marginal effects of the multinomial logistic model including bundles that combine the tillage practices and crop rotation. The marginal effects for the farmer demographic show that race and household size were significant for conventional and reduced tillage farmers. The signs suggest that non-white farmers are less likely to combine cover cropping with reduced tillage practices while larger farm households are slightly more likely to use cover crops as an initial conservation practice. This suggests that there may be some barriers to use for limited-resource ethnic farmers. Alternatively, Bergtold and Molnar 2010 suggested that cultural norms and historical discrimination against ethnic demographic groups could negatively impact the likelihood of adoption due to a lack of perceived support or incentives from government programs. Similar to crop rotation bundles, the additional labor available from family members positively impacts the likelihood of cover crop use. Farm size positively impacts the joint use of no-till and cover crops while decreasing the likelihood of cover crop use for conventional tillage operations. This seems to suggest that larger farms primarily focus on the production of staple crops, however, large farms currently implementing one carbon farming practice are more likely to consider implementing another.

Consistent with Model 1, climate and weather conditions greatly impact on the likelihood of cover crop adoption with any tillage practice. The signs show that normal and deviations in GDD are positive across all tillage practices. This indicates that optimal growing temperatures increase the likelihood of use. Conversely, normal and deviations in EDD hurt the likelihood of cover crop use with no-till and conventional tillage practices. This supports the idea that when faced with extreme growing temperatures, farmers prioritize the production of their primary crops. Again, the marginal effects for the normal precipitation are small; however, the signs

suggest the presence of a diminishing marginal impact between cover crop use for conventional tillage farms and additional rainfall.

The significant soil characteristics suggest that similar to crop rotation in Model 1, productivity and soil conditions significantly impact the likelihood of cover crop use. The soil productivity index and organic matter variables are shown to negatively impact the likelihood of using conventional and no-till practices respectively implying that higher-yielding fields are prioritized for the production of staple crops. Though the magnitudes of the marginal for soil conductivity are small, the positive signs further suggest that soil factors that indicate highly productive fields potentially decrease the likelihood of cover crop use. Examining the impact of structural characteristics of the land and soil shows that cover crops are more likely to be implemented on reduced tillage fields. Research has suggested that cover crops can effectively manage soil erosion supporting these results. Interestingly, the sign for county erosion levels is negative implying the opposite impact, thus further research on the effectiveness of cover crops as an erosion control measure may be needed. Finally, soil slope positively impacted the likelihood of cover crop use with reduced and no-till practices. Cover crops may be a prominent soil erosion control measure on fields with a greater slope.

2.5 Conclusions

This research sought to gain insight into the trends for the use of carbon farming practices in the U.S. and understand the factors that influence the likelihood of use for producers. Examining trends in carbon farming practice use over time showed that reduced and no-till practices are becoming more common among producers as the implementation of conventional tillage strategies show a downward trend through time. The number of reduced and no-till farms combined exceeded the conventional tillage operations for corn, sorghum, soybeans, and wheat

production in the U.S. The use of multiple carbon farming practices is most prevalent in the presence of soybean, cotton, and wheat production. However, the downward trend in crop rotation usage and sporadic shifts in land use suggest that farmers focus the majority of their land and inputs on the production of staple crops. Meanwhile, the adoption of cover crops appears to be steadily trending upward.

The results from both models identify a clear relationship between the likelihood of multiple practice use and climate/weather conditions. In the presence of optimal growing temperatures, the likelihood of joint use increased. However, joint use became less likely as temperatures became more extreme. Considering the downward trend in crop rotation use, it appears that this practice has been the one that farmers have transitioned away from the most in the face of rising temperatures. A prominent contribution to the literature in this analysis is the evaluation of soil characteristics. The results show that joint use is impacted by the productivity and structure of the land in use. Producers typically prioritize land and inputs into higher-yielding fields.

Research has suggested that the effectiveness of carbon sequestration practices would be optimized in environmentally sensitive soils (e.g., sandy, sloping, or eroded soils) with low carbon levels (Blanco-Canqui 2021). An opportunity to encourage practice use in less productive fields may exist, though smaller farmers prioritizing production may face challenges with the additional input requirements. As incentives for adoption are constructed, considerations about the increased input cost to farmers and the potential risk of production losses must be factored into their implementation. Results from Mengistu & Assefa (2019) suggested that when farmers and producers receive assistance with training and resources, the likelihood of adoption increases significantly. Educating small-scale limited resource and ethnic farmers through extension on

alternative management strategies for less productive fields that could yield financial opportunities could encourage using practices that have declined over time.

Future research can continue to understand the landscape of joint practice use by exploring the interactions between independent variables. For example, a relationship between farm size and productivity could exist since more acreage may or may not directly contribute to higher proportions of productive land overall. Additionally, there could be a sequential relationship between management strategies. Carbon farming practices with fewer input requirements may encourage additional practice use in the long run. Evaluating factors influencing practice use using a nested logit model could provide insight into this speculation. Finally, while previous research has explored the financial implication of individual practices continued research on how multiple carbon farming practices impact finances and welfare could provide insight that can aid in making the transition to these practices less daunting for producers.

Chapter 3 - Evaluating the Welfare Implications of Carbon Farming Practices in the U.S.

3.1 Introduction:

In response to growing global interest in finding solutions to combat climate change, both public and private organizations seek to encourage carbon sequestration and emission offset initiatives. Federal programs such as the United States Department of Agriculture's (USDA) Environmental Quality Incentive Program (EQIP) and Conservation Reserve Program (CRP) programs have offered forms of financial support in an attempt to subsidize farm operations willing to implement climate-smart management practices into their production strategies. One approach that has gained popularity is the development of carbon credit systems. Farmers can generate carbon credits by implementing carbon sequestration practices into their production management strategies. These credits are then sold to companies seeking to offset their emissions. There are currently sixty-five carbon pricing programs around the world, including mandatory and voluntary emissions trading systems (ETs) and GHG taxes (World Bank Group, 2021). Today several voluntary agricultural carbon credit programs have started or entered the development stage (Wongpiyabovorn et al., 2021).

While programs such as this may seem financially appealing for agriculture producers, challenges exist that could lead to reservations in the choice to use climate-smart practices. Accurate measurement and verification of credits from agricultural activities are often laborious and cost-intensive (Kooten, 2008). There is also the potential problem of carbon reversal when practices are no longer used after contracts for incentive programs expire (Wongpiyabovorn et al., 2022). Thus, participation in carbon credit programs cannot serve as the only motivation for using these practices. Farmers must be made aware of the potential welfare benefits of their

operation. Agriculture is very dependent on climate and susceptible to climate change with possible losses of agricultural production causing concern in the face of increasing global demand, population, and income growth (Hendricks, 2018). Therefore, identifying how management practices help farm operations protect their welfare interest from external changes in the environment could serve as motivation for their usage.

While the research surrounding the implications of carbon credit systems is ongoing, alternative methods of analysis could help evaluate the welfare implications for producers adopting carbon farming and other GHG-mitigating practices. Research suggests that producers stand to financially benefit from carbon farming practices through improved yields and crop quality as a result of improved environmental growing conditions. However, maximizing the environmental benefits often requires the use of more than one practice in production. Additional research on the relationship between carbon farming practices and producer welfare could reveal key insights to promote the implementation of climate-smart practices. In addition, concrete evidence of welfare benefits from the practices can assist policymakers by having more specific information and mechanisms to encourage regular use. The purpose of this research is to identify the welfare implications of carbon farming practices as an adaptation to climate change for agriculture producers. The specific objectives are: 1) *identify the current intensity levels of carbon farming practice usage in the U.S.*, 2) *evaluate the relationship between carbon farming management practices and welfare*, and 3) *examine the differences in welfare for different usage levels of carbon farming practices*. This research will contribute to the literature on carbon farming production strategies in the U.S. by exploring the producer surplus implications of these practices for farm operations.

3.2 Literature Review:

It is well understood that the agricultural industry is sensitive to climate change (B. R. Mendelsohn et al., 1994). According to the Inter-governmental Panel on Climate Change (IPCC), projections suggest that farmers worldwide face challenging conditions due to warmer environments, unpredictable rainfall patterns, and frequent extreme weather phenomena (Wake, 2013). The challenges that climate change presents threaten both the sustainability of agricultural products as well as the ability of farmers and ranchers to sustain their livelihoods and economic welfare. Options for adapting to climate change range from various cropping decisions, management practices, and investment tools at the farm's disposal. Thus, research analyzing the mechanisms of adaptation, what adaptation is, its primary drivers, and implications for both the productivity and revenues of agriculture producers is ongoing (e.g. Di Falco and Veronesi 2014; R. Mendelsohn and Dinar 2009). Carbon farming practices have been explored as mitigative practices against climate change due to their ability to improve soil and water conditions and reduce pollutants or emissions. The overall goal of adaptation to climate change is to protect the productivity and/or revenue of the farm in the face of extreme weather conditions.

Research suggests that the relationships between adaptive management strategies in agricultural production and farm income can be modeled as functional links. The functional relationship between the net revenue of farmland and climate variables has been well-established in the literature (Lone et al., 2017). A producer's willingness to use climate-smart management practices is driven by the desire to maintain a sustainable level of income from the farm operation in the face of environmental threats or the presence of opportunities in the market. Participation in government programs along with the sustained implementations of soil or water conservation activities can significantly increase productivity and welfare in the face of

extremely dry growing conditions (Scognamillo & Sitko, 2021). Farmer and farm demographic information is intrinsically linked to the decision to use a particular management practice. As such, the effect of said demographics would also impact the welfare of farm operations. Studies have shown that variables related directly to land use have a positive and statistically significant relationship with farm income. Land ownership, for example, is associated with higher levels of farm income along with crop diversity and conservation practice use (Bravo-Ureta et al., 2006).

Treatment effect models are often used to evaluate the differences in an observed outcome between groups in the presence of treatment or before and after an intervention. Common estimation approaches used in this space include two-stage least squares (2SLS) and two-way fixed effects estimation in an ordinary least squares (OLS) framework. Additionally, studies have utilized Difference-in-Differences as an identification strategy to take advantage of variations in space and/or time to evaluate the impact of an intervention. These techniques are optimal when using panel data as they limit the possibility of omitted variable bias by controlling for time-invariant unobservable variables (Carter et al., 2018). However, when using cross-sectional data, an alternative approach is using observations as a point of reference and comparison. Propensity score matching (PSM) is an approach that researchers have used to accomplish this objective. Developed by Rosenbaum and Rubin (1983) PSM simulates a controlled experiment for non-randomly assigned groups of observations. This is done through statistical comparisons between a treatment and a control group. Characteristics from both groups are used to calculate a propensity score, usually estimated with a logit or probit model, that gives the probability of receiving treatment. From there, observations of similar characteristics are matched to evaluate the impact of the treatment on an observable outcome of interest.

PSM techniques have been used to estimate the treatment effect of conservation efforts on farmland preservation (Liu & Lynch, 2011), risk management tool adoption on farm profit (Ifft et al., 2013), and federal crop insurance use on debt (Ifft et al., 2015). This analysis method typically requires a large number of observations and a detailed data set. Using nationally representative data can ensure that the results can remain consistent with the outcomes from a controlled experimental framework (Grout et al., 2021). There are two assumptions to consider when using this approach. The first is the common support assumption, often referred to as the overlap condition (Caliendo & Kopeinig, 2008). It requires that the probability of receiving treatment must be positive for all individuals in either the treatment or control groups (Heinrich, 2010). The second is that all characteristics relevant to treatment status must be used in calculating the propensity score. This includes variables that may simultaneously affect the outcome of choice (Grout et al., 2021).

Several matching algorithms have been used in PSM analyses. Rosenbaum and Rubin (1983) originally developed the “nearest neighbor” approach, where treated observations were paired with their most similar non-treated counterpart without replacement (Rosenbaum & Rubin, 2006). Later variations modified this approach by using “calipers” to add restrictions on matching, comparing every treated observation to every other non-treated observation, and using kernel-weighted averages for multiple untreated observations to match treated observations (see Austin, 2011; Dehejia & Wahba, 2002; Heckman et al., 1998). The best method to use in any scenario generally depends on the structure of the data. None of the approaches consistently outperform the others and the differences in results tend to converge as the sample size and quality of matching improves (Caliendo and Kopeinig, 2008). However, the primary drawback to these matching approaches is that they only allow for comparisons to be drawn at a single

treatment level. When evaluating the impact of multiple treatment levels other studies have taken advantage of Inverse Probability Weighted Regression Adjusted (IPWRA) estimation. The IPWRA uses the inverse of the estimated probability to weigh each observation in the analysis. This estimator is statistically advantageous due to its “double robustness” property meaning that when the treatment model is specified correctly the estimates are consistent (Cattaneo, 2010). Additionally, it can be effectively manipulated to account for more than one binary treatment level and accommodate interactions (Fisher et al., 2022).

3.3 Methods and Data:

3.3.1 Conceptual Framework

Research in the area of climate change regularly cites B. R. Mendelsohn et al. (1994) who was well known for developing the Ricardian climate change model. As such, research in this area follows a similar conceptual framework developed from a profit maximization approach. This allows for the evaluation of the effects of climate change on agriculture given various contextual modifications. The primary assumption is that farmers are rational and seek to maximize their profit (i.e., net revenue or income). This framework is outlined in Equation 1:

$$\text{Max } \pi_{ij} = \sum_{j=1}^m p_j f_{ij}(x_{ij}, m_{ij}, Z_{ij}) - \sum_{j=1}^m C_{ij}(x_{ij}, m_{ij}, Z_{ij}) \quad (1)$$

$$\text{Where } \pi = TR - TC; TR = PQ; TC = FC + VC$$

$$i = 1, \dots, n \text{ (farmers)}$$

$$j = 1, \dots, m \text{ (goods)}$$

In this framework, farmer i seeks to maximize profit (π_{ij}) by selecting a combination of inputs (x_{ij}) and management practices (m_{ij}) to produce an optimal level of goods captured by

their production function (f_{ij}). Here p_j represents the market price for good j that is produced and the cost function C_{ij} captures the variable cost and fixed costs associated with the inputs and production management practices the farmer needs to produce the optimal amount of good j . Additionally, Z_{ij} is a vector of stochastic variables that impact the profit externally of the farm operation inputs and management decisions. These include external factors such as economic market conditions, and regional variations in growing conditions. When seeking to observe differences between groups that participate in a particular behavior or receive treatment, the only observable difference between groups must be the outcome of interest. Equations 2 and 3 further outline this framework:

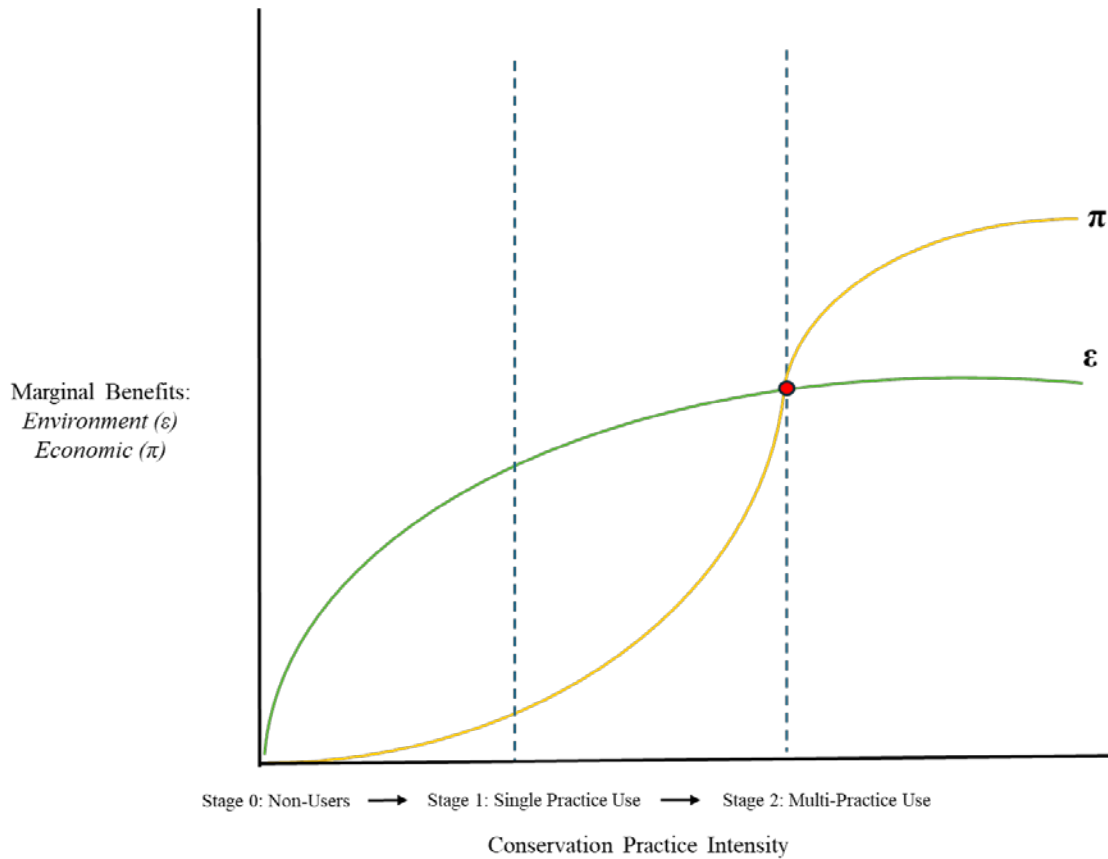
$$\pi_{0j} = p_j f_{ij}(x_{ij}, m_{ij}, Z_{ij}) - C_{ij}(x_{ij}, m_{ij}, Z_{ij}) \quad (2)$$

$$\pi_{1j} = p_j f_{ij}(x_{ij}, m_{ij}, Z_{ij}, CF_{ij}) - C_{ij}(x_{ij}, m_{ij}, Z_{ij}, CF_{ij}) \quad (3)$$

Here the income between farmers is compared given that one is observed implementing conservation management practices denoted by CF_{ij} . These practices have fixed, and variable costs associated with their implementation and are therefore distinguishable from other standard management practices. The profit levels of farmers who do not use carbon farming practices and those who do are given by π_{0j} and π_{1j} respectively. Ideally, the farmers and operations would exhibit similar enough characteristics such that the only observable difference is the use of climate-smart conservation practices. This study hypothesizes that as farmers begin to incorporate carbon farming practices into their management strategies, the benefits would lead to an observable difference in net farm income. As such, the second hypothesis this study seeks to test is whether there is a significant difference in the observed outcome at different stages of

practice use intensity. The framework for the second hypothesis can be seen displayed in Figure 3.1.

Figure 3.1. Benefits from Conservation Practice Use Framework



As seen in Figure 3.1, it is hypothesized that as farm operations begin incorporating a single carbon farming practice into production in stage 1 they may observe benefits from improvements in the environment denoted by ϵ . However, those benefits may not be maximized until farms transition to stage 2 and begin regularly implementing multiple practices into production. From an economic perspective, the monetary benefits farms might receive would be small if significant increases in yield or quality of outputs do not accompany the shifts in production input cost from using a single practice. Thus, a farmer transitioning to stage 2 would

gain the optimal benefits as the maximized environmental conditions create yield and quality improvements such that farmers experience a significant increase in monetary gains.

3.3.2 Empirical Model:

To evaluate the impact of carbon farming practices on farmer/farm welfare, this study uses a Propensity Score Matching (PSM) modeling approach. To estimate the average treatment effect on the treated (ATT) farms that use carbon farming practices will serve as the treatment group to compare to the control group comprised of conventional farm operations. As established in the previous framework farm operations have implemented a single practice at stage 1 of conservation practice intensity. Let k be an indicator variable for an operation's current stage of conservation with $k = CF_1$ for operations at stage 1 of conservation intensity and $k = CF_0$ for those at stage 0. Additionally, let the welfare indicator of net farm income for users and non-users be denoted by π_1 and π_0 respectively (e.g., net farm income). The equation for estimating the ATT can be seen outlined in equation 4:

$$ATT^{CF_1|CF_0} = E(\pi_1 - \pi_0 | k = CF_1) = E(\pi_1 | k = CF_1) - E(\pi_0 | k = CF_0) \quad (4)$$

In Equation 4 the ATT is estimated between farms at stage 0 and stage 1 of conservation intensity is the estimated difference between the observed net farm income between operations. From here, the next step is to estimate the difference in welfare (π_2) and ATT for farm operations at stage 2 of conservation use. In this scenario let $k = CF_2$ to indicate that a farm has implemented multiple practices into production. The equation to estimate the ATT for farms at stage 2 can be seen outlined in equation 5:

$$ATT^{CF_2|CF_{1,0}} = E(\pi_2 - \pi_{1,0} | k = CF_2) = E(\pi_2 | k = CF_2) - E(\pi_{1,0} | k = CF_{1,0}) \quad (5)$$

Here, the ATT is estimated for operations at stage 2 of conservation practice use. Note that farms in stages 0 and 1 are consolidated into a single control group with $k = CF_{1,0}$ and farm welfare $\pi_{1,0}$. If the estimated difference between the first two stages of conservation usage is not found to be particularly significant, the consolidation of these stages into a single group allows for more efficient controls and matching with farms at stage 2. The first step in the PSM approach is the matching process. A farm operation's propensity for using no, one, or multiple practices is first estimated using a probit regression to compare between two intensity levels. The matching algorithms used with the probit regression are the nearest neighbor method to compare the most similar farm operations against each other, and the kernel matching method using kernel-weighted averages for multiple conventional farms to match against operations using carbon farming practices. Next, the propensity for use is further evaluated by using an IPWRA multinomial regression to compare across two levels of conservation intensity. The inverse probabilities from this estimator will create a counterfactual allowing for the comparison between conventional farms, and single or multiple carbon farming practice operations. The equation for this estimation process is outlined in Equation 6:

$$\Pr(Y_i = k) = \alpha + \beta_k X_i + \gamma_i + \varphi_i + \delta_i + \varepsilon_i \quad (6)$$

$$\text{Where, Model 1: } k = \begin{cases} 0 - \text{Conventional Farms} \\ 1 - \text{Single Practice Farms} \end{cases}$$

$$\text{Model 2: } k = \begin{cases} 0/1 - \text{Conventional/Single Practice Farms} \\ 2 - \text{Multi - Practice Farms} \end{cases}$$

$$\text{Model 3: } k = \begin{cases} 0 - \text{Conventional Farms} \\ 1 - \text{Single Practice Farms} \\ 2 - \text{Multi - Practice Farms} \end{cases}$$

Here the propensity for treatment at the first or second stage is given by $P(Y_i = k)$ estimated using the covariates of observed farmer and farm characteristics X_i with β_k as the estimated parameters associated with the probability of receiving treatment. Three models were used to compare the income of farms across the stages of conservation intensity. The First two models compare conventional farms to single-practice farms, and conventional and single-practice farms to multi-practice farms. The last model is multinomial and compares all three farm types at once. Treatments in this analysis are voluntary as farmers choose how many carbon farming practices to use in production. Additionally, γ_i , φ_i , and δ_i represent fixed effects for income groups, production specialties, and regions. These effects will further enhance the matching process by allowing the algorithm to control environmental variations, market prices across specialty areas, and differences in economies of scale between farm operations.

Conservation Intensity Stage Assignment

The data for this analysis comes from the United States Department of Agriculture (USDA) Agricultural Resource Management Survey (ARMS) conducted by the Economic Research Service (ERS). This data serves as the USDA's primary source of information on the production management practices, input use, and economic welfare of farm operations in the nation. This study uses ARMS Phase 2 and 3 survey data which contains information on farm inputs, management practices, and farm and household characteristics. Phase 2 data was used to identify the current conservation practices in a field as reported by the producers being surveyed for a given crop in a year. This study uses repeated cross-sectional data from farmers surveyed between 2002 and 2019. The production practices that farms reported using include conventional, reduced, and no-till practices along with other conservation practices such as crop rotation, land use change to either pasture or range land, and cover crops. These practices were

combined to identify farm operations that used one or multiple carbon farming practices. Table 1 gives the average net farm income for farm operations that use different combinations of practices in production.

Table 3.1 Average Net Farm Income by Conservation Practice Use (U.S.\$)

Farm Management Practice	Mean	Std. Dev
Conventional Tillage	\$249,605	\$867,620
Reduced Tillage	\$207,883	\$938,850
No-till	\$172,816	\$658,418
Land Use Change	\$390,632	\$941,174
Crop Rotation	\$144,923	\$427,411
Cover Cropping	\$192,279	\$618,389
Reduced Tillage + Land Use Change	\$357,691	\$696,175
No-till + Land Use Change	\$313,672	\$1,205,201
Reduced Tillage + Crop Rotation	\$131,343	\$363,757
No-till + Crop Rotation	\$177,261	\$1,085,157
Reduced + Cover Cropping	\$278,351	\$826,326
No-till + Cover Cropping	\$228,486	\$582,015

Table 3.1 shows a large amount of variability and a high standard deviation in income between farm operations that do not use any conservation practices and operations that use at least one. Most single-practice operations except for land use change (LUC) farms were shown

to exhibit a lower net income on average even when compared to conventional tillage operations. Furthermore, the net income of farms that use multiple carbon farming practices is often higher than it is for farms that only use a single practice. Additionally, LUC is the practice that tends to result in the highest average net farm income when combined with an additional practice. Given the high variability and standard deviations, a T-test would not display a statistically significant difference from zero. A consolidation of Table 1 could better display the income difference between stages of conservation practice use. Table 2 consolidates the results from the previous table to show the difference in net farm income for farms that use none, one, and or multiple conservation practices.

Table 3.2 Average Net Farm Income by Conservation Intensity Stage (U.S.\$)

Conservation Intensity Stage	Mean	Std. Dev
Stage 0 (No practices)	\$219,646	\$870,215
Stage 1 (single practice use)	\$181,159	\$677,346
Stage 2 (multi-practice use)	\$200,650	\$871,381

In Table 2, there is again a large variability in profitability. Farm operations that have not implemented any conservation practices exhibit a higher average net farm income than those that have implemented a single practice in production. The average net farm income is also shown to be higher for farm operations that use two or more conservation practices in production. The averages presented in Table 2 seem to align with the framework previously hypothesized in this study suggesting that the environmental and economic benefits from using carbon farming practices are not maximized until multiple practices are used in production. Note that the

averages presented in Table 1 and Table 2 are aggregated and conditioned only on the specific practices or number of practices used.

Farmer Characteristics, Farm Characteristics, and Fixed Effects

Phase 3 of the ARMS data was used to identify the relevant demographic and farm characteristics for producers to estimate the propensity score for treatment for matching purposes. Age is a commonly used variable when evaluating the behavior of farm operators. Race was included as a binary variable to estimate the propensity of non-white farmers and the Caucasian majority. The ethnic groups of farmers included in the non-white category are African American, Asian-Pacific Islander, Hispanic, and Native American. Household size is used to account for additional potential labor. The final two farmer demographics used in this analysis were education and years of farming. Education is a binary variable to distinguish between farmers with and without a college degree. Years of farming were calculated based on the year a farmer reported they began working on the farm operation. This provided a way to distinguish actual farming experience from education. The log-transformed total acres of the farm were used to match farms of similar sizes. The percentage of the total land owned by the farmer and the percentage of the farmland used for growing crops were used to match farms with a similar level of production scale and ownership authority respectively. Lastly, the number of cattle on the farm operation was used in the matching process to account for farms with similar levels of alternative livestock production output. Table 3.3 shows the sample means for the treatment and control groups in both the single and multi-practice PSM models.

Table 3.3 Differences in Determinants for Single and Multi-Conservation Use (treatment and control sample means)

Matching Variables	<u>Single Practice</u>				<u>Multi-Practice</u>			
	0	1	0	1	0&1	2+	0&1	2+
Age (years)	55.09	54.86	54.91	54.86	54.11	54.52	54.78	54.52
Education (1 – college degree; 0 – no college)	0.26	0.26	0.26	0.26	0.25	0.25	0.25	0.25
Race (1 -non-white; 0 – white)	0.17	0.18	0.16***	0.18***	0.19	0.19	0.18	0.19
Household Size	2.8	2.8	2.8	2.8	2.78	2.78	2.78	2.78
Years Farming	38.57	42.06	35.45***	42.09***	50.87	54.71	50.32	54.11
Farm Size (acres)	1127.55	1125.64	1117.66	1125.64	1,085.72	1,118.79	1110.76	1119.57
% Cropland Acres	0.33	0.34	0.33	0.34	0.53	0.52	0.52	0.52
% Owned	0.47	0.47	0.46	0.46	0.46	0.46	0.45	0.44
Cattle	66.76	75.98	62.81	76.10	48.07	50.59	47.96	49.69
<i>F.E.</i>	<i>No</i>		<i>Yes</i>		<i>No</i>		<i>Yes</i>	

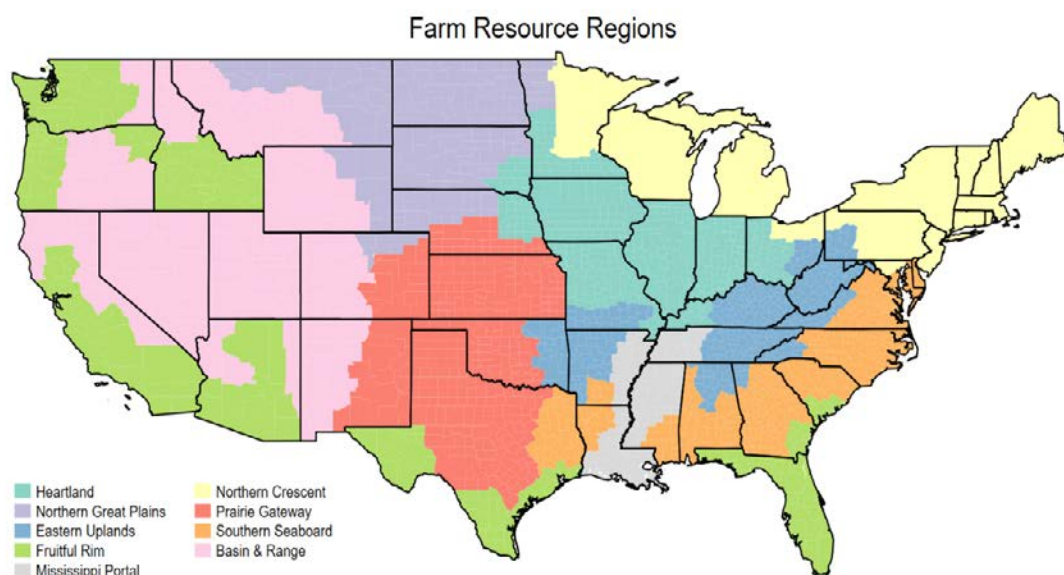
Note: Post-estimation statistical testing was performed using a T-test. Statistical significance at the 99% (***), 95% (**), and 90% (*) confidence levels.

The average age of farmers in the treatment and control groups for both the single and multi-practice PSM models is roughly 54 -55 years old. About 25 - 26 percent of farmers have a college education in the control and treatment groups in both models. Between 16-19 percent of farmers across groups identified as non-white. The average household size is about 3 members per household. Interestingly, there are a few notable differences in some of the treatment and control averages between models. The average number of years farming for example was shown to be about 38-42 years in the single-practice model and 50-54 years in the multi-practice model. The average farm size for the treatment and control groups in each model ranged from 1117 – 1127 acres and 1085 – 1119 acres in the single and multi-practice models respectively. The amount of land dedicated to crop production also exhibited a notable difference between models with the average for farms in the single-practice model being about 34 percent and 51 - 52 percent in the multi-practice model. However, the level of ownership between models was similar with farmers on average owning about 44 - 47 percent of the acres in their operation. Lastly, the average amount of livestock owned by the farm single-practice model was shown to be higher than in the multi-practice model. Farms in the control and treatment groups in the single-practice model had an average of 66 and 76 heads of cattle respectively whereas in the multi-practice model, the averages were 47 and 50. It is also worth noting that in either model, the average amount of livestock was higher in the treatment groups than in the control groups. The treatment and control group averages were examined using a post-estimation T-test to determine if there were any significant differences between the averages. The post-estimation test result indicated that the averages for years of farming and race in the single practice fixed effects model were significantly higher in the treatment group. However, this difference is

seemingly muted when moving to the multi-practice model as more observations are available for comparison overall.

To further enhance the matching procedure, three levels of fixed effects were used to account for variations across space and market conditions. The first level of fixed effects was used to match farmers in similar areas based on the USDA ERS Farm Resource Regions. These regions were created by the USDA Economic Research Service to visualize the geographic specialization in production for farm commodities via a cluster analysis of previously established regional specifications. The resource regions identify where areas with similar farm types intersect with areas of similar physiographic, soil, and climatic traits. These were used to match farmers based on similarities in environmental conditions such as soil properties, weather, and climate. The nine regions specified are the Heartland, Northern Crescent, Northern Great Plains, Prairie Gateway, Eastern Uplands, Southern Seaboard, Fruitful Rim, Basin Range, and Mississippi Portal regions. Figure 3.2 provides a map of the Farm Resource Regions as specified by the USDA ERS.

Figure 3.2 Farm Resource Regions (Source: USDA ERS, 2014)



Production specialty was used to match farms based on similarities in production output and competitive market environments. The nine production specialties in this study were: 1) barley, oats, wheat, 2) corn, soybeans, sorghum, 3) hay and other crops, 4) fruits and nuts, 5) vegetables, 6) beef, 7) hogs, sheep, and other livestock, 8) poultry, and 9) dairy. The production specialty assignment follows Whitaker (2009) in which a specialty category is assigned if the given commodity produced accounts for at least 50 percent of the total value of production. Finally, farms were separated into four different income groups to match farms that were similar in economic performance and scale. The method for assigning income groups (IG) in this analysis follows Livingston & Mishra (2013) who organized farms into revenue groups in a pseudo-panel setting. The net farm income (NFI) range for each group is as follows: IG1 ($\$1,000 \leq \text{NFI} < \$100,000$), IG2 ($\$100,000 \leq \text{NFI} < \$250,000$), IG3 ($\$250,000 \leq \text{NFI} < \$500,000$), and IG4 ($\$500,000 \leq \text{NFI}$).

3.4 Results and Discussion

Propensity for Conservation Practice Use

Table 3.4 presents the results from the probit estimation results for the likelihood of using conservation practices in both the single and multi-practice models. In both models, farm size and cropland acres are shown to be consistently statistically significant. The results show that the likelihood of both single and multi-practice use on the farm operation increases as farm size and the amount of acreage dedicated to crop production increases. This suggests that larger farms with a greater area of cropland are more likely to incorporate some amount of carbon farming practices in their management strategies overall. Practices such as cover cropping and crop rotation may be less challenging to incorporate into production management strategies with more land and/ or crop area available.

Further examination of both model estimates shows that age is significant and decreases the likelihood of using multiple carbon farming practices in production. Conversely, years of farming experience is shown to have a positive impact on the likelihood of using a single or multiple practices on a farm operation. This result is interesting as it highlights the need to distinguish between age and experience in economic analysis. While age is often used as a proxy for “experience” the results demonstrate the need for separation due to their distinct impacts. Additionally, education and household size were shown to decrease the likelihood of use in the multi-practice model, but this impact was not shown to be significant when controlling for variations across regions, production specialties, and economic scale. The opposite was the case for the percentage of owned acreage as it was shown to have a significant and positive impact on the likelihood of multi-practice use in the fixed effects model. This may suggest that land ownership allows farmers to consider a wider range of management strategies in production.

Table 3.4 Determinants of Single or Multi-Conservation Practice Use: Probit Model Estimates

Variable Coeff. (Std. Error)	<u>Single Practice</u>		<u>Multi-Practice</u>	
	<i>No F.E.</i>	<i>F.E.</i>	<i>No F.E.</i>	<i>F.E.</i>
Age (years)	-0.003* (0.001)	-0.003* (0.001)	-0.003*** (0.001)	-0.003*** (0.001)
Education (1 – college degree; 0 – no college)	0.002 (0.034)	0.001 (0.003)	-0.064* (0.030)	-0.035 (0.030)
Race (1 -non-white; 0 – white)	-0.068* (0.039)	-0.091* (0.049)	-0.042 (0.036)	0.033 (0.045)

Household Size	-0.015 (0.010)	0.007 (0.011)	-0.019* (0.010)	-0.008 (0.010)
Years Farming	0.000** (0.000)	0.000** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Farm Size (acres)	0.099*** (0.013)	0.072** (0.021)	0.027** (0.012)	0.022* (0.019)
% Cropland Acres	0.038*** (0.003)	0.411*** (0.034)	0.570*** (0.026)	0.555*** (0.028)
% Owned	0.039 (0.030)	0.038 (0.032)	0.019 (0.016)	0.042* (0.002)
Cattle (head)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Constant	-0.096* (0.134)	0.451** (0.173)	-0.755*** (0.111)	-0.0846*** (0.157)
<i>Obs.</i>	<i>8,315</i>	<i>8,302</i>	<i>11,464</i>	<i>11,448</i>
<i>R²</i>	<i>0.0221</i>	<i>0.0645</i>	<i>0.0394</i>	<i>0.0820</i>
<i>F.E.</i>	<i>No</i>	<i>Yes</i>	<i>No</i>	<i>Yes</i>

Note: Statistical significance at the 99% (***), 95% (**), and 90% (*) confidence levels. Robust standard errors are given in parentheses. Robust standard errors are given in parentheses.

Matching and Balance Checks

After estimating the propensity of single or multi-practice use in the models presented, a visual inspection of the density distributions for the propensity scores between the treatment and control groups was used to confirm that the common support condition was satisfied. The visual

inspection of the distributions revealed that the matching process did satisfy this condition as a substantial amount of overlap was present between the treatment and control groups in each model. A key goal of the propensity score estimation process is balancing the distribution of matching variables between treatment and control groups (Asfaw et al., 2012). In this analysis, both models displayed a low pseudo-R² value, insignificant p-values after likelihood ratio testing, and low mean bias percentages. This indicates that the matching specification effectively balanced the distribution of matching covariates between groups.

Impact of Single Practice Use

Table 3.5 presents the results estimated for the impact of using a single-carbon farming practice in production when compared to conventional farm management strategies. The results were estimated using the nearest neighbor (NN) and Kernel matching (KM) algorithms. The analysis reveals that on average, farms that have only used a single carbon farming practice experienced a 15 – 18 percent lower net farm income when compared to conventional farm operations with this effect shown to be statistically significant. However, when further matching is done using fixed effects for regions, production specialties, and economic size, this effect appears to be far less significant. The results show that single-practice farms exhibit roughly a 5 percent lower net farm income on average. This suggests that using a single conservation practice in production is not initially an economically advantageous production management strategy. This is perhaps because the environmental benefits of using a single carbon farming practice are not balanced by the economic benefits given the necessary input requirements if no significant increase in crop yield or quality is exhibited. The divergence of inputs away from stable commodity crop production seems to present a market disadvantage that could lead to

farmers abandoning a single carbon farming practice, thus reversing any of the environmental benefits gained from their initial use.

Table 3.5 Impact of Single Use on Net Farm Income: Nearest Neighbor – NN and Kernel Matching – KM

PSM Method	Outcome Mean (Net Farm Income)				Difference (ATT)		Mean Bias %	
	No Practice Farms		Single Practice Farms					
	<i>F.E.</i>	<i>No</i>	<i>Yes</i>	<i>No</i>	<i>Yes</i>	<i>No</i>	<i>Yes</i>	<i>No</i>
NNM	\$119,829	\$103,947	\$99,767	\$100,219	-0.183*** (0.047)	-0.005 (0.050)	1.6	1.9
KSM	\$116,934	\$103,922	\$99,767	\$100,219	-0.159*** (0.041)	-0.047 (0.043)	1.6	1.9

Note: Statistical significance at the 99% (***), 95% (**), and 90% (*) confidence levels. Robust standard errors are given in parentheses.

Impact of Multi-Practice Use

Table 3.6 presents the results for the estimated impact of using multiple carbon farming practices when compared to conventional tillage and single-practice farm operations. The analysis shows that there is a significant increase in average net farm income for farm operations that use two or more carbon farming practices in production. The average net farm income for multi-practice operation ranges is roughly \$120,800 across both model specifications whereas single-practice and conventional farms only experience an average income being about \$114,000. Farms using multiple carbon farming practices in production experience an 8 – 12 percent higher net farm income on average, or 7 - 11 percent when matching across similar regions, production specialties, and economic size. This suggests that for farms implementing

multiple carbon farming practices, the environmental and economic benefits begin to converge for agricultural producers. Multi-practice farm operations may experience this increased net farm income as a result of the yield and quality improvements that carbon farming practices have been suspected to provide in previous research. Additionally, the increased crop diversity from certain practices may allow multi-practice farm operations to take advantage of opportunities in the market.

Table 3.6 Impact of Multiple Practice Use on Net Farm Income: Nearest Neighbor – NN and Kernel Matching – KM)

PSM Method	Outcome Mean (Net Farm Income)				Difference (ATT)		Mean Bias %	
	Single/No Practice Farms		Muti-Practice Farms					
	<i>F.E.</i>	<i>No</i>	<i>Yes</i>	<i>No</i>	<i>Yes</i>	<i>No</i>	<i>Yes</i>	<i>No</i>
NNM	\$110,924	\$114,303	\$120,754	\$120,879	0.085 (0.040) **	0.117 (0.042) **	1.1	1.3
KSM	\$107,073	\$114,094	\$120,754	\$120,802	0.120 (0.034) ***	0.071 (0.035) **	1.6	0.9

Note: Statistical significance at the 99% (***), 95% (**), and 90% (*) confidence levels. Robust standard errors are given in parentheses.

Multinomial Evaluation of Conservation Practice Use

Table 3.7 presents the results of the IPWRA multinomial estimation which compares the impact of two levels of conservation practice use. Single-practice farms were used as the control in this approach due to having the highest frequency of observations in the data. An examination of the outcome means for the analysis sample set reveals a similar trend to the descriptive statistics presented in Table 3.2. Single-practice operations are shown to have a lower average

net farm income when compared to multi-practice farms and conventional operations. These differences are shown to be statistically significant when tested with the estimated ATT showing a nearly 4 percent difference in net farm income for conventional operations and an almost 10 percent difference for multi-practice farms. In both cases, the difference is shown to be positive. These results further support the hypothesis that the benefits of using a single carbon farming practice are not observable in the welfare of producers. Farm operations at this stage of conservation practice intensity must transition to stage two where the environmental and economic benefits can begin to converge. Alternatively, these operations could potentially forfeit any environmental improvements gained and revert to a more conventional production approach to improve their economic situation. Furthermore, the results suggest a \$4,000 subsidy would be required to effectively encourage the use of multiple carbon farming practices. This would offset the difference between the income for conventional farm operations and generate additional environmental benefits.

Table 3.7 Inverse Probability Weighted Regression Adjusted Multinomial PSM Results

Practice Intensity	Outcome Mean (Net Farm Income)	Difference (ATT)
No Practice	\$104,166	0.039 (0.028) *
Single Practice	\$92,112	<i>Control</i>
Multi-practice	\$100,744	0.090 (0.031) **
<i>Obs.</i>	<i>11,448</i>	

Note: Statistical significance at the 99% (***), 95% (**), and 90% (*) confidence levels. Robust standard errors are given in parentheses.

3.5 Conclusions

The objective of this study was to evaluate the economic welfare implications of carbon farming practice use for agricultural producers in the U.S. The research implemented a PSM approach to estimate the impact of single and multiple conservation practice use on net farm income. The results show that the propensity for a farm to use one or more of these production practices is significantly impacted by farm size and the proportion of land dedicated to crop production. Furthermore, when examining the differences in income between single-practice and conventional farm operations the results revealed that there is little economic incentive to use only one conservation practice in production, and doing so may potentially place agricultural producers at an economic disadvantage. Conversely, the effect of using multiple carbon farming practices was positive and significant suggesting producers experienced a significantly higher net farm income on average compared to conventional and single-practice operations. The results show that maximizing both the environmental and economic benefits of carbon farming practices requires using multiple complementary practices in farm production.

Policy Implications and Future Research

As both public and private sector organizations seek to develop policies and incentives through programs to encourage using carbon farming practices in agricultural production, increased attention must be given to farm operations that have begun implementing a single conservation practice in their management strategy. These producers may not be experiencing the economic benefits of a single practice and may choose to transition back to not using any practices. This may lead to a potential reversal of any environmental improvement originally gained. Mechanisms by which to encourage the use of these conservation practices should focus on transitioning farm operations to using multiple practices in production. This could be done by providing financial incentives or subsidies to support farms implementing additional practices

that at a minimum reflect similar economic benefits until they are achieved through increases in crop yields and quality or through advantageous market opportunities.

While mechanisms by which to encourage the use of conservation practices are continuously refined, future research could seek to evaluate the impact of previous programming efforts. For example, the USDA's Conservation Reserve Program (CRP) and the Environmental Quality Incentive Program (EQIP) are two programs that have been designed to protect and preserve the quality of the environment through policy efforts since the mid-1980s. Updates through additions and revisions in the Farm Bill have sought to further improve the effectiveness and reach of these programs. Currently, the Further Continuing Appropriations and Other Extensions Act, of 2024 extends the Agriculture Improvement Act of the 2018 Farm Bill (USDA – NRCS, 2024). Evaluating how amendments to these programs have impacted the behaviors of us farms over time through shifts in land use and production habits could provide insights that can be useful for the development of future programs.

Chapter 4 - Assessing the Impact of Policy Reform on Conservation Management Behaviors in the U.S.

4.1 Introduction

Conservation activities can enable climate change mitigation and create mechanisms for adaptation in the agriculture industry. By implementing carbon farming practices such as no-till, crop rotation, and cover cropping, agricultural producers can contribute to the sequestration of carbon dioxide and greenhouse gases while improving soil and water quality. However, many conservation practices can be cost-intensive or financially risky and farmers often seek to conserve expensive resources (Baylis et al., 2022). In response to this challenge, governments in many nations attempt to implement policies and programs to encourage conservation activities to address growing environmental concerns. Agriculture conservation programs seek to incentivize farmers' voluntary implementation of critical conservation practices by providing cost-share opportunities or subsidies to reduce the financial stress of using such practices (Howard et al., 2024).

The USDA Farm Bill is the quintessential piece of legislation that influences the agriculture sector in the United States. Revised on a four-year cycle, this legislation seeks to support farmers and ranchers by developing safety nets, farm loans, conservation, and disaster assistance programs (USDA, FSA). Farm Bill legislation has led to the development of several key environmental programs such as the Conservation Stewardship Program (CSP), Conservation Reserve Program (CRP), and Environmental Quality Incentives Program (EQIP) which offer financial assistance to agriculture producers for implementing and maintaining conservation activities in production (i.e. cover crops, no-till, crop rotation, etc.). Funding for such programs is currently estimated at over \$30 billion for the current 10-year period since the

last Farm Bill in 2018 (Pavelis & Douglas, 2011; Stubbs, 2019). However, past research has questioned whether these policies can effectively motivate producers and deliver the desired environmental quality improvements (Duke et al., 2014, 2015; Xu et al., 2022). Challenges in reaching the desired goals can include rigid program construction, cost-effectiveness, and the potential for underpayment, leading to insufficient producer motivation to implement practices and allocate land (Howard et al., 2024). Thus, there is a need to research the ongoing impact of these policies and programs on farm behaviors and activities in conservation.

The 2014 Farm Bill contributed to developing the current landscape of conservation programming in the U.S. This revision expanded funding for restructured ongoing CSP and EQIP programs and continued to emphasize conservation efforts on working lands. Additionally, it developed new programs including the Agricultural Conservation Easement Program (ACEP) which focused on land restoration and protection, and the Regional Conservation Partnership Program (RCPP) which sought improved coordination of conservation program assistance across U.S. regions. These newly developed programs were not only continuously expanded in the 2018 Farm Bill but were also protected and extended under the Further Continuing Appropriations and Other Extensions Act of 2024. The purpose of the study is to evaluate the impact of the 2014 Farm Bill on farm conservation activities in the U.S. The specific objectives of this research are: *1) estimate the change in carbon farming/conservation practice through time due to the policy change, 2) estimate the change in conservation land allocation through time, and 3) identify regional heterogeneity in practice use and land allocation.* This research seeks to contribute to the literature by clearly identifying the impact that the Farm Bill revision had on conservation behaviors. Additionally, this study contributes to the literature on overcoming the limitations of

the USDA ARMS survey data by using a pseudo-panel approach to draw out relevant implications across time.

4.2 Literature Review

Environment conservation efforts in U.S. agriculture began as a response to the Dust Bowl droughts in the 1930s when producers faced environmental stresses and low commodity prices (Baylis et al., 2022). The initial approach to supporting farmers in the Agriculture Adjustment Act of 1933, later known as the first Farm Bill, was to limit production in agriculture by setting aside land to raise commodity prices. After its inception, Farm Bill programs continued to grow in size and scope addressing broader issues facing the U.S. agriculture sector. For example, the Soil Conservation and Domestic Allotment Act of 1936 allowed direct payment to producers that planted less soil-depleting crops and was one of the first payment programs to encourage soil conservation activities on private farmland (Coppess, 2020). Later, programs such as the Soil Bank under the 1956 Agriculture Act focused on retiring less productive agricultural land for up to 10 years and served as the predecessor to what would later become the Conservation Reserve Program (CRP) (Cain & Lovejoy, 2004; Coppess, 2020). Over time, the number and variety of programs supporting conservation efforts within the Farm Bill expanded quadrennially.

The 2014 Farm Bill was a significant revision in legislation on conservation efforts. Programs such as CSP and EQIP continued to offer financial assistance to producers who maintained conservation efforts. Many programs were consolidated in an attempt to streamline the allocation of financial assistance. The Regional Conservation Partnership Program (RCPP) and the Agricultural Conservation Easement Program (ACEP) were examples of programs phased out during this change. Additionally, the 2014 bill linked insurance premium subsidies to

Conservation Compliance for the conservation of both highly erodible land and wetlands for the first time since 1996 (USDA ERS, 2024). Federal funds for passive environmental efforts, such as land retirement programs, declined drastically in the 2014-2018 legislative cycle. In contrast, more active working land conservation programs such as EQIP and CSP received increased funding allocation while authorizing the enrollment of 10 million additional acres into these programs and extending 5-year contracts (USDA ERS, 2024). Overall, the 2014 Farm Bill saw a significant shift in focus and allocation of government resources towards programs encouraging farmers to use more land to implement conservation/carbon farming practices.

Recent studies have sought to evaluate the impact of USDA programs on conservation activities. Park et al., (2023) found that EQIP payments significantly positively affected county-level cover crop adoption between 2006 and 2015. Conversely, CSP payments reduced cover crop acres demonstrating that program structure can yield different outcomes. This is further supported when examining the changes in the 2018 Farm Bill which lowered the maximum payments for the Conservation Reserve Program (CRP) by 10%–15% and increased the enrollment cap by 3 million acres. Cornish et al., (2022) found that the reduction in rental rates decreased enrollment by a little over 1 million acres from participating farms leading to roughly a 3% decrease in environmental benefits. Interestingly, the increase in enrollment cap resulted in a 2.32 million increase in enrolled acres from new farmer entrants, yielding a 6% increase in environmental benefits compensating for the initial loss from the rental rates reductions. This suggests that expanding participation opportunities may offset potential losses from reduced payment amounts. However, the trade-off between farm production returns and subsidy amounts must be accounted for in conservation programs particularly as commodity prices change. Holland et al., (2020) explored this when evaluating responses to the Conservation Compliance

mandates which *required* farms receiving subsidies to implement conservation measures on highly erodible fields. Their results showed that corn farmers' compliance with the mandates decreased as a result of the 2007 Energy Bill causing an increase in corn prices. Therefore, even mandatory conservation program participation affects commodity prices. The structure of conservation programs must be appealing to producers to yield the desired participation and environmental benefits.

ARMS Data Management and Challenges

When analyzing farm behavior, the United States Department of Agriculture (USDA) Agricultural Resource Management Survey (ARMS) from the Economic Research Service (ERS) is the U.S. Department of Agriculture's primary source of information on the current landscape of agriculture production. First conducted in 1996, the survey process involves a multi-phase series with producers to ask about information relevant to their farm operation. This rich dataset contains information on farm inputs, management practices, and farm household characteristics. Phase 1 of the ARMS survey consists of a screening process to verify that producers qualify as “farms” that grow the commodities of interest for Phase 2 of the survey. Once verified, Phase 2 involves questions to the producers of the target commodity to collect information on field characteristics, nutrient/fertilizer applications, pest management practices, field operations, and irrigation. Finally, in Phase 3, producers are asked questions related to the farm business and household. This may include information on land, livestock, production acreage, income, expenditures, debts, assets, time use, and demographics of the household. The survey is conducted jointly with the National Agricultural Statistics Service (NASS) who use two sampling frames to sample a total of about 30,000 operations for ARMS each year.

The ARMS survey is conducted using a probability-weighted stratified sampling procedure. Every year a new sample of farmers is surveyed at random based on the annual primary crop of interest to create a representative sample of farms in the country. This is achieved by assigning each observation an expansion factor or “*weight*” that reflects a farm’s probability of selection for the survey. While researchers have used this data to evaluate farmers in a cross-section of different states or regions, assessing farm behavior over time can present a different analytical challenge. Due to the nature of the ARMS survey process, every year a new sample of farmers is generated at random such that the farmers surveyed in one year are different than the next. Additionally, when a crop is surveyed again there is no guarantee that the same farmer who was surveyed will be selected to participate in the survey process again. Thus, there is no mechanism to observe the same farmers across each year of data. Though a true panel setting is not available given the nature of the ARMS data, analysis techniques have developed that provide an approach to drawing out implications over time.

Pseudo-panel data construction is a technique that researchers have used to overcome limitations in cross-sectional data. This technique was developed by Deaton (1985) and involves drawing from a series of repeated cross-sections of data to create cohorts. Cohorts are constructed based on time-invariant characteristics such as birth year or location (Verbeek, 2008). These cohorts serve as a representative sample unit of individuals who share similar characteristics within a cross-sectional space. This allows for the estimation of models by using the observed averages given by each cohort, creating a pseudo-panel. This approach has been applied in a variety of estimation settings such as fixed effects, nonlinear, and dynamic modeling (Angus Deaton, 1985; M. Dolores Collado’, 1997). Studies suggest that estimation by grouping individuals is similar to IV estimation and can satisfy the necessary conditions for consistent

estimation given that cohorts are defined such that an individual can only appear in a single cohort (Verbeek, 2008).

Pseudo-panel techniques using the USDA ARMS have been explored to address issues of nonresponse survey data and better understand the complex nature of the agriculture sector through time (Featherstone et al., 2012). The advantages of the pseudo-panel approach include reducing the impacts of sample attrition and measurement errors since averages are drawn from repeated cross-sections with newly sampled individuals (Cuesta et al., 2011). In addition, cross-sectional data is more widely available than true panel data (Cuesta et. al, 2011). However, cohorts must be defined such that a large enough number of them can create statistical power. Additionally, if not well specified, cohorts may not contain the same types of individuals, and farmers could potentially change cohorts between periods (Featherstone, 2012). Studies that have used the pseudo-panel approach with the ARMS data have formed cohorts based on farmer characteristics such as fixed assets, acreage, revenue category, and production specialty (see e.g., Livingston & Mishra, 2013; O'Donoghue & Whitaker, 2010; Paul & Nehring, 2005). In general, pseudo-panel approaches may prove useful in broadening the scope of estimation techniques that can be used with the ARMS data.

The pseudo-panel approach presented by Whitaker (2009) is consistently cited when using the ARMS data. In this approach, cohorts are constructed by the farm state and nine production specialties which have been shown to yield asymptotically consistent estimates. It also ensures that individuals who are sampled sporadically through time are always in the same cohort when observed (Savitsky & Williams, 2022). OLS and IV estimation are commonly used techniques in pseudo-panel analysis with the ARMS data. However, potentially high sampling error and slow convergence speed of these approaches can cause concerns as they are influenced

by the number of observations in a single cohort (McKenzie, 2004). This can be addressed by only including cohorts that have ten or more observations since individual farm observations represent several similar farms due to the stratified sampling structure of ARMS (Savitsky & Williams, 2022).

4.3 Methodology

4.3.1 Conceptual Framework

This research seeks to evaluate the impact of government policy on conservation behavior in the U.S. The conceptual framework combines aspects of both a utility maximization and cost minimization problem. Let Y_{it} indicate the level of conservation participation for farmer i at time t . Additionally, let the total utility received from a bundle of conservation activities j at that time be given by u_{ijt} , and the associated cost of those conservation activities be given by $C_{it}(J)$. The total amount of conservation activities a farmer participates in can then be given as a function of the utility received and the cost of implementation outlined in Equation 1:

$$Y_{it} = u_{ijt} - C_{it}(J) \quad (1)$$

$$\text{Where: } u_{ijt} = \max(\sum_{k=1}^K u_{ikt})$$

Here the level of conservation participation for farmers is determined by the potential utility gained from participation and the associated cost at that time. Farmer i can choose to implement one or more conservation management practices k where the total number of available practices is given by $k = 1, \dots, K$ with $j = 1, \dots, J$ potential combinations given by $J = 2^k$. Thus, the goal would be to maximize the utility of conservation participation from using $1 \dots J$ combinations of carbon farming practices given by u_{ijt} . The utility of the chosen

combination of practices is found by maximizing the total amount of utility from each practice k in the bundle given by (u_{ikt}) . The utilities can be observed as direct and indirect impacts on profit to the operation at a given point in time. Hence, the decision to use a given combination of practices on a certain amount of land is conditioned on the expected returns (i.e., revenue, inputs, and costs), demographic characteristics that influence the perception of non-financial benefits (age, education, experience, etc.), and environmental characteristics (weather, climate, soil conditions, etc.) experienced at time t . The utility maximization condition for a combination of practices can be further expanded as seen below in Equation 2:

$$u_{ijt} = \max(\sum_{k=1}^K u_{ikt}) = V_{ijt}(\sum_{k=1}^K \{f_{kt}(E[\pi_{ikt}; \delta_{ikt}]|A_{ikt}, X_{it}, Z_{it}, \varepsilon_{it})\}) \quad (2)$$

The expected returns from conservation practices are given by the expected direct monetary returns (π_i) and indirect non-financial benefits (δ_i) from implementation conditioned on the observed and unobserved characteristics of an individual and the environment. Here X_{it} is a set of demographic variables, Z_{it} is a vector of observable environmental conditions. Additionally, A_{ikt} represents the amount of land dedicated to conservation activities. Farmers can augment their utility by adjusting the number of acres that carbon farming practices are used on. Finally, ε_i represents the unobservable factors influencing conservation practice use. Now suppose that at time t the government institutes a policy reform to motivate farmers to increase their participation in conservation activities. Let the implementation of this reformed policy be denoted by φ_t . By substituting Equation 2 into 1 and adding this policy change, the outline for the conceptual framework can be seen in Equation 3:

$$Y_{it} = u_{ijt} - C_{it}(J) + \varphi_t \quad (3)$$

Where: $u_{ijt} = V_{ijt}(\sum_{k=1}^K \{f_{kt}(E[\pi_{ikt}; \delta_{itk}]|A_{it}, X_{it}, Z_{it}, \varepsilon_{it})\})$

$$\text{Such that: } Y_{it-1} < Y_{it+1} \mid \begin{cases} u_{ijt} + \varphi_t > C_{it}(J) \\ u_{ijt-1} < u_{ijt+1} \end{cases}$$

The government's goal is to intervene at time t such that the utility of using carbon farming practices and allotting acres towards conservation efforts increases when combined with the incentive from the reformed policy that offsets the cost. Thus, there would be an observable difference in the level of conservation participation at time $t + 1$ after the policy change when compared to time $t - 1$. Depending on the structure of the reform, producers can increase participation in conservation efforts by either implementing additional practices in production or by expanding the acres on which their farm operation uses such practices.

4.3.2 Empirical Framework

This study will evaluate the impact of the 2014 Farm Bill on conservation participation in the U.S. by implementing a fixed effects empirical model in a pseudo-panel setting using the USDA ARMs data. Let $\overline{Y_{ct}}$ be the outcome variable of interest representing the average level of conservation participation (i.e. either the number of practices used or allotted acreage) by farmers in cohort c at period t . The proposed empirical model can be seen in Equation 4:

$$\overline{Y_{ct}} = \overline{\alpha_{ct}} + \sum \beta \overline{X_{ct}} + \beta \overline{Z_{ct}} + \varphi^{2014} I_{2014} + \tau_t + \gamma_c + \overline{\varepsilon_{ct}} \quad (4)$$

$$c = 1 \dots C \text{ (cohorts)}$$

$$t = 1 \dots T \text{ (periods)}$$

Here the average level of conservation participation producers exhibit is estimated as a function of a vector of the average farmer and farm characteristics ($\overline{X_{ct}}$) and the average

environmental factors ($\overline{Z_{ct}}$) experienced by farmers within a cohort group with β given as the vectors of parameters to be estimated. Additionally, $\overline{\varepsilon_{ct}}$ is the error term for the average impact of unobservable factors. In this model, the 2014 Farm Bill policy change is denoted by I_{2014} with the effect of the treatment being captured by φ^{2014} . Additionally, τ_t and γ_c represent yearly and regional fixed effects respectively.

Three different estimation techniques will be used to evaluate the change in conservation practices used across cohorts. First, an OLS estimation will be used to estimate the proportion of farmers within the cohort using one, or more practices. This creates a bounded continuous dependent variable where each cohort can assume a value between 0 indicating that no practices were used by farmers within and 2 indicating that all the farmers in the cohort used two or more practices. Thus, every value in between represents some proportional combination of single and multi-practice users within a cohort. Next, a fractional logit regression which is, in essence, a form of generalized linear modeling (glm). This estimator converts the bounded continuous dependent variable into a proportional “share” 0-1 scale with 0 indicating the lowest share of conservation practice use within a cohort and 1 representing the maximum. Following this, a Poisson estimation is used to evaluate the change in the *count* of conservation practices used by farmers within a cohort. Finally, an OLS estimator is again used to measure the change in the average amount of conservation acres through time.

Conservation Practices and Farmer/Farm Characteristics

The data in this study comes from the USDA Agricultural Resource Management Survey (ARMS) survey Phases 2 and 3 overseen by the Economic Research Service (ERS). These surveys provide information on the production practices, resource use, and economic welfare of agriculture producers in the country. Phase 2 data was used to identify the conservation practices

used in a field reported by the producers surveyed in the crop year of interest between 2002 and 2019. This study uses data from 2002 to 2018 to examine the impact of the 2014 Farm Bill on conservation behavior in the U.S. The carbon farming practices identified in the data include reduced tillage, no-till, land use change (LUC), crop rotation, and cover cropping. These identified practices were used to construct the three dependent indicator variables for the different levels of conservation practice use. The first is a multinomial discrete indicator for no, one, or multi-practice use by farmers. The next are binary indicators to identify farms that use one or multiple practices separately. These indicators will allow the model to determine if the impact of the policy reform is encouraging new adopters of conservation practices or increasing the intensity of current users.

Phase 3 data was to identify the relevant farmer and farm characteristics used as independent variables in the analysis. The farmer demographic variables used include age, and household size to account for family labor. In addition, race is a binary control variable to compare non-white farmers to the Caucasian majority. Ethnic groups in the non-white category include African Americans, Asian-Pacific Islanders, Hispanics, and Native Americans. Finally, education is a binary indicator of whether or not a farmer has received a college degree or higher. The farm characteristics used in this study include farm size, amount of cattle owned, the percentage of acres designated as cropland, and the percentage of acreage owned by the farmer. Phase 3 data was also used to identify the number of acres used for conservation as an additional dependent variable in the analysis.

Climate and Weather Controls

This study uses climate and weather data from the PRISM Weather Database Developed by Oregon State University which provides monthly, yearly, and single-event gridded data for

average temperature and precipitation. Research has shown that exposure to extreme temperatures can negatively impact yields (Schlenker & Roberts, 2009). Thus, this study seeks to test the hypothesis that extreme weather and climate conditions motivate farmer participation in conservation activities through time. The temperature variables include modified versions of the ones presented by Schlenker & Roberts (2009) where the threshold for growing degree days (GDD) is set between 8° and 29°C with anything greater classified as extreme (EDD). The threshold range in this study is set between 0° and 30°C and accounts for all annual temperatures since practices such as crop rotation may require production outside the typical growing season for certain crops (e.g. winter wheat or legumes). In addition to temperature, precipitation is included as an additional climate/weather control. The variable is measured in millimeters as the total county-level monthly aggregate rainfall. To isolate the effects of long-term climate and short-term weather, the differences in the climate control variables were calculated by subtracting the annual values from the averages.

Pseudo-Panel Cohort Construction and Fixed Effects

The pseudo-panel construction follows the specification presented by Whitaker 2009. Cohorts are constructed based on the farm location and production specialty creating homogeneous groups unlikely to change through time (Whitaker, 2009). A farm's state is used as the location indicator for cohort assignment. Production specialty is assigned if a commodity accounts for at least fifty percent of a farm's total value of production. The nine specialization groupings include 1) barley, oats, and wheat; 2) corn, soybeans, and sorghum; 3) hay and other miscellaneous crops; 4) fruits and nuts; 5) vegetables; 6) beef cattle; 7) sheep, hogs, other livestock; 8) poultry; and 9) dairy. Crops are combined into specialization categories that require similar production technologies decreasing the chance of farms changing groups. For example,

the technologies needed in row crop production (i.e. corn, soybeans, and sorghum) are different from those of other crops (i.e. barley, oats, and wheat). Hence, a farmer in the row crop production would likely only switch to an alternative crop in that specialization. This pseudo-panel approach created 288 cohorts across 16 years of data resulting in 1,747 observations. Annual fixed effects accounted for differences in cohort averages related to time. In addition, regional fixed effects were used to explore the potential heterogeneity in conservation participation across areas of the U.S. The regional specifications used to explore these effects were the USDA National Agriculture Statistics Service (NASS) Farm Production Regions and the ERS Farm Resource Regions. Table 4.1 presents the summary statistics of the cohort averages for the variables in this analysis. Note that when examining the summary statistics before and after pseudo-panel construction, the cohort means are consistent with the averages for individual farmers in the ARMS data (See Appendix Table 2a). The results from a T-test indicated no significant differences were present between the farmer and cohort averages. This suggests that the cohort construction did not compromise the data's structure.

Table 4.1 Summary Statistics of Cohort Means

Variable	Mean	Std. Dev
Number of Conservation Practices	1.05	0.56
Single Practice Farm (1: yes/ 0: no)	0.76	0.32
Multi-Practice Farm (1: yes/ 0: no)	0.27	0.35
Conservation Acres	739.17	1465.90
Age (in years)	55.64	7.07
College Degree (1: yes/ 0: no)	0.23	0.25
Race (1: non-white/ 0: Caucasian)	0.19	0.33
Household Size (number of individuals)	2.88	1.02
Farm Size (in acres)	2093.40	3346.63
Percent Cropland Acres	0.79	0.17
Percent Owned Acres	0.63	3.84
Heads of Cattle	257.88	5516.28
Normal Growing Degree Days (Norm GDD)	242.66	22.87
Normal Extreme Degree Days (Norm EDD)	17.15	14.46
Normal Precipitation (millimeters)	705.26	260.81
Deviation Growing Degree Days (Dev GDD)	42.43	10.74
Deviation Extreme Degree Days (Dev EDD)	4.80	7.08
Deviation Precipitation (millimeters)	211.74	186.65

On average the number of conservation practices used by cohorts was one. The proportion of single and multi-practice farms within each cohort is 76 and 27 percent respectively. Cohorts also dedicated an average of about 740 acres to conservation activities. The average age of farmers in the cohorts is about 55 years old with the household size being about three family members. The average proportion of farmers within cohorts with a college degree is 23 percent and the average proportion of non-white individuals is about 19 percent. The average farm size for operations across cohorts is 2093 acres. Of these acres, an average of 79 percent is dedicated to crop production, and 63 percent are owned by farmers within the cohort. Farms within the cohort also owned roughly 257 heads of cattle. When examining environmental characteristics, the average number of GDD and EDD experienced annually by farms is about 242 and 17 respectively with the average amount of precipitation experienced being 705 mm. Finally, when examining the average annual weather deviations, the table shows that farms would experience an additional 42 GDD, nearly 5 additional EDD, and roughly 212 additional millimeters of precipitation on average.

4.4 Results and Discussion

Table 4.2 presents the estimation results for the changes in conservation participation by U.S. farms after the 2014 Farm Bill. An F-test and likelihood ratio test were used following the inclusion of the weather and climate data in the analysis to determine their impact on the model fit. The results indicated that including these variables creates a model more effective for analyzing variation in the data.

Table 4.2 Regression Results for Conservation Participation Post 2014

Variable	<u>Number of Practices</u>			Conservation	% of
Coeff.	<i>OLS</i>	<i>Fractional</i>	<i>Poisson</i>	<i>Acreage</i>	<i>Conservation</i>
Std. Error				<i>(OLS)</i>	<i>Acreage (OLS)</i>
Treat Year (Post 2014)	0.337*** (0.052)	0.337*** (0.052)	0.386*** (0.043)	533.09*** (66.75)	0.299*** (0.021)
Age	-0.004** (0.002)	-0.004** (0.002)	-0.004** (0.002)	-0.069 (6.123)	0.000 (0.000)
Education	-0.020 (0.078)	-0.020 (0.078)	-0.020 (0.068)	-99.64 (149.941)	0.036 (0.046)
Race	-0.083 (0.058)	-0.083 (0.058)	-0.078 (0.057)	82.554 (142.307)	0.008 (0.038)
Household Size	-0.019 (0.015)	-0.019 (0.015)	-0.021 (0.015)	-77.720 (56.279)	-0.026 (0.005)
Farm Size	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.283*** (0.076)	0.000*** (0.000)
% Cropland Acres	-0.170** (0.109)	-0.170** (0.109)	-0.163** (0.085)	-244.500 (236.562)	0.080*** (0.062)
% Owned	-0.004*** (0.000)	-0.004*** (0.000)	-0.002*** (0.001)	-0.881 (1.936)	-0.001 (0.001)
Cattle	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	-0.018*** (0.002)	-0.000*** (0.000)

Norm GDD	0.004*** (0.002)	0.005*** (0.002)	0.004*** (0.000)	-1.547 (3.281)	-0.002** (0.001)
Norm EDD	-0.006*** (0.001)	-0.006*** (0.001)	-0.006*** (0.001)	-10.655*** (2.912)	-0.003*** (0.001)
Norm Percip	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	-2.245** (1.162)	-0.000 (0.000)
Norm Percip ²	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	0.001* (0.001)	-0.000 (0.001)
Dev GDD	0.004 (0.003)	0.004 (0.003)	0.004** (0.003)	-5.701 (3.544)	-0.000 (0.001)
Dev EDD	0.010** (0.005)	0.010** (0.005)	0.010*** (0.003)	19.718** (3.544)	0.003 (0.003)
Dev Percip	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	1.513 (1.331)	0.000 (0.001)
Dev Percip ²	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.001 (0.001)	-0.000 (0.000)
Constant	-0.560** (0.287)	-0.560** (0.225)	-0.560** (0.225)	1438.155* (1159.980)	0.412* (0.818)
<i>Obs.</i>	1,299	1,299	1,299	1,299	1,299
R^2	0.6655	-	-	0.3977	0.1847

<i>Log pseudolikelihood</i>	-	-416.337	-13.02.070	-	-
<i>AIC</i>	-	0.685	2664.141	-	-
<i>BIC</i>	-	-8960.689	2819.221	-	-

Note: Statistical significance at the 99% (***), 95% (**), and 90% (*) confidence levels. Robust standard errors are given in parentheses.

The coefficients for the post-2014 indicator across every estimation approach showed a significant and positive increase in conservation participation in cohorts through time. The proportion of farmers within cohorts using one or more conservation practices increased by 33-38 percent on average after 2014. Additionally, the average number of acres dedicated to conservation activities across the cohorts increased by about 533 or roughly 30 percent overall. This would suggest that in the years following the 2014 Farm Bill farmers began participating in conservation efforts at a higher and more intensive rate.

Interestingly, examining the coefficients for the yearly fixed effects reveals that conservation participation was trending downward until 2017 (See Appendix Table B1). Overall, this would suggest that after the revised 2014 Farm Bill, there was a significant shift in the amount of conservation participation by U.S. farms. However, the effect of the policy reform was not observed until about 3 years later. Furthermore, though the results indicate that the average number of conservation practices used within cohorts increased after 2014, it does not provide insight into how the intensity of conservation practice use changed. Table 4.3 presents the coefficients for the single and multi-practice indicators for comparison to evaluate the post-2014 impacts on conservation behavior.

Table 4.3 Comparison of Coefficients for Conservation Practice Intensity

Indicator Variable	OLS	Fractional	Poisson
Number of Practices	0.337*** (0.052)	0.337*** (0.052)	0.386*** (0.043)
Single Practice	0.030* (0.018)	0.030 (0.035)	0.049 (0.171)
Multi-Practice	0.140*** (0.027)	0.140*** (0.029)	3.009*** (1.031)

Note: Statistical significance at the 99% (***), 95% (**), and 90% (*) confidence levels. Robust standard errors are given in parentheses.

Comparing the results for the single and multi-practice indicators shows that across all estimation approaches the proportions of farmers within cohorts identified as using one and more than one practice did increase after 2014. However, the significance and magnitude of impact on the multi-practice indicator are notably higher when compared to the single-practice indicator. The model shows that after 2014 the proportion of farmers within cohorts using a single increased by about 3 percent whereas the proportion of multi-practice farms increased by about 14 percent. This suggests that after the Farm Bill revision, farm behavior did change as producers increased the intensity of conservation practice use on average.

Continuing the exploration of the results from Table 4.2, examining the impact of farmer characteristics reveals that age is statistically significant and has a negative relationship with the average number of conservation practices used by farmers within cohorts. This suggests that older producers were less motivated to add additional carbon farming practices into production over time even in the presence of a policy reform. While not significant, the signs on the

coefficients for race do display a pattern. The sign on the impact for the proportion of farmers identified as Black, Indigenous, or Persons of Color (BIPOC) is negative across all estimation approaches for the average number of practices used, but positive for the amount of acreage used for conservation activities. This implies that cohorts with higher proportions of non-white farmers had a smaller average practice use but had greater amounts of land allocation towards conservation on average. Finally, the coefficients for both education and household size were negative across nearly every model with no notable significance suggesting that these characteristics did not motivate much additional conservation participation by farmers.

The results of the farm characteristic variables show that farm size has a positive relationship with the number of practices used and the amount of conservation acreage. This suggests that larger farms increased their participation in conservation activities over time. The percentage of owned land and cropland acres were shown to have a negative relationship with the average number of practices used across the different model estimates. This suggests that overall higher percentages of cropland and more ownership reduced the amount of conservation practices farmers used within cohorts. However, the percentage of land dedicated to conservation activities does show a significant positive relationship with cropland allocation. This may indicate that higher amounts of cropland allow for greater expansion of conservation efforts. The final farm characteristic, heads of cattle, is shown to have a positive relationship with the average number of practices used, but a negative relationship with the amount and percentage of land dedicated to conservation activities. This may suggest that cattle production is complemented by certain carbon farming practices, such as cover cropping or crop rotation allowing for more diverse feed options. Conversely, the amount of land allocated to conservation may decrease in the presence of cattle due to the possible pasture requirements.

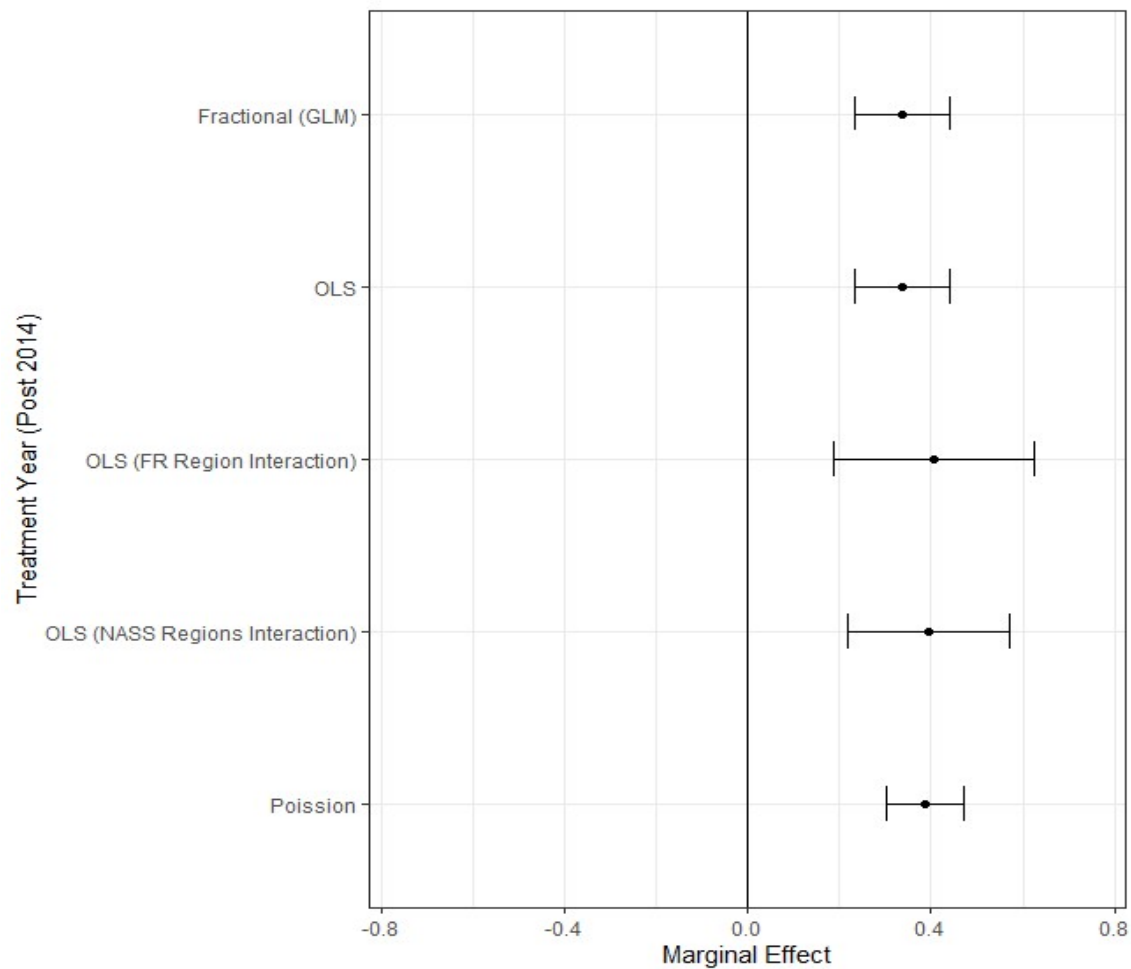
Evaluating the results for the climate and weather control variables shows that normal and deviations in growing temperatures (GDD) have a significant positive relationship with the average number of practices used. This indicates that in the presence of ideal growing temperatures farmers with cohorts steadily increased their use of conservation management practices over time. However, favorable growing temperatures slightly decrease the percentage of land dedicated to conservation activities indicating that in ideal climate conditions, farmers prioritize allocation of land resources towards crop production. Examining the coefficients for growing degree days reveals that exposure to normal extreme temperatures (EDD) significantly decreases the average number of carbon farming practices used and the amount of land dedicated to conservation activities. In contrast, deviations in EDD were shown to increase the average number of practices used and land allocated to conservation. This suggests that the increased exposure to extreme temperatures through time led to increased conservation activity by farmers within cohorts. Finally, when examining the impact of precipitation, the results show that normal precipitation levels have a positive relationship with the average number of conservation practices used but a negative relationship with conservation acreage. These signs switch when examining the squared term for precipitation. This may indicate that conservation activity by farmers within cohorts is impacted by the need to mitigate erosion in the presence of excess rainfall.

Robustness Checks

Additional models were used in this analysis to explore the potential geographical heterogeneity in conservation activities. To achieve this, regional fixed effects and interaction terms with the post-2014 impact variable of interest were added to the model specifications to examine the difference across the U.S. Examining the interest variable across the ERS Farm

resource regions required a new location indicator that led to the creation of 80 cohorts to use for the analysis. This allows for a comparison of the pseudo-panel approaches to determine the effectiveness of the cohort construction procedures by analyzing the results of different location indicators. Figure 4.1 compares the estimates for number the average number of practices used by farmers within cohorts after 2014 across the model specifications.

Figure 4.1 Coefficient Estimates for Post-2014 Impact Variable

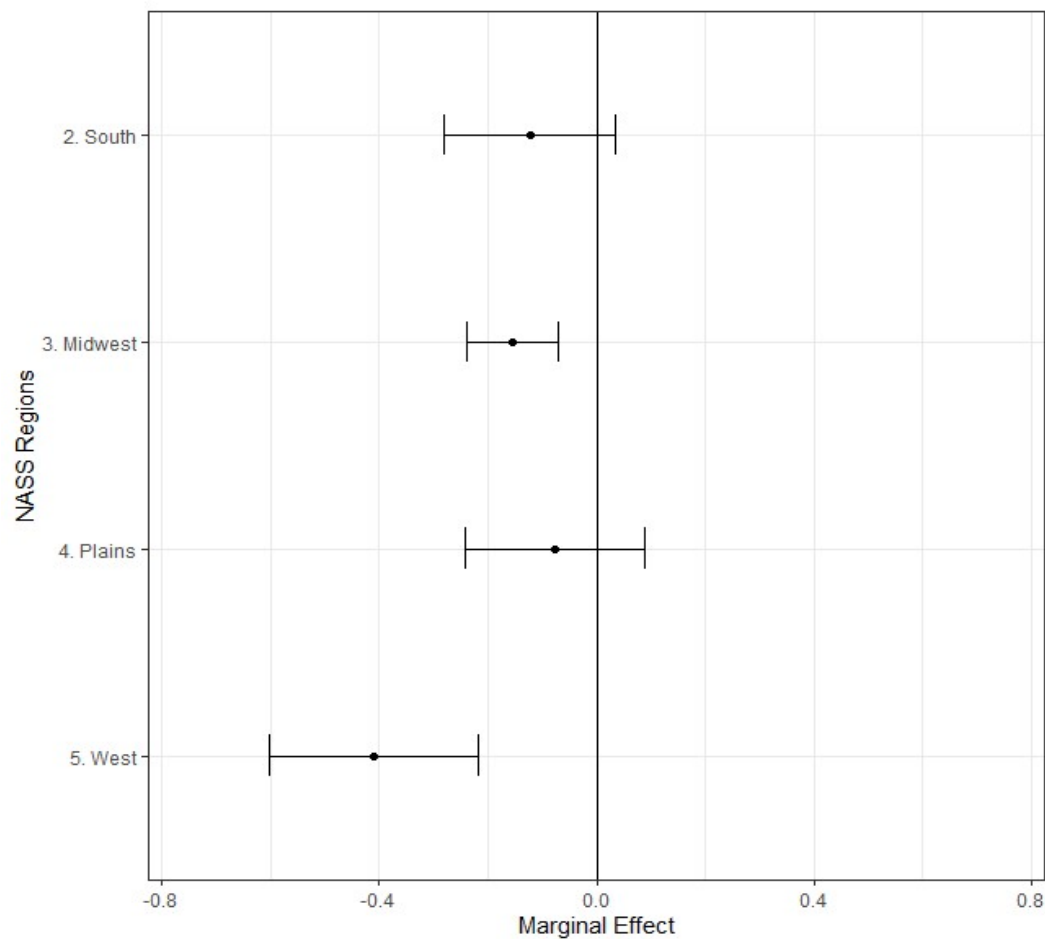


Note: Coefficients and robust standard error values can be found in Appendix Table 3a.

As seen in Figure 1, the coefficient estimates for post-2014 indicators in the models including regional fixed effects and interaction terms for the NASS Production and Farm

Resource Regions fall within a similar range to the previous model estimates. They show that roughly a 38 – 40 percent increase in conservation activity occurred through the average number of practices used within cohorts. It should be noted, however, that the standard errors displayed are higher than those in the previous model estimates. This may indicate the potential endogeneity occurring within these two models. A possible reason is that the location indicator used for cohort construction acts similarly to fixed effects causing redundancy within the model. Figure 4.2 explores the regional variation in conservation activity using the NASS Farm Production Regions identified in Phase 3 of the ARMS data. The Atlantic Region was used as the base region for comparison within the model due to the high frequency of observations from that region.

Figure 4.2 Coefficient Estimates for NASS Production Region

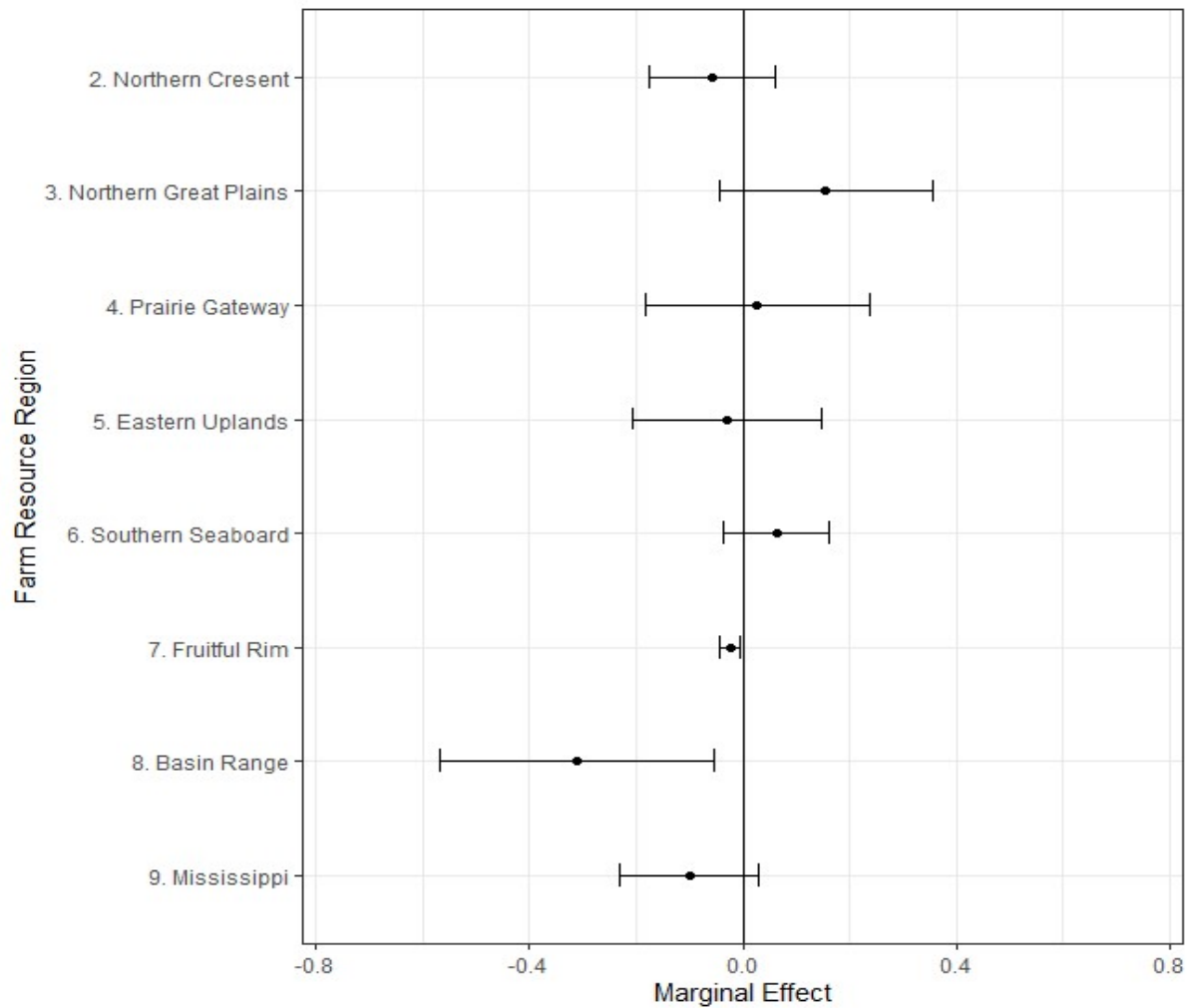


Note: The Atlantic Region was used as a base region for comparison. Coefficients and robust standard error values can be found in Appendix Table 4a.

As seen in Figure 4.2, the Midwest and West Farm Production Regions had less conservation activity on average. The estimates show that the average number of practices used was roughly 16 percent lower in the Midwest and 41 percent lower in the West. However, the interaction terms for the post-2014 interest variable displayed no significance for any region (see Appendix Table 4a). This suggests that the lower levels of conservation activities in the Midwest and West are their unique characteristics (e.g. soil or economic environment) and were not impacted by the 2014 policy reform. Figure 4.3 further examines the potential heterogeneous geographical differences by comparing the coefficient estimates for the pseudo-panel model

using the Farm Resource Regions. The Heartland Region is used as the comparison region due to the high frequency of observations.

Figure 4.3 Coefficient Estimates for Farm Resource Regions



Note: The Heartland Region was used as a base region for comparison. Coefficients and robust standard error values can be found in Appendix Table 5a.

The coefficient estimates results for the Farm Resource Regions show that the only regions with a notable difference in conservation activity were the Fruitful Rim and Basin Range. The number of conservation practices used within cohorts is about 3 percent lower in the Fruitful Rim Regions and 31 percent lower in the Basin Range. The parts of the Fruitful Rim

Region often border coastal areas of the U.S. where the conservation activities identified in this study may not complement the primary production specialty of those areas such as vegetables and tropical products. Consequently, the Basin Range accounts for the smallest share of U.S. cropland which likely explains the decreased participation in conservation activities. The interaction terms for the time indicator variable reveal that the only region to experience a significant change in conservation activity after 2014 was the Southern Seaboard Region where a 16 percent increase in the average number of conservation practices used by farmers within cohorts occurred (see Appendix Table 5a). This region is characterized by a mix of both small and large farms with a production focus on field crops. This suggests that the 2014 reformed policy offered incentives or opportunities with its programs that were appealing and encouraged farmers in this region to increase their participation in conservation activities.

4.5 Conclusion

The purpose of this research was to evaluate the potential impacts of the 2014 revised Farm Bill policies on the conservation activities of farmers in the U.S. A pseudo-panel approach was used in an attempt to overcome the limitations of the USDA ARMS data associated with its inherent cross-sectional structure and to gain insight on changes in farm behavior through time. Additionally, this research contributes to the literature in this area by exploring different estimation methods and model configurations in a pseudo-panel setting. The consistency of the results across estimation techniques, model specification, and cohort constructions suggests that this study effectively leveraged the restructured data to explore variations in the conservation behaviors of producers through time.

The results from the analysis showed that overall, there was a significant increase in the level of participation in conservation activities by U.S. farmers following the revision of the

Farm Bill in 2014. Given that the model included relevant variables to control farm behaviors, this would indicate that the 2014 bill did have a notable impact on conservation participation in the U.S. The expanded enrollment acres and incentives for working land programs such as EQIP and CSP encouraged additional participation by producers while the extension of contracts successfully kept currently enrolled farms active. However, the impacts of this reform were not observed until three years after its inception. The Southern Seaboard Region, which overlaps with states such as the Carolinas, Georgia, Alabama, Delaware, Virginia, and Maryland as well as parts of Louisiana, Arkansas, and Texas experienced the most significant increase in farmer participation in conservation program activities.

The results for farmer and farm characteristics revealed that farm size positively contributed to the overall conservation participation of U.S. farms. Age had a significant negative impact on the use of conservation practices. The presence of cattle increased the average number of practices used while the percentage of land owned, and land dedicated to crop production, had the opposite effect. Investigating the climate and weather influences showed that when temperatures were optimal, farmers explored using more conservation practices on average but dedicated less land towards conservation activities. However, as temperatures became more extreme the level of conservation activity increased overall. Additionally, more precipitation increased the average amount of conservation practices used by farms unless the challenges from potential floods required a shift in management strategies.

Future Research

Future research can continue to explore using the pseudo-panel approach to overcome the limitations of the ARMS data and explore how other estimation techniques perform within different cohort specifications. Additionally, implementing additional interaction variables may

further reveal the potential heterogeneous impacts of policy changes. Finally, examining the effects of other policy reforms and external events in or outside of the agriculture sector could provide an opportunity to continue to explore how farm behavior responds to economic and environmental stimuli. This could be achieved by examining changes in resource use or production behaviors before and after events that significantly impact market prices for commodities and inputs. An example would be events such as the 2022 conflict between Ukraine and Russia significantly impacting fertilizer prices, and potentially influencing producers' nutrient management strategies. Using external data sources for the agriculture economy such as futures price data would aid in further examinations of farm behavior.

Chapter 5 - Final Conclusions

The goal of the research presented in this dissertation was to gain insight into the use, welfare, and policy implications for conservation management practices in the U.S. This project contributed meaningful research findings in these areas and expanded the literature for the econometric analysis methods used by exploring additional independent variables in a multinomial logit discrete choice model, propensity score matching procedures, and alternative estimation techniques in a pseudo-panel setting. The results from each analysis identify relevant considerations for the current landscape of U.S. conservation management strategies at the farm level which can better inform federal policies in this area.

Chapter 2 presented a multinomial logit analysis of conservation practice used to understand the farmer demographics, farm characteristics, and environmental factors that influence the use and intensity of various bundles of carbon farming practices. The results from this chapter showed that, overall, variables related to climate, weather, and soil characteristics had the most significant impact on the likelihood of conservation practice use followed by farm and farmer characteristics. These findings address a clear gap in the literature on farmer conservation decisions in a discrete choice framework. Neglecting a sufficient number of climate, weather, and soil variables in a similar analysis approach can potentially lead to a severe overestimation of the true impact of farmer and farm characteristics. Future research should include relevant meteorological and agronomic soil data to avoid potential bias in the estimation process.

Chapter 3 analyzed the welfare implications for conservation practice use at different intensity levels using a propensity score matching approach. The results from this chapter identified a clear financial deficit of roughly \$8,000 in net income for farms implementing one

conservation practice when compared to farms that use multiple practices. Furthermore, the net income of conventional farms was still higher than multi-practice operations. Based on the differences, the analysis suggests that a \$4,000 subsidy per farm on average might effectively motivate using carbon farming practices at a higher intensity. Additionally, this chapter contributes to the literature on propensity score methods by incorporating fixed effects for the region, production specialty, and income group. Including these fixed effects enhances the matching procedures by comparing farms facing similar environmental factors and production decisions at a similar economic scale.

Chapter 3 used a pseudo-panel approach to evaluate the impact of the revised 2014 Farm Bill on conservation behaviors by U.S. farmers. The results indicate a significant spike in conservation activity occurred after 2014. After the revised bill, the use and intensity of carbon farming practices increased. Additionally, there was an increase in the acres of farmland dedicated to conservation activities. This indicates that the 2014 policy reform effectively motivated farms and boosted conservation efforts in the U.S. The impact of this policy change was particularly notable in the Southern Seaboard Farm Resource Region. This chapter expanded the literature on pseudo-panel methods using the USDA ARMS data by exploring different estimation techniques and cohort construction approaches.

Policy Implication and Future Research

The findings from the research presented in this dissertation serve to identify areas where federal policy can be further improved to increase farm participation in conservation activities. Farms respond to federal conservation initiatives provided the incentives offset the input cost requirements of implementation. The shift in focus to active land use practices after 2014 showed that the Farm Bill did influence conservation behaviors. However, much of the

conservation participation was consolidated among multi-practice farms that are increasing their level of intensity of carbon farming practices. While useful, literature on the soil agronomic side of climate change research has suggested that land can only sequester a finite amount of CO₂ from the atmosphere. Thus, there is a need to expand the land area where carbon farming practices are implemented to reduce greenhouse gas emissions including land owned by smaller farms. Many small or limited-resource farms may lack the resources or technical skills to implement multiple practices upon the initial adoption decision. This indicates the need for incentive programs to offset the cost of transitioning to multi-practice production management strategies *and* provide education on how those strategies optimize their agronomic environment while bolstering farm finances thus encouraging sustained long-term use. Larger farm operations considering conservation practices may also respond to education surrounding possible tax breaks at the state or federal level to justify any large-scale shift in production strategies.

Research in conservation and climate change can be expanded by exploring trends in adoption and use as new practices are introduced. For example, soil amendments such as biochar application can assist in carbon sequestration efforts while potentially improving the water holding capacity of the soil. Other activities such as pulverized rock dust application can also help enhance soil structure. Producing these materials to spread on the farm requires specialized equipment that can be costly. However, the potential option of buying these materials from a third-party source could make implementing these practices more cost-effective options that scale better with small farms. Additionally, there is the possibility that carbon markets could serve as a potential revenue stream for farms. However, the measurement methods for carbon verification, pricing, and transfer systems are all new or need further development. Research on

these topics can ensure that future carbon credit programs are equitable to agriculture producers and transparent about the amount of emissions sequestered from carbon farming activities.

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Appendix A - Chapter 3 Supplemental Materials

Appendix Table A.1 Fixed Effect Coefficients for Conservation Practice Use Probit Model Estimates

Variable	<u>Single Practice</u>		<u>Multi-Practice</u>	
	<i>No F.E.</i>	<i>F.E.</i>	<i>No F.E.</i>	<i>F.E.</i>
	(Std. Error)			
IG1 (\$1,000 ≤ NFI < \$100,000)	-	control	-	control
IG2 (\$100,000 ≤ NFI < \$250,000)	-	0.132** (0.053)	-	0.106* (0.048)
IG3 (\$250,000 ≤ NFI < \$500,000),	-	0.150* (0.058)	-	0.128* (0.052)
IG4 (\$500,000 ≤ NFI)	-	0.027 (0.063)	-	0.101* (0.058)
Oats, Barley, Wheat	-	control	-	control
Corn, Soybeans, Sorghum	-	-0.340*** (0.066)	-	0.078 (0.062)
Hay/ Miscellaneous Other Crops	-	-0.355*** (0.066)	-	-0.015 (0.062)
Fruits & Nuts	-	-0.434*** (0.069)	-	-0.249*** (0.068)
Vegetables	-	-0.475***	-	-0.191

		(0.128)		(0.125)
Beef Cattle	-	-0.342****	-	-0.070
		(0.074)		(0.070)
Sheep, Hogs, Other Livestock	-	-0.290****	-	-0.180**
		(0.081)		(0.074)
Poultry	-	-0.214	-	-0.087
		(0.191)		(0.139)
Dairy	-	-0.789****	-	-0.541****
		(0.086)		(0.087)
Heartland	-	control	-	control
Northern Crescent	-	-0.395****	-	-0.143****
		(0.055)		(0.050)
Northern Great Plains	-	-0.017**	-	-0.366****
		(0.058)		(0.052)
Prairie Gateway	-	-0.114**	-	-0.326****
		(0.054)		(0.047)
Eastern Uplands	-	0.253**	-	0.267****
		(0.107)		(0.080)
Southern Seaboard	-	0.344****	-	0.585****
		(0.089)		(0.064)
Fruitful Rim	-	-0.592****	-	-0.628****

		(0.066)		(0.072)
Basin Range	-	-0.466***	-	-0.386***
		(0.083)		(0.084)
Mississippi Portal	-	-0.048	-	-0.055
		(0.063)		(0.054)
Constant	-0.096*	-0.451**	-0.755***	-0.0848***
	(0.134)	(0.173)	(0.111)	(0.157)
<i>Obs.</i>	8,315	8,302	11,464	11,448
<i>R</i> ²	0.0034	0.0645	0.0394	0.0820
<i>F.E.</i>	No	Yes	No	Yes

Statistical significance at the 99% (***), 95% (**), and 90% (*) confidence levels. Robust standard errors are given in parentheses.

Appendix B - Chapter 4 Supplemental Materials

Appendix Table B. 1 Yearly F.E. Coefficients for Conservation Participation Post-2014 Regression

Variable	<u>Number of Practices</u>			<i>Conservation</i>	<i>LN</i>
	OLS	Fractional	Poisson	<i>Acreage</i> (OLS)	<i>Conservation</i> <i>Acreage (OLS)</i>
Coeff.					
Std. Error					
<i>Year. 2004</i>	0.970*** (0.042)	0.970*** (0.042)	0.997*** (0.045)	736.462*** (86.347)	0.363*** (0.026)
<i>Year. 2006</i>	0.988*** (0.032)	0.988*** (0.032)	0.940*** (0.029)	632.425*** (55.017)	0.282*** (0.018)
<i>Year. 2007</i>	0.958*** (0.050)	0.958*** (0.050)	0.952*** (0.046)	575.389*** (92.308)	0.333*** (0.027)
<i>Year. 2009</i>	0.177*** (0.051)	0.177*** (0.051)	0.208*** (0.051)	1031.475*** (120.365)	0.425*** (0.029)
<i>Year. 2010</i>	0.085 (0.051)	0.085 (0.051)	0.079 (0.052)	317.014** (100.171)	0.251*** (0.018)
<i>Year. 2011</i>	0.003 (0.046)	0.003 (0.046)	-0.080* (0.039)	480.464 (87.104)	0.313*** (0.014)
<i>Year. 2012</i>	0.982*** (0.042)	0.982*** (0.042)	0.912*** (0.038)	433.939*** (67.969)	0.232*** (0.022)
<i>Year. 2013</i>	-0.388*** (0.041)	-0.388*** (0.041)	-1.226*** (0.050)	710.181*** (154.935)	0.307*** (0.033)

<i>Year, 2015</i>	-0.251*** (0.050)	-0.251*** (0.050)	-0.296*** (0.043)	-65.593 77.376	-0.055** (0.027)
<i>Year, 2016</i>	-0.142** (0.052)	-0.142** (0.052)	-0.115** (0.041)	-102.850 81.723	-0.044 (0.029)
<i>Year, 2017</i>	0.739*** (0.032)	0.739*** (0.032)	0.682*** (0.037)	224.057* 136.808	0.008 (0.022)
<i>Constant</i>	-0.560** (0.287)	-0.560** (0.225)	-0.560** (0.225)	1438.155* (1159.980)	0.412* (0.267)
<i>Obs.</i>	1,299	1,299	1,299	1,299	1,229
<i>R²</i>	0.6655	-	-	0.3977	0.1847
<i>Log pseudolikelihood</i>	-	-416.337	-13.02.070	-	-
<i>AIC</i>	-	0.685	2664.141	-	-
<i>BIC</i>	-	-8960.689	2819.221	-	-

Statistical significance at the 99% (***), 95% (**), and 90% (*) confidence levels. Robust standard errors are given in parentheses.

Appendix Table B. 1 Summary Statistics for Individual Farm Operations

Variable Description	Mean	Standard Deviation
Age (in years)	55.01	12.07
College Degree (1: yes / 0: no)	0.28	-
Race (1: non-white/ 0: Caucasian)	0.19	-
Household Size (number of individuals)	2.8	1.45
Farm Size (in acres)	1042.13	3.26
Percent Cropland	83.51	0.21
Percent Owned	46.61	0.70
Heads of Cattle	80.24	1928.34
Normal Growing Degree Days (Norm GDD)	242.21	22.70
Normal Extreme Degree Days (Norm EDD)	17.15	14.22
Normal Precipitation (millimeters)	708.81	270.38
Deviation Growing Degree Days (Dev GDD)	44.92	10.88
Deviation Extreme Degree Days (Dev EDD)	4.70	7.62
Deviations Precipitation (millimeters)	180.57	185.55

Appendix Table B. 2 Coefficient Estimates for Number of Conservation Practices Used by Model

Model	Coeff.
	Std. Error
OLS	0.337***
	(0.052)
Fractional	0.337***
	(0.052)
Poisson	0.386***
	(0.043)
OLS NASS Production Region	0.396***
	(0.090)
OLS Farm Resource Region	0.406***
	(0.111)

Statistical significance at the 99% (***), 95% (**), and 90% (*) confidence levels. Robust standard errors are given in parentheses.

Appendix Table B. 3 Coefficient Estimates for NASS Production Region

Nass Region	Estimate	Interaction
Coeff.	Base Region	Base Region
Std. Error	1. Atlantic	1. Atlantic
Treat Year (Post 2014)	0.396*** (0.090)	-
2. <i>South</i>	-0.123 (0.080)	-0.022 (0.280)
3. <i>Midwest</i>	-0.155*** (0.043)	-0.102 (0.116)
4. <i>Plains</i>	-0.077 (0.084)	-0.028 (0.101)
5. <i>West</i>	-0.410*** (0.098)	-0.034 (0.128)

Statistical significance at the 99% (***), 95% (**), and 90% (*) confidence levels. Robust standard errors are given in parentheses.

Appendix Table B. 4 Coefficient Estimates for Farm Resource Regions

Farm Resource Region	Estimate	Interaction
Coeff.	Base Region	Base Region
Std. Error	1. Heartland	1. Heartland
Treat Year (Post 2014)	0.406*** (0.111)	-
2. <i>Northern Crescent</i>	-0.057 (0.06)	-0.156 (0.122)
3. <i>Northern Great Plains</i>	0.155 (0.102)	-0.095 (0.087)
4. <i>Prairie Gateway</i>	0.027 (0.107)	-0.039 (0.155)
5. <i>Eastern Uplands</i>	-0.030 (0.091)	0.054 (0.196)
6. <i>Southern Seaboard</i>	0.0622 (0.050)	0.160*** (0.151)
7. <i>Fruitful Rim</i>	-0.0247** (0.010)	-0.028 (0.151)
8. <i>Basin Range</i>	-0.311** (0.131)	-0.162 (0.185)
9. <i>Mississippi</i>	-0.101 (0.067)	-0.092 (0.110)

Statistical significance at the 99% (***), 95% (**), and 90% (*) confidence levels. Robust standard errors are given in parentheses.