Understanding the Impact of State Cost-share Programs on Cover Crop Adoption Rates

Lyazzat Sanat, North Carolina State University, lsanat@ncsu.edu
Roderick Rejesus, North Carolina State University, rmrejesu@ncsu.edu

Selected Paper prepared for presentation at the 2024 Agricultural & Applied Economics Association Annual Meeting, New Orleans, LA; July 28-30, 2024

Understanding the Impact of State Cost-share Programs on Cover Crop Adoption Rates

Lyazzat Sanat[1], Roderick Rejesus[1]

May 15, 2024

Abstract

Financial incentives, such as cost-share programs, play a significant role in farmers' decisions to adopt cover crops. However, previous research has often lumped together different types of cost-share programs. In this study, we contribute to the literature by specifically examining the impact of state-led programs. Using staggered difference-in-differences estimation and a unique satellite-based data, we investigate how state cost-share programs for cover cropping practices influence county-level cover crop adoption rates. Our estimation results suggest that state-level incentive payments have a statistically significant positive effect on cover crop adoption at the county level.

[1] Department of Agricultural and Resource Economics, North Carolina State University, Raleigh, NC 27695.

1 | Introduction

Conservation programs are a significant part of the Farm Bill, which is projected to be at $59.7 billion over the life of the Bill. A variety of federal and taxpayer-assisted conservation programs, including but not limited to the Conservation Reserve Program (CRP), Conservation Stewardship Program (CSP), Environmental Quality Incentives Program (EQIP), provide cost-sharing opportunities with farmers adopting conservation, resource-saving, and wildlife-based practices. Over the last several years, there was a surge in federal spending on these programs that resulted in further encouragement to adopt practices such as cover crops, nutrient management, conservation tillage, and many others. However, the effectiveness of these cost-sharing programs is complex due to the voluntary nature of the programs, spillover effects, and the possibility of slippage[2]. Thus, accurate analysis of the effect of different conservation payments can inform further development of Federal and State policies that incentivize conservation practices.

Cover cropping is one of these conservation practices adopted by farmers and studied largely in recent literature. The practice has been shown to improve soil health and water quality by scavenging excess nutrients in the soil and building organic matter. According to the last census of agriculture, the cover crop acreage substantially increased by 50 percent between 2012 and 2017 (Wallander et al., 2021). However, compared to other conservation practices such as no-till, the cover crop adoption rate is still low, accounting only for about 5 percent of the total harvested cropland in 2022, excluding alfalfa. One possible explanation for that could be the fact that farmers bear all the costs of adoption, and no-till generally involve reduced on-farm costs

[2] Slippage refers to unintended shifts in land use patterns resulting from conservation incentive payments, where cost-share payments may inadvertently prompt landowners to convert land from vegetative cover to cultivated cropland, potentially undermining conservation goals.

relative to the conventional tillage, but cover crops can require additional costs for seed purchases, field operations, and sometimes for greater use of herbicides. Thus, such financial constraints could lead to the underprovision of soil health benefits from the conservation to adopting farmers. Federal and State conservation programs partly alleviate the constraint by providing financial assistance payments. However, it is still unclear what type of incentives could efficiently encourage a greater adoption.

Given the diversity of cost-sharing programs and the gap in the studies of their separate design and effect, the objective of this study is to examine the impact of state-level conservation programs on the adoption of cover crops in the U.S. To answer this question, the paper utilizes the county-level data for cover crop adoption rates drawn from the Operational Tillage Information System (OpTIS) developed by Dagan Inc.®, Applied GeoSolutions (AGS). The data set covers counties from 16 states (mainly Corn Belt) for the period 2005-2020. We apply staggered difference-in-differences (DID) to this panel data to empirically analyze how incentives from state-level conservation programs affect the cover crop adoption rate. Compared to the traditional DID, this method allows for a more robust analysis of cases when treatment is staggered in adoption and varies with time. In contrast to federal conservation programs, which are uniformly launched for all states, the implementation of state conservation programs is contingent upon the decisions made by local state conservation districts. As a result, states may introduce cost-sharing programs in different years, for varying durations, and intensity. For this study, the exact year and duration of each state program implementation are determined by searching State websites and annual reports from AGREE and USDA ERS. The validity of online facts is further verified by phone and email correspondence.

Since the economic framework is important in understanding how various factors affect the farmers' decision to adopt soil health practices, there are a number of studies in this literature. Specifically, previous studies examined the level of "additionality"[3] from cost-share program enrollment and the results ranged from as high as 90 percent to the medium of 54 percent (Mezzatesta et al. 2013; Sawadgo and Plastina 2021). Their results suggest that 54 (90) percent of the cover crop acreage funded by conservation programs would not have been adopted without the payment. Since the treatment variables in these studies lump together all different cost-share programs, Park et al. (2021) explore whether there is a heterogeneity in effects of two major Federal programs, EQIP and CSP. Their results illustrate the significance of separately studied impacts of each program because EQIP and CSP were estimated to have opposite effects. Thus, it is important to extend this literature further by covering other programs and comparing which payment structure or design is more effective.

Despite the considerably large literature on examining the effect of cost-sharing programs on the adoption of cover crops, to the best of our knowledge, there has been no study that examined the state-level conservation programs separately from federal programs. Studying state level programs can inform design of more efficient cost-sharing programs and help in deciding future allocations of resources to these programs. Moreover, in contrast to farm-level studies this paper studies more aggregate county-level effects of cost-sharing. Finally, the findings from this study could inform future research on examining specific state-level programs and their design that could be models for never-adopted states.

The remainder of this paper is organized as follows. Section 2 gives a brief literature review and lists the contribution of this paper to the current knowledge. In Section 3 we provide a descriptive analysis of the data and summary statistics of the main variables. Section 4 outlines the empirical research design. Finally, Section 5 and 6 discusses the main results along with the

[3] Defined here as the adoption of cover crops that would not have occurred in the absence of cost-share payments.

robustness checks, and concludes the paper with the limitations of the study and future research directions.

2 | Literature Review

Prior studies have found that cover crop adoption has the potential to provide a number of ecosystem services such as reduced soil erosion, nitrate leaching, enhanced wildlife habitat, and carbon sequestration (Snapp et al., 2005; Castellano et al., 2012; Jian, 2020). Apart from external benefits, there have been studies analyzing internal benefits in the forms of greater yield stability, weed suppression, and reduced need for fumigation, pesticides, and fertilizers (Lotter et al., 2003; Conklin et al., 2002; Gebremedhin et al., 1998). However, these agronomic benefits are not necessarily followed by economic benefits in the short term. According to studies in Iowa, Plastina (2018) found that farmers, on average, spend $46.09 per acre for planting and terminating the cover crop. Most of the time, the yield expansion benefit is insufficient to cover these costs. Thus, to solve the mismatch between private/public benefits, and exclusively private costs, agricultural conservation programs have taken the initiative to encourage the adoption of cover crops with financial and technical assistance.

Two of the most extensive federal conservation programs are EQIP and CSP, which saw a substantial increase in payments over the last several years (Schechinger, 2022). Both programs target conservation on actively farmed land in contrast to land set-aside programs such as Conservation Reserve Program (CRP). Thus, they are particularly important in studying productive farm fields and their cover crop adoption. Several studies have examined the cost-efficiency of cost-share programs and their ability to incentivize conservation practices as cover crops. Fleming (2017) studied the direct and indirect effects of cover crop cost-share programs on the acres of cover crops using a survey of farmers from Maryland. The study employed a two-stage simultaneous equations approach and found an increase in cover crop acreage from 0.023 (estimated counterfactual) to 0.292 with cost-sharing. Apart from these direct effects, the paper also provides evidence of the positive and substantial magnitude of the indirect effects. However, it should be noted that the survey instrument used does not distinguish between federal and state cost-share programs, assuming Maryland Agricultural Water Quality Cost Share is the dominant funding source.

A number of recent research focused on estimating the level of "additionality" from enrollment in cost-share programs. Additionality refers to whether the conservation practice supported by cost-share program payments would have been adopted without the payment (Horowitz and Just, 2011). Due to information asymmetry, it is impossible to observe whether the enrolled farmer would have adopted the conservation practice (cover crop in our case) without payment; thus, this counterfactual needs to be estimated to study the additionality. Mezzatesta, Newburn, and Woodward (2013) used propensity score matching to estimate the additionality from federal conservation programs for six different practices. Using the farm survey data for Ohio, they found cover cropping to have the second highest percent additionality, 90.6%, after the hayfield establishment (93.3%). A similar study by Sawadgo and Plastina (2021) found a smaller percentage of additionality, 54% in Iowa, suggesting that half of the cover crop acreage funded by conservation programs would not have been planted without the payment. However, it is believed that due to the lower payment rates in Iowa, the level of additionality is less than what other studies have found. This and other studies have not separately investigated the effects of different cost-share programs to determine whether there are differing impacts.

A recent study by Park et al. (2021) focused on the abovementioned problem. It separately estimated the impact of two federal programs, EQIP and CSP, on the cover crop adoption rates in the Corn Belt. The results were unexpected since the effects of EQIP and CSP payments are estimated to be different. Their empirical findings suggest that aggregate EQIP payments encourage higher county-level cover crop adoption. In contrast, aggregate CSP payments have a negative and statistically significant effect on the cover crop adoption rate. Syntheses of findings from these discussed independent studies have shown a substantial step forward in understanding the impact of cost-share programs on cover crop adoption rates. However, there are still promising avenues for future research.

While previous research has studied the effectiveness of cost-share programs in the United States, it has been focused solely on federal-level programs. However, different payment structures and designs of state-level programs could also provide important insights into policy formation. For example, the Maryland Agricultural Water Quality Cost Share program has been the primary source of cost-share payments, with state spending significantly outpacing federal spending under EQIP and CSP (Fleming et al., 2018). After heavily promoting cover crops for almost a decade through this program, the state experienced both a high adoption rate and a high growth rate (USDA, 2021). An extensive, in-depth study by Feldmann et al. (2019) argues that state programs are more than just an additional funding source. They highlight at least three important purposes that state-level agricultural conservation programs serve: (i) provide significant direct environmental benefits; (ii) establish state-specific approaches to tackling environmental concerns that are more tailored to the state; and (iii) function as hubs for generating ideas that could be replicated in other states or even on a federal level (Feldmann et al., 2019). Thus, this paper aims to contribute by estimating the adoption effects of state-level cost-share programs for cover cropping, a specific focus often overlooked in existing literature that tends to aggregate various sources of financial assistance.

In contrast to studies utilizing farm-level data, this paper will also contribute to the literature by using more aggregate county-level data over a longer period of time. This will allow the study to better account for time-invariant unobservables that might create an endogeneity (Park et al., 2021).

3 | Data Sources and Summary Statistics

This study utilizes the Operational Tillage Information System (OpTIS) data by Dagan Inc.®, Applied GeoSolutions (AGS) (now Regrow Ag ®). OpTIS uses satellite-based remote sensing to monitor the adoption of conservation practices like cover cropping at the farm-field level but distributes the data at the aggregate county level to protect the privacy of individual producers. The data encompasses 16 states, with complete statewide coverage in Illinois, Indiana, Iowa and Kansas, and partial coverage in 12 other states: Colorado, Kentucky, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, Oklahoma, South Dakota, Tennessee, and Wisconsin. We observed cover crop acreage in a total of 966 counties spanning the period from 2005 to the 2020 crop year. A crop year is defined in this study as the period from November 1 of the previous year to October 31 of the current year. For example, the 2005 crop year extends from November 1, 2004, to October 31, 2005. For this study, we specifically use cover crop adoption rate, the proportion of cover crop acres planted after any of the following cash crops: corn, soybeans, small grains, and other cash crops. Looking at adoption rates, rather than total acreage, allows for comparison across regions.

Winter cover is estimated using a series of images showing how vegetation changes over time, from November to July each year. To determine cover status each pixel is categorized as having either less than 30% green cover or at least 30% green cover during winter (See Hagen et al., 2020 for more details). Ground-level verification photos and collected survey data from several representative counties were used for OpTIS data validation. According to the latest report, remote sensing accuracy in identifying cover crop adoption is 87.9% with 0.03 false-positive rate (Hagen et al., 2020). However, there are some known discrepancies between OpTIS estimated cover crop acreage and county-level estimates from other data sets like AgCensus and the Environmental Working Group (EWG) (Hagen et al., 2020). Some portion of this discrepancy might stem from different methodologies employed to estimate the adoption of conservation practices. OpTIS utilizes data from satellite observations analyzed via computer algorithms, whereas the AgCensus conducts a comprehensive census of growers. As a result, OpTIS does not account for grower intent, unlike the AgCensus, which may capture it. For example, if a farmer plants cover crops in the fall but encounters adverse weather conditions, the cover crop may struggle to grow adequately. Consequently, OpTIS might not detect cover crop, whereas the AgCensus could still report it. Nevertheless, OpTIS mapped cover crops are moderately correlated with those reported by the AgCensus (67% correlation for 2017-2018), and the EWG (69% correlation for 2015-2016) (Hagen et al., 2020).

After collecting cover crop adoption data from OpTIS, we gather information on state-level programs that incentivize cover crops. It was compiled from various publicly available sources, including the state and conservation districts' websites, conservation program reporting, and the summary reports of AGREE (2019) and USDA ERS (2021). The validity of online information was further verified by phone and email correspondence. The main objective was to determine the starting date of the state cost-share programs for cover cropping practice.

States that implement local cost-share programs at a particular year, t, were then classified as being treated till the end of the study period, T.[4] If state-level incentives were implemented by the end of 2019, they were classified as "not-yet-treated" until the treatment year; otherwise, they were classified as "never-treated". The data set contained only two states that were never treated, Colorado and Tennessee, as well as the state of Wisconsin that was already treated at the beginning of the period.[5]

In addition to OpTIS data, we also gathered data on several weather variables from the Parameter-elevation Regression on Independent Slopes Model (PRISM) climate group. It is a widely used climate dataset developed by Oregon State University that provides high-resolution spatial data for various climatic parameters, including precipitation, temperature, and other related variables. Numerous studies have utilized this data source to investigate various climate change issues over the years (See Shlenker & Roberts, 2009, and Annan & Schlenker, 2015, for example). The relevant weather variables used in the study include: the number of growing degree days (8–29°C) and harmful degree days (above 29°C), precipitation, and precipitation squared (Schlenker & Roberts, 2009). The daily observations are accumulated over the growing season months from May to September. We include these variables as controls in our model specification since environmental conditions in each county vary over time and can influence the decision to adopt cover crops.

<Table 1 about here>

The summary statistics (e.g., means and standard deviations) of the variables utilized in this study, as well as their descriptions, are presented in Table 1. Overall, the mean cover crop

[4] It was verified that the programs were active till the end of the study period.
[5] According to verified data, the Wisconsin cover crops cost-share program started in 2002, and to the best of our knowledge, there were no statewide cover crop cost-share programs implemented in CO and TN till 2019. Thus, we assume that they were never-treated during the study period.

adoption rate for our 2005–2020 data is at 4.96%. Since state cost-share programs for cover cropping (i.e., treatment) were implemented in different years by each individual state, we summarize the main variables in two timing groups: an early treatment group, which implemented state cost-share in 2008; and a late treatment group, which implemented it in 2016. We then compare their adoption rate in the pre- and post-treatment periods with those of the never-treated group (i.e., control). The mean cover crop adoption rate for the early-treated group was initially lower than that of the never-treated group. However, it increased by a greater magnitude, 3.15 percentage points, after the treatment. The percentage point increase among the later-treated group was significantly high, at 7.21 Additionally, the control group also experienced an increase in the adoption rate after the treatment period. It is worth noting that in 2008, only one state, Illinois, was treated, whereas in 2016, there were four treated states: Indiana, Minnesota, Missouri, and Oklahoma. Summaries of weather variables are also reported in Table 1.

4 | Empirical Approach

In order to estimate the effect of state-led program implementation on cover crop adoption, we use an extension of the basic two-way fixed effects (TWFE) difference-in-differences (DID) method for staggered roll-out and heterogeneous treatment effect cases. There is an extensive and active literature that continuously proposes methods for estimating average treatment effects when the timing of the intervention varies across groups and treatment effect heterogeneity is present (e.g., de Chaisemartin, D'Haultfoeuille, 2020, Borusyak, Jaravel, Spiess, 2021, Callaway, Sant'Anna, 2021, Goodman-Bacon, 2021, Wooldridge, 2023). This literature argues that traditional DID regressions are appropriate only in settings with no treatment timing heterogeneity (i.e, there is a single treatment period) or where the treatment effect is homogeneous. Otherwise, we should use TWFE DID with caution, as there is a potential for bias in estimates due to time-varying treatment effects. In our case, counties were treated at different times, and those treated later might experience stronger treatment effects than those treated earlier, as the effectiveness of treatment may diminish over time.

The main parameter of interest in our empirical specification is the group-time average treatment effect. This is a generalization of the popular average treatment effect on the treated (ATT) for setups with multiple treatment groups and time periods. Specifically, we use $ATT(g, t)$ as the building block of our empirical framework, denoted by

$$ATT(g, t) = \mathbb{E}\left[Y_t(g) - Y_t(0) \mid G_g = 1 \right]$$

where g is the group of units treated at a particular time period t, and $ATT(g, t)$ is the group-time average treatment effect. The estimator does not impose any restriction on treatment effect heterogeneity, thus we can analyze whether the ATTs are heterogeneous across groups and how the length of exposure to the treatment affects the average treatment effects. In order to identify $ATT(g, t)$, we need to impose three important assumptions. First, we assume that once a county receives treatment in a particular period, it continues to be treated in subsequent periods until the end of the study. With that, we can fully define a unit's trajectory of treatment participation by its "group", where the group indicates the time period when the unit first receives treatment. Thus, we exclude counties that were already under the treatment in the initial period (i.e., whole Wisconsin counties in our case), since it will not contribute to recovering the trajectory of untreated potential outcomes for other groups (Caetano et al., 2022). For the rest of the data we verified that the imposed treatment is active till the end of the study period. Second, limited treatment anticipation assumption states that prior to receiving treatment, the outcomes observed for a unit represent its untreated potential outcomes. This ensures that the treatment does not begin influencing outcomes before it is administered. However, it is relatively simple to modify this condition to allow for some level of anticipation before treatment, an aspect we will explore further in sensitivity analyses. Third, we also assume conditional parallel trends based on "not-yet-treated" groups. Conditioning on covariates becomes important when there are unique trends in outcomes over time associated with the set of covariates, and when the covariate distribution differs across various groups (Callaway, Sant'Anna, 2021). We include to our framework time-varying weather variables, which are not influenced by the policy intervention but can affect the trend of cover crop adoption. Additionally, we impose these conditional parallel trends between group g and "not-yet-treated" groups by time t, because the fraction of "never-treated" counties is relatively small (6\%). Thus, we consider a not-yet-treated group as a more appropriate approach for our application that would potentially allow for more informative inference.

5 | Results and Discussion

5.1 | Main estimation results

The main empirical results are given in Table 2. In the following table, we present various sets of results derived from different identification strategies. Specifically, we examine scenarios where the parallel trends assumption is assumed to hold unconditionally, as well as cases where it holds only after accounting for observed time-varying covariates. In the main text, we focus on the scenario where not-yet-treated counties serve as the comparison group and where no anticipation effects are considered. The group-time average treatment effect estimates provide support for the view that introducing state-level incentive payments for cover cropping practice led to an increase in cover crop adoption rate. For 6 out of 7 group-time average treatment effects, there is a clear statistically significant positive effect on cover crop adoption rate. The group-time average treatment effects range from 1.2 percentage points higher adoption rate to 5.02 percentage points higher adoption rate. The simple average (weighted only by group size) is 2.07 percentage points higher adoption rate.

6 | Conclusions

This paper provides an empirical analysis of the impact of state-level conservation programs on the cover crop adoption rate. Given soil health's significant role in sustainable agricultural productivity and environment, there is an increasing trend in promoting conservation best practices in the agricultural sector. Cover cropping is one of such practices that annually receive technical assistance and cost-sharing payments from Federal and State conservation programs. Despite such cost-share programs that are present for a long time, the cover crop adoption is still relatively rare at a 5.1 percent adoption rate which questions the effectiveness of conservation program payments on the take-up. Previous literature examined the additionality effect of different cost-share programs, including both at federal and state level. However, there has been no study that examined the state-level conservation programs separately from other programs.

Given the diversity of cost-sharing programs and the gap in the studies of their separate design and effect, the objective of this study is to examine the impact of state-level conservation programs on the adoption of cover crops in the U.S. To answer this question, the paper utilizes the county-level data for cover crop adoption rates drawn from the Operational Tillage Information System (OpTIS) developed by Dagan Inc.®, Applied GeoSolutions (AGS). The data set covers counties from 16 states (mainly Corn Belt) for the period 2005-2020. We apply staggered difference-in-differences (DID) to this panel data to empirically analyze how incentives from state-level conservation programs affect the cover crop adoption rate. Our estimation results suggest that state-level incentive payments have a statistically significant positive effect on cover crop adoption at the county level.

References

Arkhangelsky, D., Athey, S., Hirshberg, D.A., Imbens, G.W. and Wager, S., 2021. Synthetic difference-in-differences. American Economic Review, 111(12), pp.4088-4118.

Castellano, M.J., Helmers, M.J., Sawyer, J.E., Barker, D.W. and Christianson, L., 2012, November. Nitrogen, carbon, and phosphorus balances in Iowa cropping systems: Sustaining the soil resource. In Proceedings of the 24th Integrated Crop Management Conference (pp. 145-56). Ames: Iowa State University Digital Repository.

Conklin, A.E., Susan Erich, M., Liebman, M., Lambert, D., Gallandt, E.R. and Halteman, W.A., 2002. Effects of red clover (Trifolium pratense) green manure and compost soil amendments on wild mustard (Brassica kaber) growth and incidence of disease. Plant and Soil, 238(2), pp.245-256.

Fleming, P., 2017. Agricultural cost sharing and water quality in the Chesapeake Bay: Estimating indirect effects of environmental payments. American Journal of Agricultural Economics, 99(5), pp.1208-1227.

Fleming, P., Lichtenberg, E. and Newburn, D.A., 2018. Evaluating impacts of agricultural cost sharing on water quality: Additionality, crowding in, and slippage. Journal of Environmental Economics and Management, 92, pp.1-19.

Gebremedhin, B., G. Schwab, R. Harwood, D. Christenson, and C. Bricker. 1998. A stochastic dominance analysis of alternative sugar beet– and navy bean–based crop rotations in Michigan. Staff Paper. Dep. of Agric. Econ., Michigan State Univ., East Lansing, MI.

Horowitz, John K., and Richard E. Just. 2011. “Economics of Additionality for Environmental Services.” Working paper. Washington, DC: U.S. Department of Agriculture, Economic Research Service.

Jian, J., X. Du, M.S. Reiter, and R.D. Stewart. 2020. A meta-analysis of global cropland soil carbon changes due to cover cropping. Soil Biology and Biochemistry 143:107735.

Lotter, D.W., Seidel, R. and Liebhardt, W., 2003. The performance of organic and conventional cropping systems in an extreme climate year. American Journal of Alternative Agriculture, 18(3), pp.146-154.

Mezzatesta, M., Newburn, D.A. and Woodward, R.T., 2013. Additionality and the adoption of farm conservation practices. Land Economics, 89(4), pp.722-742.

Park, B., Rejesus, R.M., Aglasan, S., Che, Y., Hagen, S.C. and Salas, W., 2021. Payments from agricultural conservation programs and cover crop adoption. Applied Economic Perspectives and Policy.

Plastina, A., Liu, F., Sawadgo, W., Miguez, F. and Carlson, S., 2018. Partial budgets for cover crops in Midwest row crop farming. Journal of ASFMRA, pp.90-106.

Sawadgo, W. and Plastina, A., 2021. Do cost-share programs increase cover crop use? Empirical evidence from Iowa. Renewable Agriculture and Food Systems, 36(6), pp.527-535.

Snapp, S.S., Swinton, S.M., Labarta, R., Mutch, D., Black, J.R., Leep, R., Nyiraneza, J. and O'neil, K., 2005. Evaluating cover crops for benefits, costs and performance within cropping system niches. Agronomy journal, 97(1), pp.322-332.

Table 1. Summary Statistics

	Early Group				Late Group			
	Treat		Control		Treat		Control	
	Pre	**Post**	**Pre**	**Post**	**Pre**	**Post**	**Pre**	**Post**
cc_pct	1.84	4.99	3.17	4.85	4.62	11.83	3.12	7.63
	(3.02)	(7.29)	(5.18)	(7.39)	(8.06)	(15.91)	(5.02)	(9.49)
GDD	2033.76	2091.18	1815.6	1861.33	1959.06	2025.18	1837.26	1886.85
	(190.66)	(211.62)	(401.58)	(424.58)	(319.13)	(320.35)	(416.23)	(428.57)
HDD	2.38	3.37	1.25	1.92	6.63	2.11	2.38	0.50
	(2.94)	(7.84)	(3.18)	(5.64)	(17.1)	(6.21)	(6.13)	(1.99)
Precip	0.44	0.56	0.46	0.52	0.52	0.62	0.48	0.57
	(0.10)	(0.15)	(0.12)	(0.16)	(0.16)	(0.15)	(0.15)	(0.15)
N	306	1326	174	754	2981	1355	638	290

Notes: The table provides summary statistics (i.e., mean and standard deviations in parentheses) for percentage of acreage planted with cover crops (cc_pct), growing degree days (GDD), harmful degree days (HDD), and growing season precipitation (in 1000 mm). The table reports outcomes in three groups: a control group, which is never treated; an early treatment group, which receives the treatment in 2008; and a late treatment group, which receives the treatment in 2016. There are two sub-periods for each treatment group: pre-treatment and post-treatment.

Table 2. State-level conservation programs aggregated treatment effect estimates

	Unconditional parallel trends		Conditional parallel trends	
	JWDID	**CSDID**	**JWDID**	**CSDID**
Group-specific effects				
G2008	1.209^{***}	0.948^{**}	0.511	0.014
	(0.399)	(0.421)	(0.474)	(0.604)
G2012	2.943^{***}	1.825^{***}	2.571^{***}	1.699
	(0.633)	(0.692)	(0.599)	(1.531)
G2014	-1.104^{***}	-1.029^{***}	-1.266^{**}	-1.108^{**}
	(0.285)	(0.349)	(0.612)	(0.551)
G2016	3.632^{***}	4.539^{***}	3.318^{**}	4.727^{***}
	(0.655)	(0.694)	(1.160)	(0.792)
G2018	5.017^{***}	-0.985	3.178^{**}	-2.955^{*}
	(1.772)	(1.516)	(1.567)	(1.597)
G2019	1.748^{**}	3.477^{***}	4.051	2.427
	(0.794)	(1.052)	(4.298)	(2.723)
G2020	4.053^{***}	7.342^{***}	2.628	2.381
	(1.286)	(1.564)	(2.908)	(1.547)
Group avg.		3.244^{***}		2.079^{***}
		(0.498)		(0.599)
Simple weighted avg.	2.07^{***}	2.106^{***}	1.696^{**}	1.588^{***}
	(0.33)	(0.352)	(0.807)	(0.442)

Notes: The table reports aggregated treatment effect parameters under the unconditional and conditional parallel trends assumptions. Columns labeled "JWDID" and "CSDID" report Wooldridge (2021) and Callaway and Sant'Anna (2021) estimates (using the not-yet-treated comparison group), respectively. The 'Group-specific effects' summarizes average treatment effects by the timing of implementation of state-level cost-share for cover cropping; here, G indexes the year that a county is first treated. The row "Simple weighted avg." reports the weighted average (by group size) of all available group-time average treatment effects.