Farmer-Led Conservation Programs and Nonpoint Source Pollution Abatement

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Abstract

Nonpoint source pollution from agriculture is the leading cause of nutrient pollution in the US. This paper addresses whether localized, farmer-led programs can cost-effectively reduce nonpoint source pollution by increasing the adoption of agricultural conservation practices. We study this in the context of an innovative program in Wisconsin that incentivizes farmers to take collective leadership of improving water quality in their local watersheds. Using a shift-share instrumental variables design, we find that a 10 percentage point increase in farmer participation in these programs leads to a 0.03 mg/L reduction (14%) in ambient phosphorus concentrations in local streams and rivers. We also show that farmer participation in local watershed programs causes an increase in the adoption of cover crops, conservation tillage, and more diverse crop rotations. Importantly, this localized approach achieves water quality and conservation improvements at a substantially lower cost than existing federal subsidy

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programs, demonstrating the potential for bottom-up approaches to address nonpoint source pollution in other contexts.

JEL Codes: Q15, Q25, Q53, Q58

Keywords: nonpoint source pollution, agricultural conservation, water pollution, group incentives

1 Introduction

Agriculture is the leading contributor of nonpoint source water pollution in the United States (Del Rossi et al., 2023). While regulatory interventions, like the Clean Water Act (1972), are associated with water quality improvements over the last 50 years, most farms are exempt from past regulations due to the nonpoint source nature of agricultural nutrient runoff (Keiser and Shapiro, 2018). By definition, nonpoint source pollution enters water bodies from many dispersed locations (e.g., agricultural fields), making emissions difficult to observe and monitor (Griffin and Bromley, 1982). Furthermore, localized environmental conditions imply different emission and delivery rates over time and space (Helfand and House, 1995). These realities of nonpoint source pollution make traditional first-best policy instruments challenging to implement. Thus, much of the existing efforts to reduce nonpoint source pollution rely on large annual expenditures to subsidy programs through the US Department of Agriculture. These programs contain a host of inefficiencies of their own (Wu et al., 2004; Fleming, Lichtenberg, and Newburn, 2018), and empirical evidence on their success is mixed (Liu, Wang, and Zhang, 2023; Sun, Gramig, and Delgado, 2025).

We evaluate a unique policy initiative in which local farmers collectively govern themselves and their practices to cost-effectively improve water quality in their watershed. We study a novel state-level program in Wisconsin, the Producer-Led Watershed (PLW) Grant Program. The PLW program provides start-up grant funding for farmers to take collective leadership in improving local agricultural and water quality outcomes. Local farmers manage those grant funds to best address local barriers to adoption in their area through education, peer influence, and offering modest subsidies to new adopters. In 2023, the PLW program provided $1 million to 43 watershed groups in Wisconsin, which comprise about a third of the state's total agricultural acreage. Relative to other existing policy efforts that administer programs through a central agency, the program takes a bottom-up approach, where the polluters themselves design policies and activities best adapted to their local characteristics and to influence neighboring farmers' decisions. By doing so, this program attempts to overcome some of the shortcomings associated with more centralized regulations that set uniform standards and incentives across large regions.

We assess the program's effectiveness by estimating how PLW participation influences local water quality and management decisions. First, we study how the presence of PLW participation changed ambient water quality outcomes within those watersheds. In particular, we focus on phosphorus and nitrogen concentrations in surface water, which are the two leading fertilizer inputs in agriculture and impose significant welfare costs at excessive levels in surface water (Jones, 2019; Wolf et al., 2019; Kuwayama et al., 2020). Second, the PLW groups accomplish their goals by attempting to increase the adoption of conservation practices and by growing less fertilizer-intensive crops. We estimate the extent to which PLW participation accelerated the adoption of conservation practices, specifically focusing on cover crops, reduced tillage, and diversified crop choice.

Importantly, participation in the PLW program is voluntary, which presents a common causal identification challenge in the agricultural conservation literature (Claassen, Duquette, and Smith, 2018; Pannell and Claassen, 2020; Aspelund and Russo, 2025). To overcome the concern that farmers may opt into the program in non-random ways, we implement an instrumental variables strategy that exploits state-level changes in the program's budgetary cap — which is annually determined by the governor and approved by the state legislature — interacted with local subwatershed crop acreage in 2010 before the program was conceived. In the first stage of our instrumental variables strategy, we use the temporal variation from the state-level change and the cross-sectional variation from local crop intensity to predict participation in the program. Then, the second stage regresses our outcomes of interest on the predicted PLW participation from the first stage. This approach is analogous to the class of *shift-share IVs*, where identification stems from exogenous variation in the *shifts* (Borusyak, Hull, and Jaravel, 2021). In our setting, identification relies on the assumption that the state-level changes are not correlated with local water quality and cropping decisions, except through the channel of the local subwatershed's participation in the program.

To estimate these relationships, we build a panel dataset that measures the level of participation in the program, local surface water quality, land use and cropping decisions, and local weather variables. First, we obtain a detailed record of the PLW program from the Wisconsin Department of Agriculture, Trade, and Consumer Protection (DATCP). These proprietary data provide annual measures of each group's size (i.e., number of acres), the 12-digit Hydrologic Unit Code (HUC 12), and the amount of funding they received. Second, we assemble monitor-level phosphorus and nitrogen readings in Wisconsin from the US Geological Survey (USGS) Water Quality Portal and harmonize the raw readings according to the method introduced by Krasovich et al. (2022). Third, remotely sensed data from Regrow Agriculture Inc. provides annual conservation practice acreage at the HUC 12 level. Lastly, we collect granular precipitation and weather data from PRISM as control variables. These panel data allow us to control for local time-invariant factors (e.g., soil type) and time-varying shocks (e.g., commodity prices) through location- and time-fixed effects.

We find that a 10 percentage point increase in PLW group participating acreage (approximately 1,220 acres at the mean subwatershed) leads to a statistically significant 0.03 mg/L reduction in phosphorus concentrations. Nitrogen-related concentrations also decline, but the treatment effect is less precise. These changes in water quality are plausibly driven by increases in conservation practice adoption. The same 10 percentage point increase in PLW acres leads to a 2.8 percentage point increase in cover crop adoption, 7.7 percentage point increase in conservation tillage, and a 0.8 percentage point increase in diversified crop rotations. A back-of-the-envelope calculation estimates that the additional cover crop acres cost \$11.54 per acre while tillage reductions cost \$4.19 per acre. Both costs are about 20% of the cost of traditional USDA-Natural Resource Conservation Service (NRCS) cost-share program payments. These findings demonstrate that localized approaches to conservation incentives can be a more cost-effective way to administer water quality improvements and conservation uptake.

We support the validity of our identifying assumptions by showing that plausible confounders to PLW participation do not change our primary point estimates when included as controls. Furthermore, we construct random permutations of the time-varying and cross-sectional components of our instrument to construct placebo instruments and re-estimate our model under 1,000 hypothetical alternative instrument assignments. The distributions of the estimates from these placebo tests are centered around zero, and we reject the hypothesis that our true estimates from the observed data are equal to the average estimates from the placebo distribution. These tests provide support that the changes in water quality are driven by the true PLW participation and not by location-specific or time-specific confounders.

We contribute to the existing literature in several distinct ways. First, we offer empirical evidence on the relationship between agricultural production and water quality. A growing body of work estimates how marginal changes in agricultural production affect ambient water quality outcomes, which generally shows that additional fertilizer and livestock contribute to higher nitrogen and phosphorus concentrations in nearby surface water bodies(Paudel and Crago, 2021; Raff and Meyer, 2022; Metaxoglou and Smith, 2025). Other work has shown that regulations, through both local and federal policies, have led to surface water improvements (Skidmore, Andarge, and Foltz, 2023a; Chen et al., 2025). (Karwowski and Skidmore, 2025) find that USDA-NRCS wetland easements improve nitrogen and ammonia concentrations, while Liu, Wang, and Zhang (2023) provides evidence that USDA-EQIP payments also improve ambient nitrogen and ammonia levels, but also lead to worse phosphorus outcomes. We uniquely contribute to this literature by studying the effects of a policy intervention on water quality outcomes and by comparing its cost-effectiveness relative to those established in previous studies. Furthermore, we inform the behavioral mechanisms through which environmental outcomes change, as we empirically show that the policy intervention changed farmers' production practices.

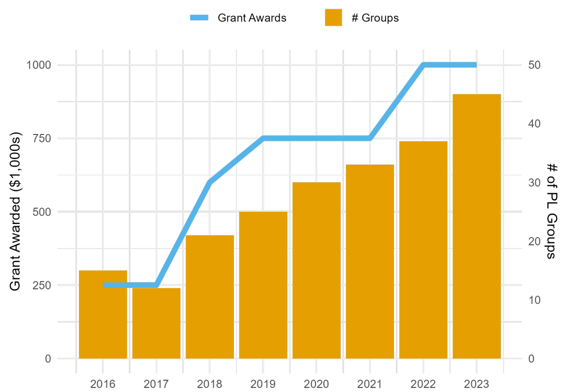
Second, we contribute to the economics literature on the collective management of natural resources in agriculture. Specifically, the policy intervention in our setting is a unique application of a group incentive for environmental protection (Segerson, 2022), because it rewards a collective of polluters (farmers) for locally governing themselves to improve environmental outcomes. Much of the evidence on the efficacy of group incentives for environmental improvement has been theoretical (e.g., (Segerson, 1988)) or lab experiments (e.g., (Suter and Vossler, 2014; Palm-Forster, Suter, and Messer, 2019). Outside of water pollution, observational studies on collective action among farmers has proven to be effective at reducing common-pool resource externalities (Ostrom, 2010), primarily in groundwater management, where agricultural irrigators self-impose incentives to conserve groundwater (Smith et al., 2017; Drysdale and Hendricks, 2018; Orduña Alegría et al., 2024). To date, however, these policy approaches have been largely untested at scale to address nonpoint source pollution. We offer some of the first empirical evidence of a large-scale policy rollout of a group incentive scheme for the management of nonpoint source pollution from agriculture. This policy design leads to more conservation participation and environmental improvement than traditional, individual incentive policy approaches and at a smaller public expense. Our findings offer empirical support that this policy design can be successful, especially in settings where traditional first-best approaches are infeasible.

Finally, we contribute to a growing literature on the role of peer and network effects in agricultural practice adoption. Much of the economic work on this topic has been conducted in low-income country contexts throughout South Asia (Foster and Rosenzweig, 1995; Munshi, 2004), Africa (Conley and Udry, 2001, 2010; Beaman et al., 2021), and elsewhere, though several studies have also investigated farmer behavior in the United States (Mase et al., 2015; Prokopy et al., 2019; Asprooth, Norton, and Galt, 2023; Burlig and Stevens, 2024). In general, these studies have found that social networks and peer groups play an important role in disseminating information and prompting the adoption of new production practices. Our findings support this conclusion: Wisconsin's PLW program leverages local networks of peers to both organize and benefit from the groups' activities, and social networks within these initiatives likely contribute to the efficacy of the program in our setting.

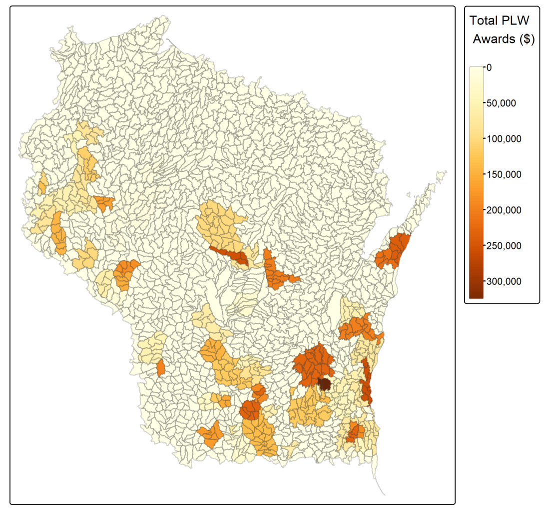
2 Background

The Wisconsin Producer-Led Watershed Program

To mitigate nonpoint source pollution, the Wisconsin Governor and State Legislature first approved funding for the Producer-Led Watershed (PLW) Grant program as a part of the 2016 budget. The program, which is administered by the Wisconsin Department of Agriculture, Trade and Consumer Protection (DATCP), allows for a group of farmers located in the same watershed to jointly sub-



((a)) Awarded by Year



((b)) Grants Awarded: 2016-2023

Figure 1: Grants Awarded through Wisconsin's Producer-Led Watershed Program
Note: Panel A shows the size of the PLW program over time. The blue line represents the state-level budget for the program each year. The yellow bars count the number of active PLW groups in the state each year. Panel B shows the spatial distribution of the 43 PLW groups in Wisconsin and the total amounts they have received between 2016-2023.

mit a grant application outlining a nonpoint source abatement proposal. DATCP then announces awards up to $40,000 for the following calendar year based on a competitive evaluation of the grant proposals.[1] The grant funds are managed by each group's farmer leadership team to facilitate educational events, on-farm research and demonstrations, and to directly subsidize best management practices. In its initial year, the legislative budget was capped at $250,000, and based on that budget, DATCP distributed funds to 14 spatially distinct groups. The legislative budget has been a perennial binding constraint, with grant requests consistently exceeding the amount that can be awarded. The governor proposed multiple increases to the budget since 2016, which allowed DATCP to roll out the program at a larger scale. In 2023, it funded 43 watersheds a total of $1 million. Figure 1(a) plots the expansion of the program over time, and Figure 1(b) maps the distribution of the sum of grant awards between 2016 and 2023.

[1] The Wisconsin state legislature typically approves the state budget in June or July for the following year. Grant applications from farmers are submitted to DATCP by mid-September. Awards are then announced for the following year around the beginning of December.

This program is distinct from other non-point source abatement policies in a few ways, which likely contribute to its success. First, the program incentivizes farmers themselves to be the leaders of water quality improvement. Similar to the setting of Smith et al. (2017), the bottom-up nature of the policy increases farmers' willingness to engage in conservation activities more so than policies administered by higher levels of government. Second, it leverages social networks among farmers with existing trusted relationships, which is known to be a key behavioral factor associated with agricultural practice adoption (Mase et al., 2015). Therefore, while PLW groups incentivize similar conservation cropping practices as traditional programs (e.g., cover crops and conservation tillage), social and educational spillovers are more likely to occur than if the programs were purely monetary in nature. Third, it allows peer farmers to engage in pollution abatement activities that are best suited for the distinct environmental (e.g. soil, climate, water resources), agricultural (e.g. types of crops grown), and social contexts across the state's unique geography. This feature is particularly relevant to this approach's success in an agriculturally diverse state, like Wisconsin, which contains large row crop, specialty crop, and livestock sectors in distinct regions of the state (Deller and Hadachek, 2024). The nuances of this program relative to others are captured by a quote from one participating farmer:[2]

> "The Producer-Led program has allowed farmers and non-farm partners to develop innovative watershed-level strategies to benefit the environment while providing a platform to highlight and share these success stories to a broader audience. Often times, the ideas brought forth by farmers are very quickly adopted by other farmers because of the *credibility that comes when you can identify with your peers*, because you know they know." - PLW Farmer Member (2018 DATCP Impact Report, pp. 24)

Farmers may be incentivized to participate in this program for several key reasons. First, they may be direct recipients of grant dollars for the implementation of conservation practices. At a maximum budget of $1 million per year, however, this funding is relatively scarce within a group,

[2]Similar sentiments are captured by many participating farmers, collected in the program's annual reports (Department of Agriculture, Trade, and Consumer Protection, 2018).

and only a handful of farmers in a given group may directly benefit each year from these funds.[3] The grant funding is largely intended to be seed funding for groups to cover administrative cost barriers, rather than purely being devoted to practice subsidies. Over time, groups may generate additional outside funding from environmental non-profits or private sponsorships, which lessens the reliance on government funding. Second, farmers may participate for social or educational reasons, since group events typically involve socializing, a free meal, and presentations from conservation professionals (e.g., peer farmers or agronomists). Lastly, voluntary participation in this program is often cited as a reason that more strict regulatory measures are not needed in Wisconsin, and that farmers can act collectively and voluntarily to reduce nonpoint source pollution. This latter sentiment aligns with the principles of collective action arrangements, and mirrors other contexts where farmers self-impose environmental objectives in order to avoid future regulation that they do not have direct control over (Ostrom, 2010; Smith et al., 2017).

From its inception, the program has been widely viewed within the state as an overarching success from agricultural and political perspectives. From a participatory standpoint, the reported number of farmers, agricultural acres, and conservation acres has increased every year since 2016 and the number of new requests for PLW grants has grown every year. While many local stakeholders believe this program to be successful from these participatory metrics, it is unclear what environmental outcomes and agricultural decisions would have been in a counterfactual world without the program in place.

Conservation Practices and Water Quality

Agriculture is a major contributor to water pollution, primarily through soil erosion, runoff, and nutrient leaching. Soil erosion is the process by which topsoil is removed from the land by natural forces or human activity, such as farming. Runoff occurs when water flows over fields, carrying soils, nutrients, and chemicals into nearby waterways. Nutrient leaching happens when nutrients

[3] Compare this, for example, to $30 million that was distributed to Wisconsin farmers through the NRCS-Environmental Quality Incentives Program in 2023.

from fertilizers, decomposing organic matter, and manure filter down through the soil into groundwater. Together, these processes make agriculture the leading source of water quality impairment in US waterways (EPA, 2022).

Farmers may undertake a number of best management practices to alleviate soil erosion and water impairment. One of the most popular of such practices is cover crops. Cover crops are typically planted between the harvest and planting of primary crops and provide a range of agronomic and environmental benefits. Cover crops are generally effective at reducing water and sediment runoff and nutrient leaching (Feaga et al., 2010; Kaspar et al., 2012; Heinrich, Smith, and Cahn, 2014; Meisinger and Ricigliano, 2017). These benefits may also stem from nutrient scavenging, where cover crops absorb excess water and nutrients in the soil.

An alternative conservation activity aimed at improving water quality, often paired with cover cropping, is tillage management in the form of reduced till or no till. Soil tillage has traditionally been used to improve soil quality by aerating the soil, distributing nutrients, suppressing weeds, and creating a suitable seed bed. However, it is also associated with negative externalities——most notably soil erosion. Frequent tillage can degrade soil structure, reduce microbial activity, and even contribute to yield losses.

The goal of no-till and reduced-till is to minimize erosion, thereby improving soil health and organic matter while also reducing sediment runoff into surface waters. By leaving residue on the soil surface, reduced tillage creates a protective barrier that slows water flow during rainfall or snowmelt events, allowing more water to infiltrate the soil rather than running off into nearby waterways. Notably, no-till adoption has been linked to higher farmland values, suggesting that producers recognize the private, long-run value of maintaining healthy soils and preventing degradation (Chen et al., 2023).

Studies routinely show that conservation tillage is effective at reducing sediment and total solid runoff. Because total phosphorus particles adhere to soil particles, these practices also decrease total phosphorus runoff. Conservation tillage has been linked to lower phosphorus losses in surface waters in a number of field simulation studies (Drury et al., 1993; Sharpley and Smith, 1994; Zhao et al., 2001; DeLaune and Sij, 2012; Mubvumba and DeLaune, 2023). Extending beyond field simulations, Yates, Bailey, and Schwindt (2006) find that watersheds with higher adoption of no-till cropping have lower amounts of suspended solids and total phosphorus in stream water.

3 Data

Our empirical approach combines panel data on cropping practices, water quality outcomes, and program participation across Wisconsin subwatersheds. Subwatersheds, or HUC 12s, are the smallest hydrological unit code delineations of surface water drainage boundaries. Table 1 displays the summary statistics for the primary variables of interest. The mean and standard deviation of each variable are weighted by the HUC 12's crop acreage to reflect the regression weighting that we later use.

Producer-Led Watershed Grant Program

We obtained information on the PLW grant program via a Freedom of Information Act request to Wisconsin DATCP. This data provides a record of the grant amounts awarded to each group, which HUC 12 watersheds each group covers, and the years that each group exists between 2016 and 2023. Figure 1(b) displays which HUC 12 watersheds in Wisconsin have had an active PLW group between 2016 and 2023 and the dollar amount that each of the groups received over that timeframe. We obtained additional survey data from DATCP that they began collecting in 2019, which required active groups to report the number of farmers and the number of agricultural acres represented by active participants each year.[4]

To arrive at our final measurements, we make two assumptions about the raw observations. First, since survey data on group sizes did not exist until 2019, we impute the missing values for the first three years of the program: If a group was active between 2016-2018, we impose the minimum

[4]"Active participation" was allowed to be a subjective interpretation by the survey respondent, but typically this captures the number of unique attendees that registered or attended events throughout the year.

Table 1: Summary Statistics

Variable	Obs	Weighted Mean	Std. Dev.	Min	Max
Panel A. HUC 12 Measures					
% PL Acres	34276	1.3	7.3	0	100
Dollars (per 10 acres)	34276	0.34	2.1	0	111
2010 Crop % * Budget ($100,000)	34276	1.6	2.4	0	9.7
HUC 12 Area (acres)	34276	23041	9844	3329	152179
HUC 12 Crop Area (acres)	34276	12199	6222	0	91151
Corn %	34274	31	12	0	100
Soy %	34274	14	7.8	0	100
Small Grain %	34274	3	3	0	100
Cover Crop %	10591	2.9	3.5	0	95
Reduced Tillage %	10591	32	16	0	131
Spring Living Root	10344	3.2	0.46	1.7	6.9
Panel B. Monitor-Level Measures					
Spring P (mg/L)	38462	0.18	0.24	0.006	1.8
All Year P (mg/L)	97272	0.17	0.23	0.006	1.8
Spring TKN (mg/L)	16507	1.2	0.95	0.12	6.6
All Year TKN (mg/L)	40652	1	0.88	0.12	6.6
Spring Ammonia (mg/L)	15664	0.13	0.27	0.0046	2
All Year Ammonia (mg/L)	39720	0.1	0.23	0.0046	2

Note: Figure displays the summary statistics for primary variables. Panel A summarizes the measures that are aggregated or observed at the HUC 12 level. Panel A measures are weighted by HUC 12 agricultural acres, aligning with regressions. Agricultural activity includes corn, soybeans, and small grains. Panel B summarizes measures observed at the water quality monitor level. Panel B is weighted by agricultural acres times the inverse density of monitors per HUC 12, aligning with water quality regressions.

acreage size from that group's observed sizes later in the sample. Typically, this was the first reported value (2019) since group sizes tend to grow over time.[5] Second, since groups are often a cluster of neighboring HUC 12 watersheds, and since we only observed a group's aggregated size, we assume that the participating acreage is distributed proportionally to the cropland areas of the eligible subwatersheds within the same group.

Together, these data form the treatment variables of interest for our analysis. The primary variable of interest is the percentage of a HUC 12's crop acres that are actively participating in a PLW group. This variable adjusts for the fact that groups are differentially representative of a subwatershed's farmers, and that some watersheds are treated with more intensity than others. In additional analyses, we also use the grant award amounts as a regressor of interest. However, since this is primarily seed funding capped at $40,000, and groups can generate revenue through other streams that we do not observe (e.g., registration fees, non-profit partnerships, private sponsorships), we believe this to be a noisy measure of a group's actual size.

Water Quality

Our water quality data stems from the harmonized version of the US Geological Survey's Water Quality Data Portal, called the Standardized Nitrogen and Phosphorus Dataset (SNAPD) (Krasovich et al., 2022). We amass daily nutrient readings at the monitor-level from 2005-2023. Notably, the original dataset only spans the Mississippi/Atchafalaya River Basin from 1985-2018. We extend the dataset to include Northern Wisconsin and the most recent years by using the same process described in Krasovich et al. (2022). This harmonization process allows us to compare standardized readings taken by over 5,600 unique monitors in Wisconsin at different points in time.

We aim to examine the impacts of the PLW program on both phosphorus and nitrogen concentrations. These nutrients are closely linked to crop production and the dairy industry, both of which are prominent in Wisconsin. Nutrient runoff from these activities has contributed to hypoxic conditions, harmful algal blooms, eutrophication, and the degradation of aquatic ecosystems

[5] This approach could lead to an overestimation of our treatment size in the early years which would bias our coefficients towards zero.

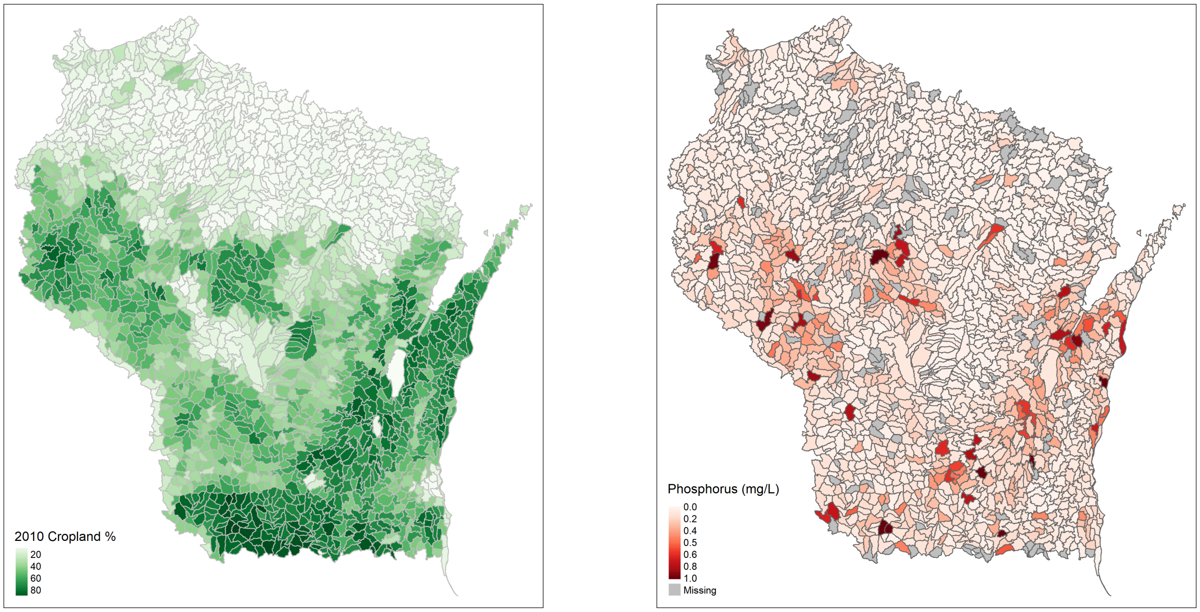
(Del Rossi et al., 2023).

Although the ecological effects of nutrient pollution on water quality are well-documented, the connections between these physical changes and their impacts on people and wildlife remain relatively understudied. The economic damages associated with excess nutrient pollution are complex and multifaceted. Excess nutrients have been linked to diminished recreational opportunities, aesthetic degradation, health risks, increased costs of water treatment, and elevated greenhouse gas emissions (Del Rossi et al., 2023).

Specifically, higher phosphorus concentrations have been associated with decreased recreational travel (Keiser, 2019) and reduced angler welfare (Zhang and Sohngen, 2018). Moreover, the occurrence of harmful algal blooms has been capitalized in housing markets, reflecting their negative externalities (Wolf, Gopalakrishnan, and Klaiber, 2022; Zhang, Phaneuf, and Schaeffer, 2022). Excess nitrogen levels also impose significant costs, particularly related to drinking water treatment for both public water systems (Mosheim and Ribaudo, 2017) and private well owners (Keeler and Polasky, 2014). When nitrate pollution is not effectively managed, it can result in serious human health impacts (Knobeloch et al., 2000; Hadachek, 2024).

All water quality readings, measured in units of milligrams per liter (mg/L), are taken from rivers and streams. We Winsorize readings at the 99th percentile concentration for each nutrient, mirroring previous approaches with this data (Keiser and Shapiro, 2018). Our primary focus is on how the program impacts unfiltered Total Phosphorus, which offers the best coverage, the most observations, and is likely to be more strongly influenced by the practices that PLW groups implement. The term "total" indicates the water quality sample includes readings for phosphate-phosphorus, phosphorus, and phosphate plus organic phosphorus (U.S. Environmental Protection Agency, 2017). For phosphorus, we rely on unfiltered readings that capture both particulate and aqueous fractions. The adopted conservation practices are particularly well suited to reduce particulate (i.e. unfiltered) phosphorus concentrations. [6]

[6] Cover cropping and conservation tillage are aimed at reducing soil erosion. Since total phosphorus particles adhere to soil particles because of P chemistry adhesive properties, erosion control practices are also effective at decreasing total phosphorus runoff.



((a)) Percent of Land Used for Crops ((b)) Average Phosphorus (mg/L) by HUC 12

Figure 2: Land Use and Water Quality in Wisconsin
Note: Panel A shows the percent of each HUC 12 subwatershed area that is devoted to agriculture in 2010. This data is compiled from the Cropland Data Layer. Panel B shows the average ambient phosphorus level in our sample aggregated to the HUC 12 level.

We measure nitrogen two-fold, as ammonia and Total Kjeldahl Nitrogen (TKN). We retain both filtered and unfiltered readings since nitrogen readings are more typically taken using the filtered method (approximately 2/3 of the raw sample). We also focus our analysis on water quality readings from March-June when more than 75% of annual nutrient runoff occurs, due to the confluence of fertilizer applications, winter snowmelt, and heavy precipitation events (Zegler, n.d.). For robustness, we also investigate water quality effects by season and over the full year.

Conservation Practice Adoption

We obtain our data on conservation practice adoption for the years 2015–2021 through a paid data use agreement with Regrow Agriculture Inc. Using a proprietary classification model, Regrow analyzes Landsat satellite data to detect several different conservation practices and aggregates them to the subwatershed (HUC 12) level. Specifically, we use Regrow data measuring: (1) the proportion of agricultural land in a HUC 12 practicing cover cropping,[7] (2) the proportion of agricultural land in a HUC 12 practicing reduced tillage (including no-till), and (3) a proprietary measure from 0 to 7 of “living root" or the extent to which land in a HUC 12 is in an active state of greening. Cover cropping and reduced tillage are established agricultural conservation practices that aim to reduce soil erosion and improve soil health. Similar conservation data have been used in a number of related studies that estimate the impact of federal spending on conservation adoption (Park et al., 2022) and the impacts of conservation on crop revenue losses (Aglasan et al., 2023).

Land Use

We compile annual HUC 12 land uses from the remotely sensed Cropland Data Layer (CDL). This data gives us a granular view at farmers’ cropping decisions year to year that more aggregated measures do not (e.g., county-level crop area collected by the National Agricultural Statistics Service). We construct measurements of total annual agricultural acreage and the percent of crop acres devoted to specific row crops. To aggregate agricultural acreage, we count acreage devoted to all crops and pasture land.[8] We include pasture to be inclusive of all types of potentially polluting agricultural activity, since some PLW groups focus specifically on grazing cattle and manure management. To test for behavioral change in crop choices, we focus on the percentage of acres that grow corn, soybeans, and small grains (i.e. wheat, barley, and oats), which are the dominant crops in the state of Wisconsin.

Weather

We control for weather conditions that impact the level of nutrients in the water. We use daily weather measures from PRISM. We aggregate raster data at the 4x4km grid level to the subwatershed level to reflect the weather conditions that may influence nutrient concentrations at a given

[7] The timing of the cover crop adoption data corresponds to the winter months between the harvest of the previous cash crop and the planting of the next. We are unable to distinguish whether these are winter cash crops or subsidized conservation cover. The mechanisms through which these impact water quality are similar; however, the implications for the net costs and benefits differ.

[8] CDL does not distinguish between grasslands not used for grazing and pasture lands used for grazing. Instead, our measure categorizes both land uses as agricultural land.

monitor. Our preferred specification controls for daily temperature, daily precipitation, precipitation squared, cumulative precipitation over the previous week, and monthly growing degree days.

We control for daily mean temperature as is common in the literature (Keiser and Shapiro, 2018; Raff and Meyer, 2022). Temperature impacts nutrient dynamics both directly and indirectly (Dory et al., 2024). Higher temperatures accelerate weathering, mineralization, and microbial processes in the nutrient cycle, leading to an increase in the rate and amount of phosphorus released into the water (Guo et al., 2024). We introduce a measure of the monthly growing degree days (0-29 degrees Celsius) to capture the accumulated heat effects that impact nutrient levels through plant activity. Higher degree days are associated with plant growth which will increase the take-up of nutrients, potentially reducing nutrient runoff.

We account for the effects of precipitation in a number of ways. We control for daily precipitation as well as squared daily precipitation. Rainfall causes surface runoff which transports nutrients to rivers, increasing nutrient concentration. Conversely, increased river flow can also dilute nutrient concentrations, making the net effect of precipitation ambiguous (Tilahun et al., 2024). To capture this non-linearity, we include both the linear and squared terms of daily precipitation. Additionally, we account for whether the week preceding a water quality reading included an extreme rainfall event, defined as more than 0.5 inches of rain in a single day. Such heavy precipitation events can trigger runoff by eroding the soil and carrying sedimentized nutrients into surface waters. Skidmore, Andarge, and Foltz (2023b) find evidence of significantly higher surface water phosphorus levels a week after heavy precipitation events. This effect is especially pronounced in the spring—our primary period of analysis—when fertilizers are applied to frozen or uncultivated fields.

4 Empirical Design

Our empirical strategy measures how local water quality and agricultural practices change in response to the spatially and temporally explicit PLW participation.

However, PLW groups are not randomly created and assigned. For example, farmers must select into the application process in a given year, and that propensity to apply may be correlated with water quality and agricultural outcomes. Therefore, we implement a research design in the spirit of a shift-share IV. Our instrumental variables approach leverages supply shifts made to the program by the Wisconsin Governor and State Legislature, which allowed new groups to form and be funded. Specifically, we interact temporal changes in the program's budget (i.e. *the shifts*) with the time-invariant percentage of a watershed's area that is devoted to agriculture in 2010 (i.e. *the shares*). The intuition behind this approach is that exogenous shifts in the program's overall budget differentially affect PLW participation across subwatersheds based on agricultural intensity, which we measure in 2010 before the program was conceived.

To estimate the impact of farmer-led initiatives on local water quality, we estimate the two-stage equation (1):

$$\begin{aligned} WQ_{iwdy} &= \beta_1 \hat{PLW}_{wy} + \Gamma X_{iwdt} + \alpha_i + \lambda_{dy} + \varepsilon_{iwdy} \\ PLW_{wy} &= \pi_1 Crop_{w,2010} \times Budget_y + \Pi X_{iwdt} + \alpha_i + \lambda_{dy} + \mu_{iy}, \end{aligned} \tag{1}$$

where WQ_{iwdy} measures nutrient concentrations at monitor i in subwatershed w on day d of year y. The treatment variable PLW_{wy} is the percent of the subwatershed's (w) agricultural acres that participate in a PLW group in year y. In the first stage, PLW_{wy} is predicted by the instrument $Crop_{w,2010} \times Budget_y$, which is the interaction of the time-invariant 2010 agricultural acreage in subwatershed w and the state-level, time-varying budget for the PLW program in year y. Following the literature, our exposure shares are fixed in a pre-period before our panel starts (Borusyak, Hull, and Jaravel, 2021).

In both stages, control variables in vector X_{iwdt} capture other panel variables that may be meaningful to local water quality outcomes (e.g., local weather). Fixed-effects control for fixed station level characteristics (α_i) and factors that change uniformly over time at a state level (λ_{dy}), like commodity prices. Regressions are weighted by 2010 crop acres in the subwatershed divided by the number of water quality readings within a subwatershed in a given month.[9] Standard errors are multi-clustered at the HUC 10 and year level to allow for correlation among monitors in neighboring HUC 12 watersheds that may have been simultaneously been treated and among observations sampled from a monitor in the same year (Abadie et al., 2023).

Given the set of fixed-effects, the identifying variation from the instrument compares outcomes within location in years with higher PLW budgets to lower-budget years (or pre-treatment years) and where those annual shocks are realized differentially across space according to an area's agricultural land use intensity. Intuitively, this approach exploits similar variation to a difference-in-difference design with a continuous treatment measure. With our IV approach, our primary estimates isolate the *Local Average Treatment Effect* of PLW participation that is driven by budgetary expansion.

We use a similar strategy to identify the effects of PLW participation on local conservation outcomes as specified in equation (2). The outcome of interest here is C_{wy}, which captures the conservation variable of interest (e.g., % cover crops) in subwatershed w and year y. These models are weighted by 2010 crop acres in the HUC 12 subwatershed to estimate the treatment effect representative of the average agricultural acre. Standard errors are clustered at the HUC 10 level.

$$\begin{aligned} C_{wy} &= \beta_1 PL\hat{W}_{wy} + \Gamma X_{wy} + \alpha_w + \lambda_y + \varepsilon_{wy} \\ PLW_{wy} &= \pi_1 Crop_{w,2010} \times Budget_y + \alpha_i + \lambda_y + \mu_{wy} \end{aligned} \tag{2}$$

Identification

Shift-share designs may derive consistency in two ways: either the shares (Goldsmith-Pinkham, Sorkin, and Swift, 2020) or the shifts (Borusyak, Hull, and Jaravel, 2025) need to be exogenous. In our setting, we rely on the assumption that the shifts– policy changes made by the Governor and State Legislature to the statewide PLW program budget– isolate a supply-driven component of

[9] We first weight by HUC 12 crop acres since we are interested in measuring agricultural nutrient flows. Hence, this approach places more weight on monitors in agriculturally intensive areas than areas that may be susceptible to other forms of pollution, like urban sources. Then, multiplying by the inverse number of water quality readings ensures that stations with multiple readings in a month (or areas with multiple monitors) are not implicitly weighed more heavily than stations (or areas) that report just once.

PLW participation and are exogenous to local deviations in average water quality. Identification stems from the premise that a share-weighted average of the policy shifts is itself random, even if shares are possibly endogenous (Borusyak, Hull, and Jaravel, 2025).[10].

This strategy would be undermined if other pollution abatement activities were implemented *in the same time* and *in the same places*. While other pollution abatement activities do indeed exist in this context, like county-level nutrient management regulations (Skidmore, Andarge, and Foltz, 2023a) and the Wisconsin Phosphorus Rule (Raff, Meyer, and Wardle, 2025), it is unlikely they are correlated spatially and temporally with PLW groups since they have different scopes, are implemented by different agencies, and at different times.[11] Nevertheless, we later test the sensitivity of our primary estimates with a battery of robustness checks and falsification tests that include the most likely potential confounders as control variables.

There are two other requirements for the exogenous shifts approach to result in a consistent estimator in a panel data setting. First, it requires that there be a sufficient number of unique shocks that identify the effect. While our full panel comprises 19 years of data, policy shocks only occurred in the last 8 years (2016-2023). However, Borusyak, Hull, and Jaravel (2021) argues that this condition may be satisfied in shorter panels such as ours if the number of unique units and/or industries are sufficiently large. In our setting, with 1,800 unique subwatershed cropland shares and 8 years of policy levels, our identifying variation stems from about 14,400 unique subwatershed-year shocks.[12] Second, the shares must add up to one for the instrument to be interpreted as a share-weighted average of shifts. In our case, this requirement is satisfied since agricultural land and non-agricultural land shares sum to one (by construction). However, non-agricultural land share is effectively omitted since it is collinear with the agricultural land share and the fixed effects.

[10]Similar designs that rely on the exogeneity of shifts with time-invariant shares include Nunn and Qian (2014); Berman et al. (2017); Greenstone, Mas, and Nguyen (2020); Panza and Karakoç (2021); Lang (2021); Kern, Reinsberg, and Shea (2024); Davis and Haltiwanger (2024)

[11]The Wisconsin Phosphorus Rule, for example, is administered by the Department of Natural Resources and places requirements on point-sources, like municipal treatment plants, and was implemented in 2010.

[12]For reference, in a single-industry setup with panel data variation most similar to ours, Nunn and Qian (2014) uses 36 years of US wheat production (shifts) and 125 cross-sectional measures of propensity to trade with the US (4,500 shocks) to identify the effects of US food aid on domestic conflict in Africa.

Additionally, our approach must satisfy the two traditional identifying assumptions of instrumental variables models. First, the exclusion restriction in our setting requires that the legislative appropriations to the program cannot be correlated with local subwatershed outcomes except through the channel of the watershed groups that form, conditional on location and time-fixed effects. We believe that this assumption holds in practice, because the legislative body only determines the overall program budget and does not direct the funds to specific watersheds. A DATCP panel reviews grant applications and determines which subwatersheds are awarded each year, subject to the legislative budget constraint. Because requests have consistently exceeded the budget, an expansion of the overall budget allows new PLW groups to form and be awarded. Individual PLW groups then organized and engaged in pollution abatement activities and programming. Therefore, we believe the exclusion restriction holds in our setting due to the fact that individual farmers who eventually participate in PLW groups have no feasible way to endogenously influence the overall budget for the program in a systematic way.

Second, the instrument must be a meaningful predictor of the endogenous treatment variable. Table 2 shows the results from the first stage. The table shows that an increase in the state budget for the PLW program multiplied by the 2010 crop acreage share is a strong predictor of local subwatershed participation in the period of the budget shock with F-Statistics that exceed conventional thresholds. Column 1 displays the results from the full sample. Column 2 displays the first-stage results for 2015-2021 and corresponds to the subsample of years that we observe conservation practices as discussed above. This strong first-stage relationship is explained by the fact that demand for PLW grants perennially exceeds the program's budgetary cap. Therefore, the expansion of the budget is a necessary condition for new PLW groups to be able to form. And when new groups do form, they tend to form in areas that are agriculturally intensive in the state.

Table 2: First Stage IV: PLWG Participation and Program Budget Expansion

	% PLW Acres	
	(1) 2005-2023	(2) 2015-2021
2010 Crop Pct * Program Budget	1.082**	1.307**
	(0.429)	(0.576)
Num.Obs.	34276	10591
F Stat	618.0	124.7
HUC 12	X	X
Year	X	X

* p < 0.1, ** p < 0.05, *** p < 0.01

Note: Regression results are the first-stage estimates of PLW participation on the shift-share instrument. Column 1 includes the full-sample of years from 2005-2023, and Column 2 is the sub-sample corresponding to the conservation practice data from 2015-2021. Standard errors are clustered at the HUC 10 and year level. Regressions are weighted by the 2010 crop acreage in the HUC 12 watershed.

5 Results

We organize our results into four categories. First, we report the direct effect of PLW groups on water quality. Second, we report the impact of PLW groups on different conservation practices that are likely the mechanisms behind our headline results. Third, we assess heterogeneity within our main findings. Finally, we conduct a number of robustness and placebo exercises.

Water quality

Table 3 contains estimates of the effect of PLW groups on surface water phosphorus concentrations measured in milligrams per liter. Panel A displays the results from the OLS specification, and Panel B presents results from the two-stage least squares (2SLS) model, where participation is instrumented by the shift-share approach described earlier. In each specification, the independent variable of interest is the proportion of agricultural acreage in a HUC 12 that belongs to a PLW group. Specifications in column (1) only include monitor-, year-, and month-fixed effects as controls. Specifications (2) through (5) gradually add additional controls. Our preferred specification (specification (5)) includes weather controls, year-by-day fixed effects, and monitor-by-month

Table 3: Effect of Producer-Led Groups on Phosphorus Concentrations

	Phosphorus (mg/L)				
	(1)	(2)	(3)	(4)	(5)
Panel A. OLS					
% PLW Acres	−0.001*	−0.001*	−0.001*	−0.001*	−0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B. 2SLS					
% PLW Acres	−0.003**	−0.003**	−0.003**	−0.003**	−0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Dep. Var. Mean	0.21	0.21	0.21	0.21	0.21
Observations	38462	38462	38462	38462	38462
1st Stage F Stat	1248.5	1273.0	1266.8	1256.5	1379.9
Weather Controls			X	X	X
Fixed Effects:					
Monitor	X	X	X	X	
Year	X				
Month	X				
Year x Month		X	X		
Year x Day				X	X
Monitor x Month					X

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The dependent variable is the phosphorus concentration (mg/L) in levels at the monitor-level. Standard errors are multi-clustered at the HUC10 and Year. Regressions are weighted by 2010 crop acres divided by the number of water quality monitors per watershed per month. Cragg-Donald F-statistics for the first stage

fixed effects. Both OLS and 2SLS offer evidence that PLW participation reduces ambient phosphorus amounts, but we focus on the 2SLS estimates as our central results because they control for potential endogeneity bias in the OLS estimates.[13] In each of the 2SLS specifications, we find that an additional 10 percentage points of agricultural acreage belonging to a PLW group decreases phosphorus concentrations by 0.03 mg/L (a 14% reduction). In our preferred specification (column 5, Panel B), the point estimate is significant at the 1% level.

The results in Table 3 include observations from March through June, when over 75% of

[13]The OLS estimates are more conservative than the 2SLS, indicating that selection in our setting is correlated with worse water quality. This also appears to be true in the cross-section when comparing average phosphorus concentrations (Figure 2(b)) and PLW groups (Figure 1(b)).

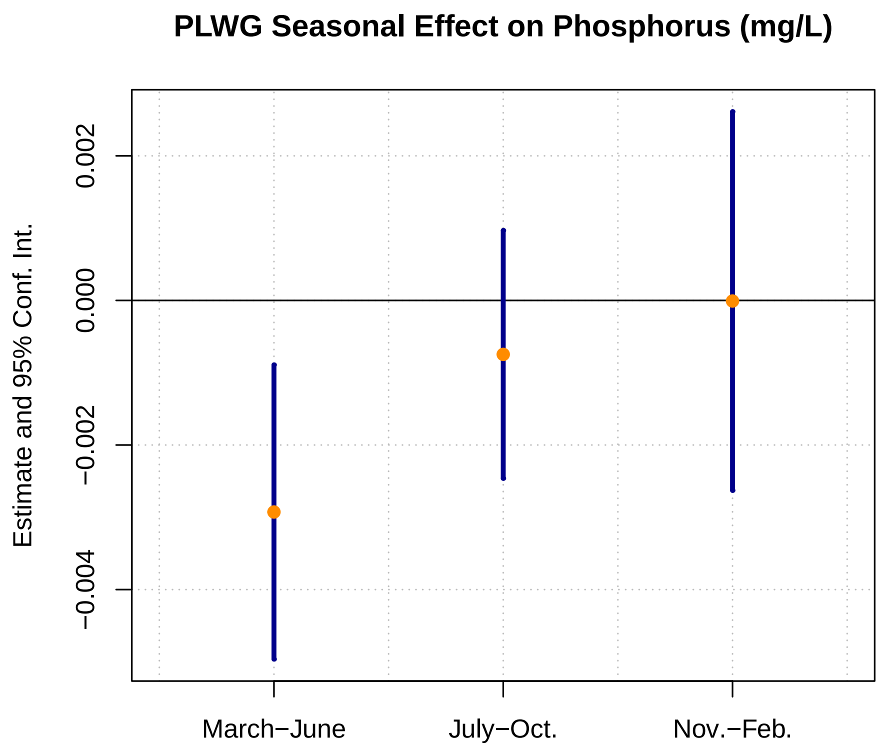


Figure 3: Seasonal Effects of PLW Groups on Phosphorus Concentrations
Note: Figure displays the regression coefficients of phosphorus concentrations on PLW participation. The regression allows for treatment effect heterogeneity by the season of the year in which concentration is observed. Regressions are weighted by 2010 crop acres in the HUC 12 watershed, divided by the number of monitors per subwatershed per month. Standard errors are clustered at the HUC 10 and year level.

annual runoff and water quality impairment occur (Zegler, n.d.), and when primary agricultural conservation practices are in place and likely to be most effective. Figure 3 supports this choice. The figure reports our coefficient of interest estimated using observations from three different seasons: March-June, July-October, and November-February. The largest and most significant effects of PLW participation on water quality occur in the spring months.

Table 4 presents the 2SLS estimates of PLW participation on alternative water quality measures both during the spring (March through June) and throughout the entire year. Columns (1)–(2) present estimates for phosphorus, columns (3)–(4) for TKN, and columns (5)–(6) for ammonia. First, we note that PLW groups have a larger impact on water quality in the spring than at other

Table 4: Effect of Producer-Led Groups on Alternative Water Quality Measures

	Phosphorus (mg/L)		TKN (mg/L)		Ammonia (mg/L)	
	(1) Spring	(2) All Year	(3) Spring	(4) All Year	(5) Spring	(6) All Year
% PLW Acres	−0.003***	−0.001*	−0.004	0.001	−0.001	0.001
	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)
Dep. Var. Mean	0.21	0.19	1.22	1.05	0.20	0.16
Observations	38462	97272	16507	40652	15664	39720
1st Stage F Stat	1379.9	3690.8	1987.9	4779.7	1629.3	4030.1

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The dependent variables are the phosphorus, TKN, and ammonia concentrations (mg/L) in levels at the monitor-level. Each regression includes weather controls, year-by-day fixed effects, and month-by-month fixed effects. Standard errors are multi-clustered at the HUC10 and Year. Regressions are weighted by 2010 crop acres divided by the number of water quality monitors per watershed per month.

times of the year. Second, we note that PLW groups have a larger impact on phosphorus concentrations than on nitrogen concentrations (TKN and ammonia). The results in column (3) suggest that a 10 percentage point increase in PLW acres decreases springtime TKN by 0.04 mg/L (less than a 3.5% reduction). However, none of the results on TKN or ammonia are statistically significant. One plausible explanation for the significant results on phosphorus but not nitrogen measures is that PLW groups and activities are particularly effective at reducing soil erosion. Phosphorus tends to bind to soil particles, while nitrogen compounds are more soluble and are prone to leaching downward through the soil into groundwater sources (which we do not observe here). Further, if cover crops themselves require additional fertilizer for growth — which is sometimes applied to maximize biomass for weed suppression — they may also add nitrogen to the soil, contributing to a mixed response.[14]

Conservation Mechanisms

We hypothesize that the effects of PLW groups on water quality are likely attributable to changes in producer behavior, including the increased adoption of conservation practices. We evaluate

[14] An alternative statistical explanation is that fewer measurements for both nitrogen compounds in this setting, relative to phosphorus, may limit statistical power and precision.

Table 5: Effect of Producer-Led Groups on Cropping Decisions

	Cover Crop (1)	Reduced Till. (2)	Liv. Root (3)	Corn (4)	Soy (5)	Small Grain (6)
% PLW Acres	0.280**	0.774**	0.022*	−0.015	−0.025	0.075**
	(0.135)	(0.387)	(0.012)	(0.074)	(0.058)	(0.037)
Dep. Var. Mean	2.7	27.8	3.2	24.1	10.7	3.1
Observations	10591	10591	10344	34274	34274	34274
1st Stage F Stat	145.6	145.6	147.7	652.3	652.3	652.3
Fixed Effects						
HUC12	X	X	X	X	X	X
Year	X	X	X	X	X	X

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The dependent variable is the share of agricultural acreage in a HUC 12 that implements the conservation practice or that grows a given crop, except for column 3. Column 3 dependent variable, the index of Living Root (0,7), measuring the degree of perenniality in a HUC 12. Standard errors are clustered at the HUC10 level. Regressions are weighted by 2010 crop acres in the watershed.

this hypothesis in Table 5. Each column uses our preferred 2SLS specification to evaluate the effect of PLW participation on a different production practice: cover cropping, reduced tillage, maintenance of living roots, corn production, soy production, and small grain production. We find that a 10 percentage point increase in PLW acreage increases the prevalence of cover cropping, reduced tillage, living roots, and the production of small grains by 2.8 pp, 7.7 pp, 0.2 pp, and 0.8 pp, respectively. However, PLW participation does not have a statistically significant impact on the prevalence of corn or soy acreage.

These results are consistent with the explanation that PLW groups drive producers to adopt conservation practices that maintain living cover on agricultural land and minimize soil disruptions. These practices, in turn, have been previously shown to improve soil erosion and nearby water quality, especially through the reduction of phosphorus in surface water.

Downstream Impacts

Upstream practices may impact downstream water quality outcomes. We empirically explore this in our setting by linking monitors with upstream PLW participation based on upstream-downstream relationships established by the National Hydrography Dataset (NHD). [15] In cases where multiple upstream subwatersheds flow into a single downstream watershed, we construct upstream treatment in three ways: 1) the simple average of upstream PLW acreage percentage, 2) weighted average by upstream crop acres, and 3) weighted average PLW acreage percentage by streamflow amounts. Using these alternative upstream metrics, we estimate our primary specifications on phosphorus and include upstream treatment. Results from these regressions are presented in Table A1.

These results show that upstream PLW participation does not lead to a detectable downstream effect on phosphorus in our setting across all three methods of constructing upstream treatment. The primary coefficient from our main treatment – the PLW participation in the same HUC 12 – remains approximately the same size with and without inclusion of upstream treatment. The standard errors of the primary coefficient in the upstream models are larger, but this is likely due to the limited sample of upstream-downstream relationships, as shown by comparing Column 1 (full sample) with Column 2 (upstream-downstream sample).

Heterogeneity

We explore heterogeneous treatment effects along dimensions of group and environmental characteristics. First, Figure A1 displays a coefficient plot that partitions the treatment effect by the median group's age (>4 years old), the median group size (>53 farmers), and the median amount of primary crops they grow (corn and soybean acreage). This figure shows that treatment effects do not significantly differ across group characteristics, but the confidence intervals appear to be narrower for older and larger groups and groups that are less corn and soybean intensive.

Second, we investigate how environmental characteristics, like weather and soil, affect the average treatment effect. Figure A2 displays coefficients for treatment broken down by median

[15] Notice that our sample size decreases when we link HUCs to their upstream subwatersheds. In Wisconsin, there are 1,807 subwatersheds, which flow into 930 unique downstream subwatersheds. This implies that many subwatersheds have no upstream contributors. In such cases, water may flow into adjacent watersheds, collect in the lowest point within the HUC 12, or infiltrate into groundwater. We leave these upstream values as missing rather than assigning a value of zero, so as to avoid incorrectly including them in our regressions.

rainfall in that month, median growing degree days, and by median amount of the HUC 12 area that is covered by water. Figure A3 shows results decomposed by SSURGO soil characteristics. Again, this set of results does not show significant differences across these dimensions. But the treatment effect is marginally larger and more precise in less rainy months, months with less GDDs, and areas with more open water (Figure A2), and in soils that are more highly susceptible to erosion and runoff (Figure A3). In general, we cannot draw substantive conclusions about treatment effect heterogeneity in this setting. If anything, PLW participation seems to improve phosphorus concentrations the most in areas that we expect the conservation cropping mechanisms to be most effective, aligning with the agronomic research on these practices.

Robustness Checks

Our results may be biased if other factors that affect water quality simultaneously change in the same locations as the PLW program. We test this possibility by including control variables for four other factors that have been shown to impact ambient water quality in this setting: 1) localized regulations, 2) participation in other conservation programs, 3) simultaneous changes in other agricultural activity, and 4) trends in phosphorus emissions from point sources. First, if other local programs or regulations were simultaneously implemented with PLW groups, our estimates may reflect the cumulative effect of these mechanisms rather than one that is solely attributable to the PLW program. Perhaps most concerning in this setting is the possibility that counties implement new rules that have been shown to affect local water quality, like county regulations on nutrient management plans (Skidmore, Andarge, and Foltz, 2023a). We test for possible omitted variable bias through this channel by including a control variable, taken from Skidmore, Andarge, and Foltz (2023a), indicating whether the county that the water quality monitor is located in requires nutrient management planning in a given year. The results from this regression are presented in Column 1 of Table A2, and show that our primary estimates on PLW participation remain unchanged.

Second, our estimates may be biased if participation in the PLW program was correlated with participation in other conservation programs, like USDA Environmental Quality Incentives

Program (EQIP) or the Conservation Stewardship Program (CSP). Using our main IV specification, we test whether participation in PLW affects the likelihood of receiving funding from these USDA programs.[16] Table A3 examines whether PLW participation is associated with a higher likelihood of EQIP and CSP uptake in that county, but these results show that there is no meaningful change in these programs due to PLW participation. We further test whether participation in USDA programs introduces omitted variable bias that may affect our results by including funding support from these two programs as control variables in separate regressions. Results from these models are displayed in columns 2 and 3 of Table A2. While these variables may be bad controls, the magnitude of our primary point estimates on PLW participation remains stable with and without these controls. These models are marginally less precise than the main specifications, but this is attributable to the smaller sample size, because EQIP and CSP payment data are only available for a limited number of years.

Third, simultaneous changes in local agricultural production may also affect local water quality. In Wisconsin, dairies and dairy cattle are a well-known source of nutrient pollution (Raff and Meyer, 2022). We control for changes in county-level dairy cattle populations in column 4 of Table A2.[17] Fourth, point sources, like municipal wastewater plants or manufacturing facilities, emit phosphorus to water bodies and are regulated under federal and state laws, like the Clean Water Act. In column 5, we include a control variable for the annual pounds of phosphorus emissions by point sources within the HUC 12, retrieved from the EPA's Discharge Monitoring Report. The marginal effect of PLW groups remains unchanged across columns 4 and 5, and if anything, the estimated effect is more precise by including dairy cattle and point source controls.

In column 6 of Table A2, we control for a HUC 8 by year fixed effect in an attempt to control for all other potential localized factors or policy changes that may change throughout our sample. This encompasses participation in federal programs as well as state- or county-level initiatives (e.g., Wisconsin Great Lakes Restoration Initiative, DATCP county conservation grants). Rather than

[16] County-level USDA NRCS payment data from 2014-2023 are obtained from publicly available sources, and can be accessed here: `https://www.farmers.gov/data/financial-assistance-download`.

[17] County-level cattle inventory are integrated from the annual NASS Survey.

attempting to control for each program individually, the fixed effects plausibly capture these local time-varying changes. This model compares monitor readings within the same HUC 8 and year with and without a PLW group. This set of fixed effects absorbs a meaningful share of identifying variation in our primary treatment variable–a tradeoff that reduces our statistical precision but helps control for potential sources of biases. Still, the estimates in this model remain relatively stable in magnitude to this granular set of controls.

To support that our results are not sensitive to model specification, Table A4 reflects the primary results on phosphorus concentrations, but where the outcome is logged concentration. These point estimates are similar to Table 3 in both magnitude and statistical precision. Second, Table A5 presents the results on phosphorus concentrations – in both the spring months and year-round – when monitor readings are aggregated to the monthly HUC 12 level. The magnitude of these results are comparable to our main estimates. We lose the ability to control for monitor-level unobservables in these models, and thus, the standard errors are larger in these estimates. These sets of alternative specifications are two common approaches in the literature, and they give evidence that our results are consistent across the modeling and aggregation choices that we made in this paper.

Finally, Appendix Section A2 replicates our main specifications on water quality and conservation practices, but replaces the endogenous treatment variable with the awarded amounts of grant dollars. Table A7 and Table A8 provide similar qualitative evidence that PLW grants decrease ambient phosphorus levels and increase the adoption of agricultural conservation practices. However, these results are generally less precise, likely due to grant dollars being a noisy measure of actual group size.

Randomization Tests

As discussed earlier, the primary estimates rely on the assumption that budgetary changes to the PLW program are exogenous to farmers' decisions. We provide descriptive support for this assumption in section 4. We also quantitatively support this assumption with two sets of Fisher randomization tests (Fisher, 1971). In particular, we construct random permutations of the instrument and test the likelihood that we would observe the same estimates under alternative distributions of the shifts and shares over time and across space.

We first randomize the cross-sectional 2010 crop acreage shares across different subwatersheds, $Crop_w, 2010$, but preserve the temporal budgetary shifts across the years, $Budget_y$. We construct new instrumental variables with the randomized shares and the actual budget level and re-estimate the reduced-form version of the model. We perform this process 1,000 times, and save the point estimates from each iteration. This analysis examines whether there are unobserved, temporal confounders that drive the results. If the unexplained errors are correlated with $Budget_y$, we would expect the distribution of point estimates from this exercise to be non-zero. Figure 4(a) presents the distribution of point estimates from this exercise, and Figure 4(b) presents the distribution of t-statistics. Both distributions are centered around zero, supporting the exogeneity of the budgetary shifts, and the reduced form point-estimate from the observed data ($\beta = -0.012$) lies outside of the empirical 95% confidence interval.

In the same manner, we perform this exercise, but instead randomize the temporal shifts across the data and preserve the crop shares. This tests whether unobserved, cross-sectional factors drive the results. For example, if certain HUC 12s in the state receive disproportionate support from other programs, and that support affects water quality, we would anticipate that the distribution of randomized instruments to be statistically different from zero. Figures 4(c) and 4(d) present the distribution of point estimates and t-statistics from this exercise. Again, the distributions are centered around zero, and the realized estimates are outside the empirical 95% confidence interval. When taken together, these results support the primary assumption that the results that our results are driven by the unique observed combination of crop shares and budgetary shifts and reinforce the IV approach in this paper.

Table 6: Estimated Conservation Impacts and Costs from PLWG Program

	Cover Crop	**Reduced Till**
Marginal Conservation Effects from Program		
PLWG acreage pp increase from $100,000 budget increase	1.08	1.08
Conservation pp increase from 1 pp increase in PLWG acreage	0.28	0.77
Conservation pp increase from $100,000 budget increase	0.30	0.83
Total Statewide Acreage Effects from Program		
Mean crop acreage of subwatershed	12,199	12,199
Conservation acreage increase from $100,000 at avg. HUC	37	101
Number of active HUC12 Watersheds (2021)	235	235
Additional statewide conservation acres	8,669	23,840
Cost per acre of conservation	$11.54	$4.19

6 Discussion

To contextualize the environmental impacts of the program, we (1) estimate the costs of conservation adoption to benchmark against other policy initiatives, (2) compare the magnitude of phosphorus reductions to those found in other program evaluations, and (3) assign a monetary value to the phosphorus reductions using the methodology of (Raff and Meyer, 2022).

We use a back-of-the-envelope calculation to estimate the marginal cost of expanding cover crops and reduced tillage coverage through the program. Table 6 summarizes our approach. We begin with our first-stage estimates (from Table 2), which show that an additional $100,000 in the budget increases program acreage by 1.08 pp. From Table 5, we know that a 1 pp increase in PLW acreage leads to a 0.28 pp increase in cover crops and a 0.77 pp increase in reduced till. Combining these estimates tells us the marginal increase in conservation activity: A $100,000 budget increase translates into a 0.30 pp increase in cover crops and a 0.83 pp increase in reduced tillage.

To estimate the total induced conservation activity, we multiply these marginal effects by the average agricultural acreage per subwatershed in Wisconsin. This implies that a $100,000 budget increase leads to 37 additional acres of cover crops and 101 additional acres of reduced tillage per subwatershed. For context, the average subwatershed has 354 cover crop acres and 3,904 reduced till acres. These estimates represent 10.45% and 2.59% increases, respectively.

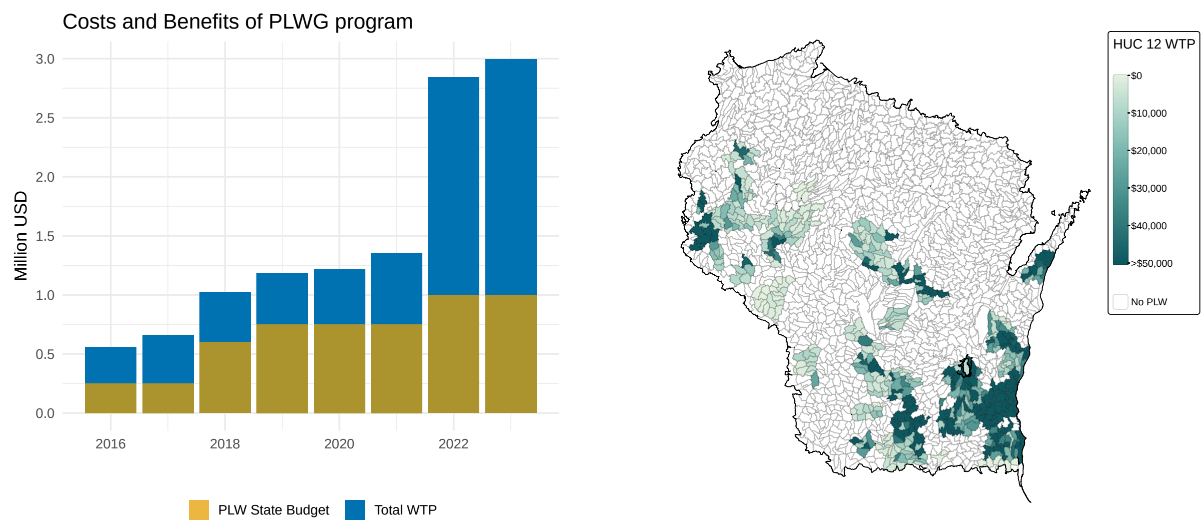
There were 235 subwatersheds involved in the program as of 2021. The total statewide impact from the budget increase aggregates to approximately 8,700 acres of cover crops and 24,000 acres of reduced till. Dividing the $100,000 budget increase by the total induced acreage yields marginal costs of $11.54 per acre for cover crops and $4.19 per acre for reduced tillage.[18] In comparison, in Wisconsin, the NRCS pays farmers $42–$73 per acre for cover crop and $16–$43 per acre for reduced tillage (2023).[19]

A 1 percentage point increase in cropland enrolled in the program reduces phosphorus concentrations in surface water by 0.003 mg/L, representing a 1.42% decline relative to the mean concentration of 0.21 mg/L. This level of water quality improvement is comparable to that achieved through other interventions. For instance, similar phosphorus reductions could result from the removal of 0.75 concentrated animal feeding operations from a watershed (Raff and Meyer, 2022), implementing nutrient management planning on 60% of watershed acreage (Skidmore, Andarge, and Foltz, 2023a), or achieving a 10.3% reduction in fertilizer application within the watershed (Paudel and Crago, 2021).

To contextualize the benefits induced by the PLW program, we translate our phosphorus reductions to a monetized value through a benefits transfer function (U.S. Environmental Protection Agency, 2009), similar to the approach by Raff and Meyer (2022). Step-by-step details of this calculation are provided in Appendix A3. We find that the PLW grant program provided annual social benefits ranging from $0.5 - $3 million, exceeding the program's annual budget threefold in the most recent years, as shown in Figure 4(a). The program benefits are largest near population centers, like Milwaukee and Madison, and in areas that had high baseline phosphorus levels. This valuation exercise reveals that, to date the program's benefits substantially outweigh the costs. However, given that PLW groups already exist in the most populated areas of the state, there may be diminishing social returns to expansion of the program into new areas in the future. Agri-

[18] Using an alternative estimation based on dollar point estimates from Tables A8 and A6 yields similar results: 12,642 acres of cover crops at $7.91 per acre, and 34,831 acres of reduced tillage at $2.87 per acre.

[19] In a state level water quality program in Maryland, farmers were paid $45 per acre of cover crops in 2009 ($68 per acre in 2025 dollars) (Fleming, Lichtenberg, and Newburn, 2018). In Michigan, Surdoval et al. (2024) estimates that every additional EQIP dollar for cover crops increases cover crop adoption by 0.0247 acres ($40 per acre).



((a)) PLW Benefits vs. Costs

((b)) Calculated WTP for PLW Program

Figure 4: Benefits of the PLW program Over Time and Across Subwatersheds
Note: Panel A compares the estimated benefits of the PLW program to the actual state-level budgets from 2016-2023. Panel B displays the spatial distribution of willingness to pay (WTP) benefits across HUC 12 subwatersheds. Methods for the benefits calculations are in Appendix A3.

cultural conservation programs in other states may be most beneficial by prioritizing agricultural production near population centers.

We show in this paper that an alternative, farmer-led policy approach to nonpoint source pollution can provide improvements in water quality at a relatively cost-effective rate. Furthermore, we document that these improvements in water quality likely stem from the increased adoption of key conservation practices, like cover cropping and reduced tillage, four to five times more cost-effectively than traditional conservation subsidy programs. This approach to nonpoint source pollution mitigation is unique to existing approaches, because it allows the polluters themselves to make decisions and influence peers. This approach stands in contrast to traditional conservation programs in the US that solely address financial barriers to adopting conservation practices. While some caveats exist, the evidence in this paper gives support that farmer-led conservation initiatives in other locations may be a viable alternative where first-best approaches are infeasible.

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Appendix

A1 Additional Tables and Figures

Table A1: Effect of Producer-Led Groups on Phosphorus Concentration: Robustness to Upstream Treatment

	Phosphorus (mg/L)				
	(1)	(2)	(3)	(4)	(5)
% PL Acres	−0.003***	−0.003*	−0.014	−0.002	−0.014
	(0.001)	(0.001)	(0.041)	(0.002)	(0.046)
Upstream % PL Acres			<0.001		
			(0.002)		
Upstream % PL Acres (weight=acres)				<0.001	
				(<0.001)	
Upstream % PL Acres (weight=streamflow)					<0.001
					(0.002)
Dep. Var. Mean	0.21	0.18	0.18	0.18	0.18
Observations	38462	23478	23478	23477	23478
F Stat	1379.9	623.6	357.7	330.8	366.5
Year x Day	X	X	X	X	X
Monitor x Month	X	X	X	X	X
Upstream HUC Sample		X	X	X	X

* p < 0.1, ** p < 0.05, *** p < 0.01

Note: The dependent variable is phosphorus concentration (mg/L) in levels at the monitor-level. Standard errors are multi-clustered at the HUC10 and Year. Regressions are weighted by 2010 crop acres divided by the number of water quality monitors per watershed per month.

Table A2: Effect of Producer-Led Groups on Phosphorus Concentration: Robustness to Alternative Controls

	Phosphorus (mg/L)					
	(1)	(2)	(3)	(4)	(5)	(6)
% PL Acres	−0.003**	−0.002	−0.003*	−0.003***	−0.003***	−0.002
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Dep. Var. Mean	0.21	0.22	0.22	0.22	0.21	0.21
Observations	38462	20676	18097	32532	38462	38462
1st Stage F Stat	1224.0	873.6	690.6	1210.3	1376.3	660.8
Year x Day	X	X	X	X	X	X
Monitor x Month	X	X	X	X	X	X
Controls	Co. NMP	EQIP $	CSP $	Dairy Cows	Point Sources	HUC8xYr

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The dependent variable is the phosphorus concentration (mg/L) in levels at the monitor-level. Standard errors are multi-clustered at the HUC10 and Year. Regressions are weighted by 2010 crop acres divided by the number of water quality monitors per watershed per month.

Table A3: Impact of PLW Participation on Uptake of Other Conservation Programs

	NMP Regulation	EQIP ($1,000)	CSP ($1,000)	EQIP #	CSP #
	(1)	(2)	(3)	(4)	(5)
% PL Acres	−0.008	2.794	1.207	0.449	−0.290
	(0.005)	(7.508)	(4.568)	(0.854)	(1.389)
Dep. Var. Mean	0.35	491.90	293.07	72.86	109.71
Observations	38462	20676	18097	20676	18097
F Stat	1379.9	873.3	693.8	861.5	693.8
Year x Day	X	X	X	X	X
Monitor x Month	X	X	X	X	X

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Standard errors are multi-clustered at the HUC10 and Year. Regressions are weighted by 2010 crop acres divided by the number of water quality monitors per watershed per month, consistent with primary specifications.

Table A4: Effect of Producer-Led Groups on Water Quality: Logged Concentration

	Phosphorus (mg/L)				
	(1)	(2)	(3)	(4)	(5)
% PLW Acres	−0.010*	−0.009*	−0.008*	−0.007*	−0.007**
	(0.005)	(0.005)	(0.004)	(0.003)	(0.003)
Dep. Var. Mean	−2.17	−2.17	−2.17	−2.17	−2.17
Observations	38 462	38 462	38 462	38 462	38 462
1st Stage F Stat	1248.5	1273.0	1266.8	1256.5	1379.9
Weather Controls			X	X	X
Fixed Effects					
Monitor	X	X	X	X	
Year	X				
Month	X				
Year x Month		X	X		
Year x Day				X	X
Monitor x Month					X

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The dependent variable is the phosphorus concentration (mg/L) in levels at the monitor-level. Standard errors are multi-clustered at the HUC10 and Year. Regressions are weighted by 2010 crop acres divided by the number of water quality monitors per watershed per month.

Table A5: Effect of Producer-Led Groups on Phosphorus Concentrations: Aggregated

	Phosphorus (mg/L)					
	Spring			All Year		
	(1)	(2)	(3)	(4)	(5)	(6)
% PL Acres	−0.004	−0.004	−0.004	−0.002	−0.002	−0.002
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Dep. Var. Mean	0.15	0.15	0.15	0.14	0.14	0.14
Observations	12514	12514	12514	37035	37035	37035
1st Stage F Stat	331.6	339.3	292.5	1003.9	1026.7	897.9
Fixed Effects						
HUC12	X	X		X	X	
Year	X			X		
Month	X			X		
Year x Month		X	X		X	X
HUC12 X Month			X			X

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The dependent variable is phosphorus (mg/L) aggregated to the HUC 12 and month level. Standard errors are multi-clustered at the HUC10 and Year. Regressions are weighted by crop acres in the HUC 12.

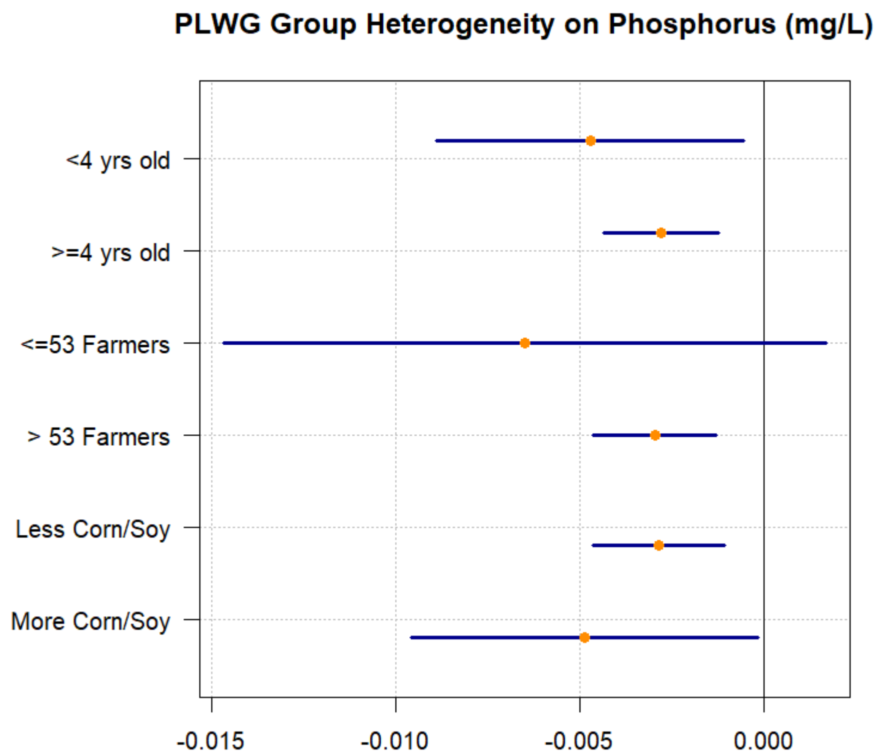


Figure A1: Heterogeneous Treatment Effects by Group Characteristics

Note: Figure displays the regression coefficients of phosphorus concentrations on PLW participation. The three regressions allow for treatment effect heterogeneity by the median group age, median group size (# of farmers), and median corn and soy acreage share, respectively. Regressions are weighted by 2010 crop acres in the HUC 12 watershed, divided by the number of monitors per subwatershed per month. Standard errors are clustered at the HUC 10 and year level.

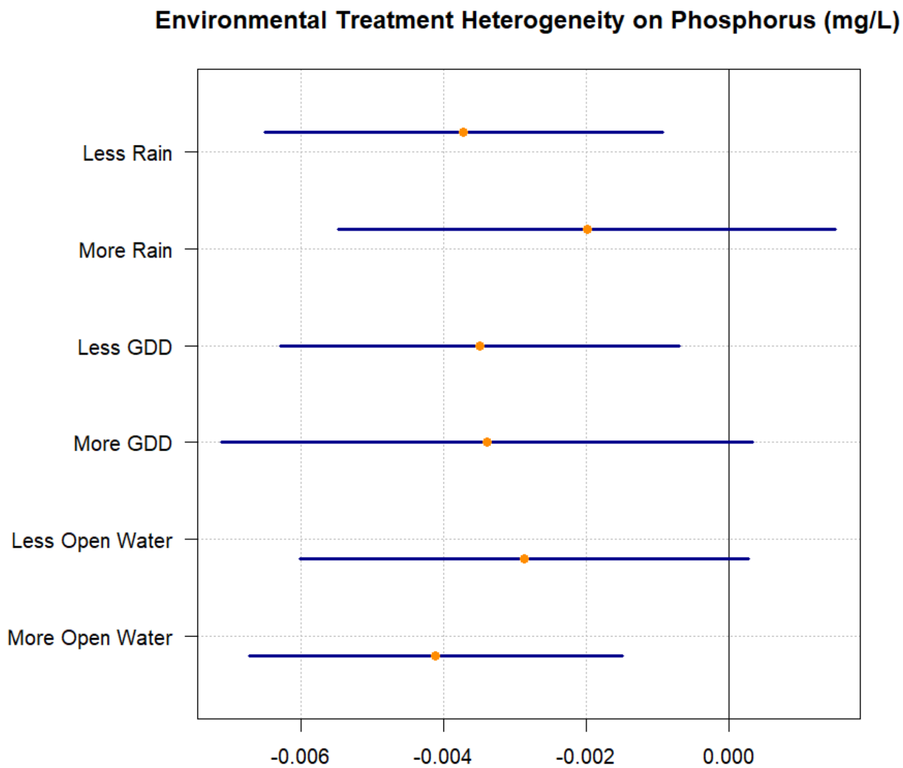


Figure A2: Heterogeneous Treatment Effects by Environmental Characteristics
Note: Figure displays the regression coefficients of phosphorus concentrations on PLW participation. The three regressions allow for treatment effect heterogeneity by the median rainfall amount, median growing degree days, and median water area share, respectively. Regressions are weighted by 2010 crop acres in the HUC 12 watershed, divided by the number of monitors per subwatershed per month. Standard errors are clustered at the HUC 10 and year level.

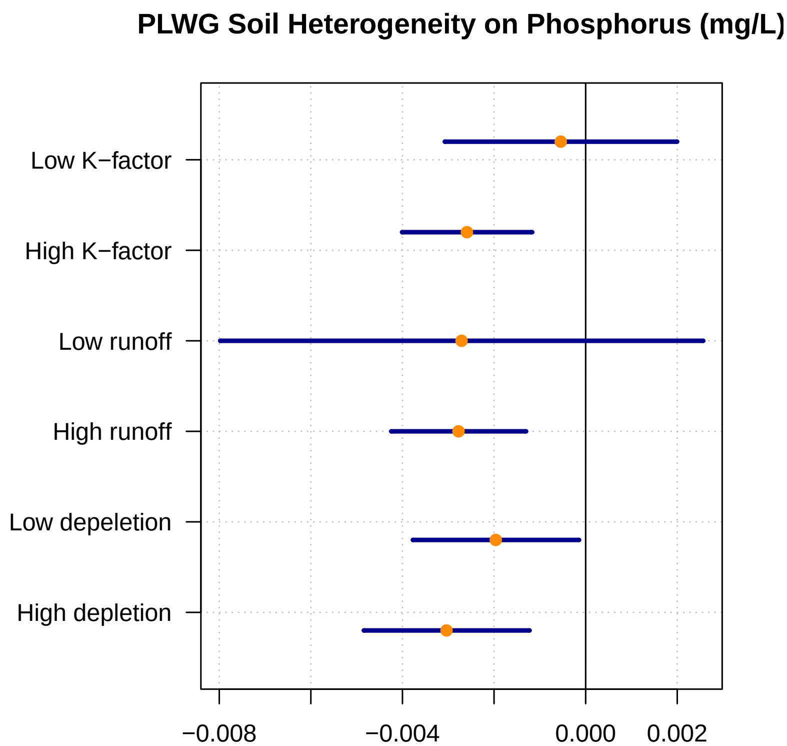
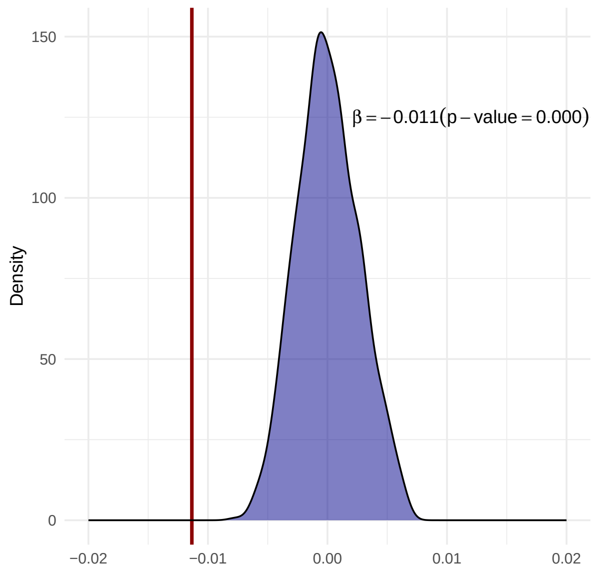
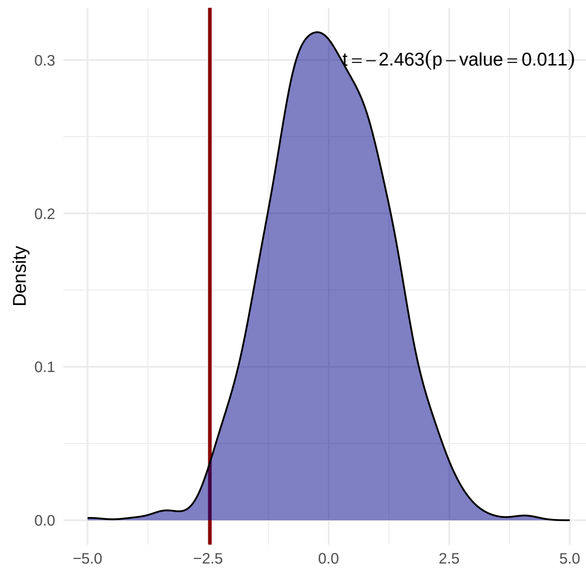


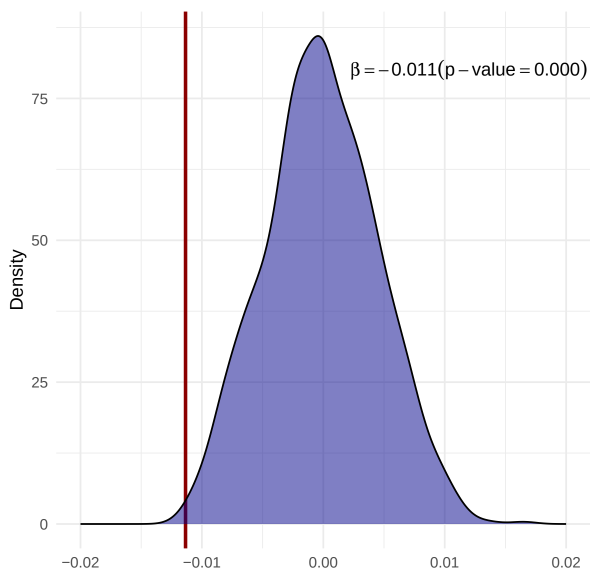
Figure A3: Heterogeneous Treatment Effects by Soil Characteristics
Note: Figure displays the regression coefficients of phosphorus concentrations on PLW participation. The three regressions allow for treatment effect heterogeneity based on soil metrics from the Soil Survey Geographic Database. K-factor is a soil erodibility index that measures how easily soil particles detach and move by water. Runoff potential is a measure of how likely soil is to produce runoff during rainfall, based on the infiltration rate and permeability of the soil. Soil organic matter depletion is a rating of the extent to which soil organic matter has been lost. Regressions are weighted by 2010 crop acres in the HUC 12 watershed, divided by the number of monitors per subwatershed per month. Standard errors are clustered at the HUC 10 and year level.



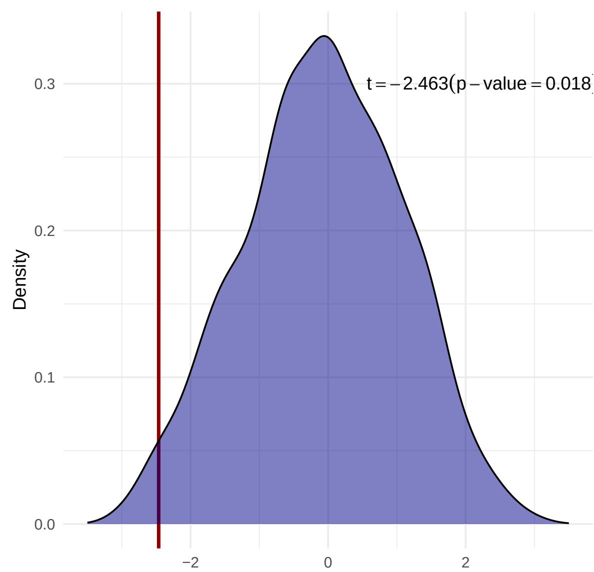
((a)) β: Cross sectional randomization



((b)) $t - statistics$: Cross Sectional randomization



((c)) β: Temporal randomization



((d)) $t - statistics$: Temporal randomization

Figure A4: Placebo Tests for Instrument Validity

Note: Figures display the distribution of coefficients from 1,000 regressions with random sampling permutations along cross-sectional (a-b) and temporal dimensions (c-d). The red line displays the estimate from the corresponding regression with the true observed data.

A2 Using Grant Dollars as Treatment Variable

Our preferred treatment variable measures the share of the total agricultural acreage that is represented by participating farmers in a PLW group. An alternative treatment measure is the amount of grant funding awarded to PLW groups from the Wisconsin DATCP. However, it should be noted that PLW groups typically generate funding from a variety of sources, including nonprofits (e.g., the Nature Conservancy) and private sponsorships (e.g., local agribusinesses), and the observed grant amounts from Wisconsin DATCP may be a poor measure of actual group size and programming.

We estimate the same model as before, except replacing the endogenous regressor of interest by the amount of grant dollars that a group receives divided by the HUC 12's agricultural acreage. Table A6 shows that the shift-share instrument remains a strong predictor of local grant awards. Table A7 reports the summary of these results with the main 2SLS specification. In general, these results imply that an additional dollar per 10 agricultural acres in a HUC 12 would reduce phosphorus concentrations by 0.04 (mg/L). At the average HUC 12, this would be an additional \$12,200/year. In comparison, an equivalent improvement in water quality would cost \$136,000 in technological abatement technology or \$23,600 in offset trading costs (Raff, Meyer, and Wardle, 2025). For context, groups are currently funded on average at 0.34 dollars per 10 acres (Table 1), so this one unit increase reflects a tripling of the current program size. These estimates are less precisely estimated than those on participation, likely stemming from the measurement error associated with using grant award amounts as a proxy for PLW group size.

We also show how grant dollars affect conservation practice adoption in Table A8. Again, these results support the primary findings from PLW participation, but with less statistical precision. Tripling the current budget of the programs would lead to increased cover crop adoption by 4.9 pp (182% increase from current levels) and reduced tillage adoption on 13.9 pp (49% increase from current levels) of acres.

Table A6: First Stage IV: PLWG Dollars Awarded and Program Budget Expansion

	2005-2023	2015-2021
2010 Crop Pct * Program Budget	0.070**	0.072*
	(0.028)	(0.039)
Num.Obs.	34 273	10 591
HUC12	X	X
Year	X	X

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Regression results are the first-stage estimates of grant dollars awarded per 2010 crop acre on the shift-share instrument. Column 1 includes the full-sample of years from 2005-2023, and Column 2 is the sub-sample corresponding to the conservation practice data from 2015-2021. Standard errors are clustered at the HUC 10 and year level. Regressions are weighted by the 2010 crop acreage in the HUC 12 watershed.

Table A7: Effect of Producer-Led Grant Dollars on Phosphorus

	Phosphorus (mg/L)				
	(1)	(2)	(3)	(4)	(5)
Dollars (per 10 acres)	−0.048	−0.045	−0.040	−0.035**	−0.035**
	(0.031)	(0.028)	(0.024)	(0.015)	(0.014)
Dep. Var. Mean	0.21	0.21	0.21	0.21	0.21
Observations	38 462	38 462	38 462	38 462	38 462
1st Stage F Stat	168.3	175.1	175.0	232.5	269.1
Weather Controls			X	X	X
Fixed Effects					
Monitor	X	X	X	X	
Year	X				
Month	X				
Year x Month		X	X		
Year x Day				X	X
Monitor x Month					X

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The dependent variable is the phosphorus concentration (mg/L) in levels at the monitor-level. Standard errors are multi-clustered at the HUC10 and Year. Regressions are weighted by 2010 crop acres divided by the number of water quality monitors per watershed per month.

Table A8: Effect of Producer-Led Dollars on Cropping Decisions

	Cover Crop (1)	Reduced Till. (2)	Liv. Root (3)	Corn (4)	Soy (5)	Small Grain (6)
Dollars (per 10 acres)	4.907*	13.548*	0.380*	−0.231	−0.377	1.120**
	(2.645)	(7.225)	(0.225)	(1.102)	(0.899)	(0.544)
Dep. Var. Mean	2.7	27.8	3.2	24.1	10.7	3.1
Observations	10591	10591	10344	34274	34274	34274
1st Stage F Stat	19.8	19.8	20.6	133.5	133.5	133.5
Fixed Effects						
HUC12	X	X	X	X	X	X
Year	X	X	X	X	X	X

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The dependent variable is the share of agricultural acreage in a HUC 12 that implements the conservation practice or that grows a given crop, except for column 3. Column 3 dependent variable, the index of Living Root (0,7), measuring the degree of perenniality in a HUC 12. Standard errors are clustered at the HUC10 level. Regressions are weighted by 2010 crop acres in the watershed.

A3 Description of Benefit Transfer Exercise

We monetize the value of phosphorus reductions following the methods of Raff and Meyer (2022). This approach translates changes in ambient phosphorus to changes in the water quality index (WQI). Then, the WQI serves as an input into the U.S. Environmental Protection Agency (2009) benefits transfer function to estimate how households value improvements to surface water quality under counterfactual scenarios.

We compile nutrient measurements for phosphorus, nitrogen, and total suspended solids and convert them to water quality sub-indices that range from 10-100 using the equations specified in U.S. Environmental Protection Agency (2009) Table 10-1.[20] We then calculate the geometric mean of the three subindices, weighting each component by approximately one-third. The average water quality index across our Wisconsin sample (2006–2023) is 56.13, indicating conditions classified as suitable for game fishing.

We investigate a counterfactual world in which we eliminate the PLW program. In a counterfactual dataset, we set the % PLW Acres to 0 for all observations. We use our main econometric model equation 1 to predict phosphorus levels under these counterfactual conditions. We then create a new water quality index with these counterfactual phosphorus readings, holding nitrogen and total suspended solids constant. In a scenario with no PLW acres, the mean water quality index is 54.2, signifying a two-point drop in water quality, or a 3% change. We then calculate the difference in the WQI between the original state of the world and our simulated counterfactual for each observation.

Next, we use the benefit transfer function to find the willingness to pay (WTP) for water quality improvements in our setting.[21] We then plug in the baseline water quality index, and the

[20] We convert our ammonia concentrations to nitrogen using nitrogen=0.865 + 7.094 x ammonia, and then calculate the mean nitrogen value for each subwatershed-year. The total suspended solids subindex requires eco-region specific thresholds, so we overlay the subwatersheds with the eco-region map and use the eco-region with the largest overlap. To address missing nitrogen or total suspended solids data, we substitute the mean of other readings within the subwatershed; if no subwatershed-level data exist, we use the state-level mean for Wisconsin.

[21] Like Raff and Meyer (2022), we use the assigned parameters in Table 10-11, with the exception of changing the mail variable to 1. For the income parameter, we use the mean annual household income in Wisconsin, $51,690 in 2023 dollars, from the American community Census in 2006 (U.S. Census Bureau, 2025)

percent change in water quality to solve for the WTP. The WTP per household for the program is \$5.44 per year at the mean and \$4.69 at the median. In comparison, the median Wisconsin household would be willing to pay \$11.92 per year to avoid a marginal CAFO in their watershed according to Raff and Meyer (2022). This matches intuition, since CAFOs contribute to both nitrogen and phosphorus concentrations, but we only observe changes in phosphorus in our setting.

We construct aggregate benefit measures by combining subwatershed-level population data with WTP estimates. Population estimates stem from a 2015 snapshot of 1km by 1km raster data from the Center for International Earth Science Information Network (CIESIN), Columbia University (2018). For each HUC 12, we calculate the average population density by taking the mean of all intersecting grid cells. We then multiply this density by the area of the HUC 12 to estimate its total population, which sums to approximately 6 million across the state. Assuming an average household size of 2.3, we derive the approximate number of households in each subwatershed. To reflect seasonal variation in water quality impacts, we divide estimated benefits by three, assuming improvements occur primarily during the spring months.

We aggregate by year and find the total statewide WTP per year for the PLW program. These benefits range from \$0.5-\$3 million USD per year. We compare these benefits with program costs in Figure 4(a). We find that our estimated benefits are about three times the program costs in the most recent years. However, it is important to note that subwatershed groups often receive additional funding from other NRCS programs, as well as from private and nonprofit partners. As a result, our cost estimates do not reflect the full expenses, but only focus on the known expenses to the state government to facilitate the program.

Finally, we find the total benefits in each subwatershed over our time period to spatially identify the areas with the highest benefits. We showcase these findings in Figure 4(b). We find that water quality benefits are highest in the southeastern part of the state, near urban centers where population levels are highest, baseline phosphorus levels are initially high, and the water quality improvements are estimated to be substantial.