Can Farmer-Led Initiatives Reduce Nonpoint Source Pollution?

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

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1 Introduction

Agriculture is the leading source 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 an alternative 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 overcomes 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 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 nutrient-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). To overcome the concern that farmers may opt into the program in non-random ways, we implement a shift-share instrumental variables strategy that exploits exogenous state-level changes in the program's budgetary cap—*the shifts*—interacted with local watershed crop acreage in 2010— *the shares*. 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 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 watershed'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 how much funding they received. Second, we assemble monitor-level phosphorus and ammonia 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 estimated annual conservation practice acreage at the HUC 12 level. Lastly, we collect annual precipitation and weather data from PRISM. These panel data allow us to control for local time-invariant unobservables through location-fixed effects and state-level shocks, like commodity price movement, through time-fixed effects.

We find that a 10 percentage point increase in PLW group participating acreage leads to a statistically significant 0.03 mg/L reduction in phosphorus concentrations. Ammonia 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 came at the cost of \$11.54 per acre and \$4.19 per acre for tillage reductions. 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 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 water quality outcomes, which generally shows that additional fertilizer and livestock contribute to higher nitrogen and phosphorus concentrations downstream (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 (Chen et al., 2019; Skidmore, Andarge, and Foltz, 2023a). On the other hand, Liu, Wang, and Zhang (2023) provides evidence that USDA-NRCS programs improve nitrogen and ammonia concentrations, but conversely, lead to worse phosphorus outcomes. We uniquely contribute to this literature by studying the effects of a novel 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. The policy intervention in our setting is unique, because it empowers the polluters (farmers) to locally govern themselves to improve environmental outcomes. These arrangements have proven to be effective in common-pool resource settings (Ostrom, 2010), primarily in groundwater management, where agricultural irrigators self-impose incentives to conserve groundwater (Smith et al., 2017; Orduna Alegria et al., 2024). However, we offer the first empirical evidence of collective governance managing nonpoint source pollution from agriculture. These regimes do not form organically, but are instead incentivized through modest grant funding. However, in our context, this bottom-up approach leads to more conservation participation and environmental improvement than traditional policy approaches and at a smaller public expense. Our findings offer a framework for the expansion of this policy approach into other settings, where traditional first-best approaches are infeasible.

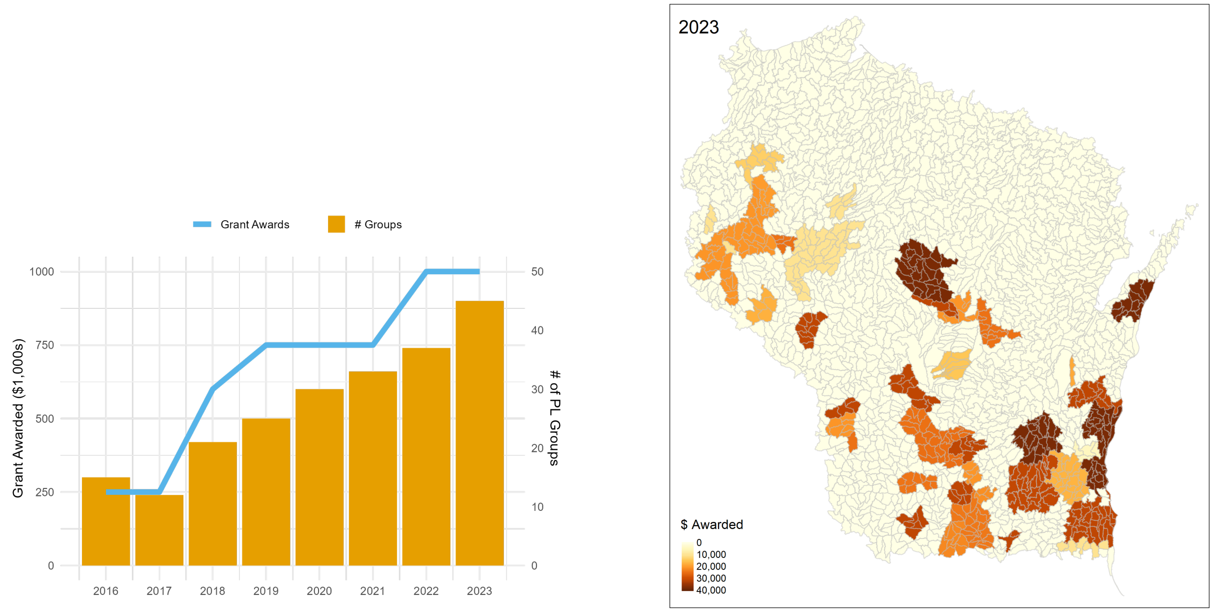
Finally, we contribute to a growing literature on the role of peer and network effects in agricultural practice adoption. Much of the economic work on this topic has been conducted in low-income country contexts throughout South Asia (Foster and Rosenzweig, 1995; Munshi, 2004), Africa (Conley and Udry, 2001, 2010; Beaman et al., 2021), and elsewhere, though several studies have also investigated farmer behavior in the United States (Kolady et al., 2021; 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 individuals to both organize and benefit from the groups' activities. This differs from a traditional model of agricultural extension where external "experts" are the source of new information or recommendations.

2 Background

The Wisconsin Producer-Led Watershed Program

To mitigate nonpoint source pollution, the Wisconsin Department of Agriculture, Trade and Consumer Protection (DATCP) created the Producer-Led Watershed (PLW) Grant program in 2016. The program allows for a group of farmers located in the same watershed to jointly submit a grant application outlining a nonpoint source abatement proposal. DATCP then awards up to $40,000 per year to each qualifying group. The grant funds are managed by each group's leadership team to facilitate educational events, on-farm research and demonstrations, and to directly subsidize best management practices. The legislative budget was capped at $250,000 in its initial year and funded 14 watershed groups. The program's budget has expanded multiple times over the following years, and it funded 43 watersheds a total of $1 million in 2023. Figure 1(a) plots the expansion of the program over time, and Figure 1(b) maps the distribution of active watershed groups in 2023.

This state-level program is a novel, bottom-up approach to reducing nonpoint source pollution from agriculture. It allows peer farmers to engage in pollution abatement activities that are best suited for the distinct environmental (e.g. soil, climate, water resources), management (e.g. crops versus livestock operations), and social contexts across the state. As an example, some groups



((a)) Awarded by Year

((b)) Awarded to Watersheds: 2023

Figure 1: Grant Awarded through Wisconsin's Producer-Led Watershed Program

in intensive dairy regions of the state have annual programming focused on manure management plans. While other regions of the state focus on mitigating nutrient losses in traditional row crop farming operations. Importantly, the program is designed to allow farmers themselves to be the leaders of water quality improvement, rather than strict, top-down regulatory measures.

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, and only a handful of farmers in a given group may benefit each year from these funds.[1]. 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. 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., extension educators, other farmers,

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

or agronomy consultants). 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 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).

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 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).

Cover crops are typically planted between the harvest and planting of main crops and provide a range of agronomic and environmental benefits. They enhance soil health by improving structure, increasing organic matter, supporting soil microbiology, and reducing erosion and compaction (Service, 2024). In Wisconsin and the Midwest in general, there are three broad types of cover crops: small grain/grass species (ryegrass, oat, sorghum, barley, wheat), brassicas (radish, rapeseed, turnips), and legumes/broadleaves (clover, cowpea, hairy vetch, field pea) (Smith et al., 2019). Their effectiveness in managing nutrient runoff depends heavily on the type used. While legumes fix atmospheric nitrogen and may increase nitrogen levels in the short term, grasses and brassicas scavenge residual nitrogen and reduce erosion and nitrate leaching (Blanco-Canqui et al., 2013; Gabriel, Vanclooster, and Quemada, 2014; **?**).

In theory, cover crops reduce surface water pollution by limiting soil erosion, nutrient runoff, and leaching. Cover crops are generally effective at reducing water and sediment runoff; however, the literature finds mixed impacts on nutrient runoff (Blanco-Canqui et al., 2013; Liu et al., 2014; Siller, Albrecht, and Jokela, 2016; Smith, Huang, and Haney, 2017). Many studies do find that cover crops significantly reduce nutrient leaching, particularly in corn-soybean systems with small grain covers (Feaga et al., 2010; Kaspar et al., 2012; Heinrich, Smith, and Cahn, 2014; Meisinger and Ricigliano, 2017). These benefits stem from nutrient scavenging, where cover crops absorb excess water and nutrients. Additional advantages include weed and pest suppression, which can reduce future fertilizer and pesticide needs. However, termination practices and cover crop selection may increase herbicide use or contribute nutrients in the short term. These competing processes mean that the relationship between cover crops and water quality is non-linear.

An alternative conservation activity aimed at improving 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 USDA defines conservation tillage as practices that manage the amount, orientation, and distribution of crop and plant residue on the soil surface throughout the year (Natural Resources Conservation Service, 2016a,b). 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. A minimum of 30 percent of land coverage is needed to prevent erosion, while conservation greater than 50 percent is recommended to increase organic matter (Bergtold and Sailus, 2020). Conservation tillage practices include no-till, mulch-till, ridge-till, strip-till, and chisel plowing. Notably, no-till adoption has been linked to higher farmland values, suggesting that producers recognize and long-run value of maintaining healthy soils and preventing degradation (Chen et al., 2023).

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. However, research on how these practices affect surface water quality, particularly nutrient pollution, shows mixed results. Results seem to vary based on the specific tillage practices, the slope of the land, the rainfall patterns, the type of nutrient outcomes measured, and whether water quality was measured at the surface or subsurface level.

Studies routinely show that conservation tillage is effective at reducing sediment and total solid runoff. Because total phosphorous particles adhere to soil particles, these practices also decrease total phosphorous runoff. Conservation tillage has been linked to lower phosphorous 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

Table 1: Summary Statistics

Variable	Obs	Weighted Mean	Std. Dev.	Min	Max
% 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

adoption of no-till cropping have lower amounts of suspended solids and total phosphorous in stream water. However, other studies find evidence that conservation tillage has null or even positive effects on nutrients, particularly for nitrogen levels in tile drainage water sources (Kanwar, Colvin, and Karlen, 1997; Zhao et al., 2001; Tan et al., 2002; Thoma et al., 2005).

3 Data

Our empirical approach pairs together 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

Information on the PLW grant program is obtained 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 are active in 2023 and the dollar amount that each of the groups received that year. 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 cropland acres represented by active participants each year.[2]

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 make a conservative assumption to fill in the missing values for the first three years of the program: If a group was active between 2016-2018, we impose the minimum acreage size from that group's observed sizes later in the sample. Typically, this was the 2019 reported value since group sizes tend to grow over time. 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 percentage is uniform throughout those eligible watersheds within the same PLW group.

Together, these data form the primary 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 watershed'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 (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.

[2]"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.

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 livestock 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 (Del Rossi et al., 2023).

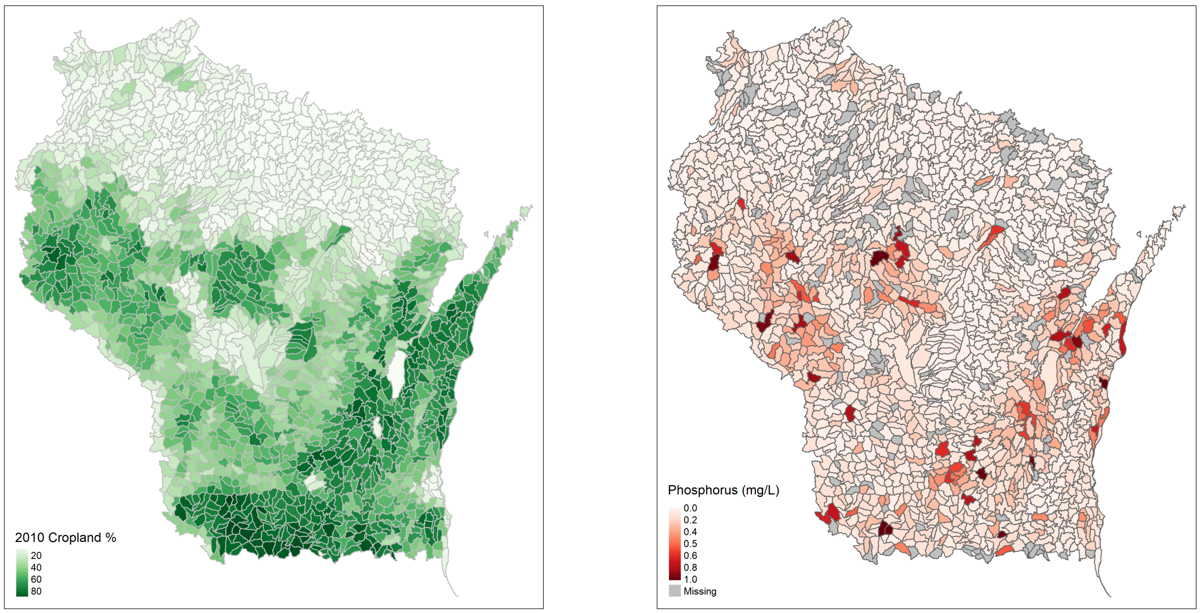
Although the ecological effects of nutrient pollution on water quality are well-documented, the connections between these physical changes and their impacts on people and wildlife remain relatively understudied. The economic damages associated with excess nutrient pollution are complex and multifaceted. 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 exclude outliers, effectively winsorizing our sample. 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. [3]

We measure nitrogen two-fold, as ammonia and Total Kjeldahl Nitrogen (TKN). We retain

[3]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 Watershed Area used for Crops

((b)) Average Phosphorus (mg/L) by HUC 12

Figure 2: Land Use and Water Quality in Wisconsin

both filtered and unfiltered readings since nitrogen readings are more typically taken using the filtered method (approximately 2/3 of our sample). We also focus our analysis on water quality readings from March-June when more than 75% of annual runoff occurs in Wisconsin (Zegler, n.d.). For robustness, we also investigate water quality effects by season and year round.

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, (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.[4] 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. For this paper, we focus on the percentage of acres that grow corn, soybeans, and small grains (i.e. wheat, barely, and oats), which are the dominant crops in the state of Wisconsin.

Weather

We control for weather trends 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 at a water quality monitor at a more aggregate level. Our preferred specification controls for daily temperature, growing degree days, daily precipitation, precipitation squared, and cumulative precipitation over the previous week.

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 (Schlenker, 2024). Higher degree days are associated with plant growth which will increase the take-up of nutrients, reducing nutrient runoff.

[4]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.

We account for the effects of precipitation in a number of ways. We control for daily precipitation as well as squared daily precipitation.[5] 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.

SSURGO Soils

To explore heterogeneity by soil conditions, we pull information from the NRCS Soil Survey Geographic Database (SSURGO). We aggregate the map units to the subwatershed level to analyze how soil conditions on the landscape interact with program water quality benefits. We include variables that represent the erodibility, drainage conditions, and health of the top soil; conservation practice effectiveness is linked to these soil conditions. The specific variables we include are the runoff potential class (indicator for how likely soil is to produce runoff during rainfall, based on the infiltration rate and permeability of the soil), T-factor (a soil loss tolerance factor which measures the maximum amount of erosion at which the quality of a soil as a medium for plant growth can be maintained), the drainage class (the natural drainage conditions of the soil that describe how long the soil stays wet under natural conditions), K-factor (an erodibility value that measures how easily soil particles detach and move by water), and soil organic matter depletion (the rating for the extent that soil organic matter has been depleted). For the continuous variables (t-factor and K-factor), we take a weighted average for the subwatershed and then divide the units by those below and above the mean. For the categorical variables (runoff, drainage class, and runoff potential), we organize the subwatersheds into a low and high valued groups. We hypothesize that the PLW program will be more effective at filtering nutrients in subwatersheds with high runoff potential, low T-factor,

[5] Our results are robust when we use alternative measures using cumulative precipitation levels from the previous week.

high drainage class, high K-factor, and high depletion levels.

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 shift-share instrumental variables approach that leverages state-level, temporal changes in the program's budget (i.e. *the shifts*) interacted with the time-invariant percentage of a watershed's area that is devoted to cropland in 2010 (i.e. *the shares*). The intuition behind this approach is that when there is an exogenous shift in the state program's budget, the more heavily cropped areas of the state are the areas likely to respond the most.

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

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

where WQ_{idmy} measures nutrient concentrations on day d of year y. The treatment variable PLW_{wy} is the percent of the watershed'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 product of the time-invariant 2010 agricultural acreage in watershed w and the state-level, time-varying budget for the PLW program in year y.

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 over time at a state level (λ_{dy}, like commodity prices. Regressions are weighted by 2010 crop acres in the watershed divided by the number of water quality readings within a watershed in a given month.[6] Standard errors are

[6] Weighting by the inverse number of water quality readings ensures that stations with multiple readings in a month are not implicitly weighed more heavily than stations that report just once.

multi-clustered at the HUC 10 and year level to allow for correlation among neighboring HUC 12 watersheds that may be treated simultaneously.

We use a similar strategy to identify the effects of producer-led participation on local cropping outcomes as specified in equation (2). The outcome of interest here is C_{wy}, which captures the cropping variable of interest (e.g., % cover crops) in watershed w and year y. These models are weighted by 2010 crop acres in the HUC 12 watershed. Standard errors are again multi-clustered at the HUC 10 and year level.

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

Identifying Assumption

There are two primary identifying assumptions with the instrumental variables model to estimate the causal impacts on these sets of outcomes. First, the exclusion restriction requires that state-level expansion of the program cannot be correlated with local watershed outcomes except through the channel of the watershed groups that form, conditional on location and time-fixed effects. A threat to this assumption would be if multiple state-level programs or regulations occurred at the same time and place as producer-led watershed groups. In robustness checks, we test the validity of this assumption by including controls for the presence of other programs and policies most likely to influence water quality in our setting. As we will later show, our primary estimates are robust to the inclusion of these controls.

The second identifying assumption is that the instrument is 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 percent is a strong predictor of local watershed participation in the period of the budget shock. Column 1 displays the results from the full sample. Column 2 displays the first stage results for the sub-sample of 2015-2021 and corresponds to the subsample of years that we observe conservation practice as discussed above.

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

	(1) 2005-2023	(2) 2015-2021
2010 Crop Pct * Program Budget	1.082**	1.307**
	(0.429)	(0.576)
Num.Obs.	34276	10591
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 five 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, drawing on our first two sets of results, we discuss the costs and benefits of the PLW program in comparison to other policy approaches. Fourth, 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. In each specification, the independent variable of interest is the proportion of agricultural acreage in a HUC 12 that belongs to a PLW group. All specifications instrument for PLW participation using the shift-share approach described earlier. Specification (1) only includes 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 fixed effects. In each specification, we find that an additional ten percentage points of agricultural acreage belonging to a PLW group

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

	Phosphorus (mg/L)				
	(1)	(2)	(3)	(4)	(5)
% 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
F Stat	1248.5	1273.0	1266.8	1211.1	1350.5
Weather Controls			X	X	X
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.

decreases phosphorous concentrations by 0.03 mg/L (a 14% reduction). In our preferred specification, this result is significant at the 1% level with p< 0.01.

The results in Table 3 include observations from March through June, when over 75% of annual runoff occurs (Zegler, n.d.) and when primary agricultural conservation practices are in place and likely to be most influential. 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 effects of PLW groups on alternative water quality measures both during the spring (March through June) and throughout the entire year. Columns (1) and (2) report impacts on phosphorous (column (1) in Table 4 is the same as column (5) in Table 3), columns (3) and (4) report impacts on TKN, and columns (5) and (6) report impacts on ammonia. First, we note that PLW groups have a larger impact on water quality in the spring than at other times of the year. Second, we note that PLW groups have a larger impact on phosphorus concentrations

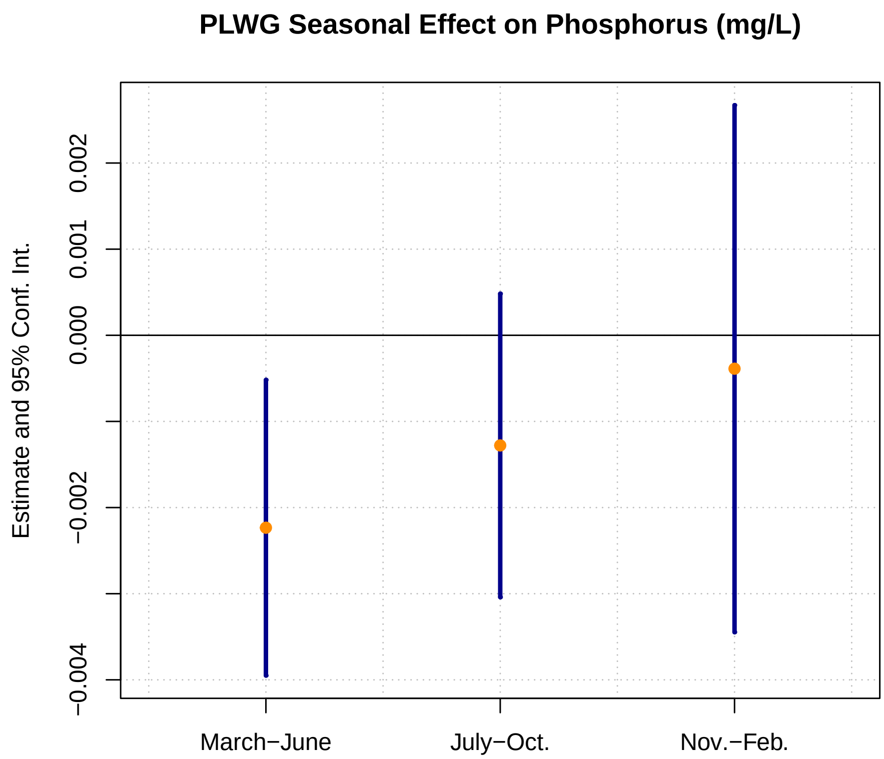


Figure 3: Seasonal Effects of PLW Groups on Phosphorus Concentrations

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
% PL Acres	−0.003***	−0.001*	−0.007*	0.000	−0.001	0.000
	(0.001)	(0.001)	(0.004)	(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
F Stat	1350.5	3860.2	1867.6	4597.2	1612.4	4236.1

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

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.

than on nitrogen concentrations (TKN and ammonia). The results in column (3) suggest that a ten percentage point increase in PLW acres decreases springtime TKN by 0.07 mg/L (less than a 6% reduction). However, this result is only statistically significant at a 10% level and none of the results for ammonia are statistically significant.

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 this hypothesis in Table 5. Each column uses our preferred 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.

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** (0.135)	0.774** (0.387)	0.022* (0.012)	−0.015 (0.074)	−0.025 (0.058)	0.075** (0.037)
Dep. Var. Mean	2.7	27.8	3.2	24.1	10.7	3.1
Observations	10591	10591	10344	34274	34274	34274
F Stat	145.6	145.6	147.7	652.3	652.3	652.3
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.

These practices, in turn, have been previously shown to improve water quality, especially through the reduction of phosphorus in surface water.

Effect of Grant Dollars

Our preferred treatment variable above measures the share 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., equipment dealerships), 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 that HUC 12's agricultural acreage. Table 6 reports the summary of these results with the same specifications as above. 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). 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 cur-

Table 6: 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	−0.040*	−0.038**
	(0.031)	(0.028)	(0.024)	(0.021)	(0.017)
Dep. Var. Mean	0.21	0.21	0.21	0.21	0.21
Observations	38462	38462	38462	38462	38462
F Stat	168.3	175.1	175.0	202.9	243.5
Monitor	X	X	X	X	
Year	X				
Month	X				
Year x Month		X	X		
Year x Day				X	X
Monitor x Month					X

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

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.

rent 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 7. 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.

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). In cases where multiple upstream subwatersheds flow into a single downstream watershed, we construct upstream treatment

Table 7: 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
F Stat	19.8	19.8	20.6	133.5	133.5	133.5
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.

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 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. 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 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). We test how this channel may affect our results by matching annual county-level EQIP and CSP payments between 2014-2023 and by including funding support from these two programs as control variables in separate regressions.[7] Results from these models are displayed in columns 2 and 3 of Table A2. Again, the magnitude of the point estimates remains stable across specifications. These models are marginally less precise, 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. [8] The marginal effect of PLW groups remains unchanged, and if anything, the estimated effect is actually more precise by including dairy cattle controls.

In column 5 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 model compares monitor readings within the same HUC 8 and year with and without a PLW group. This set of fixed effects likely absorbs a meaningful share of identifying variation in our primary treatment variable. Still, the estimates in this model remain relatively robust to this granular set of controls.

To support that our results are not sensitive to model specification, Table A3 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. Lastly, Table A4 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 slightly larger in these estimates. These sets of alternative specifications are two common approaches in the literature, and they give evidence that our results are robust to the modeling and aggregation choices that we made in this paper.

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 as-

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

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

sumption 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 significantly different than 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 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 validate the IV approach in this paper.

6 Discussion

To contextualize the environmental impacts of the program, we estimate the costs of conservation adoption to benchmark against other policy initiatives. 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 8 summarizes our approach. We begin with our first-stage estimates (from Table 2),

Table 8: 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

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 cropland 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 10.43% and 2.60% increases, respectively. There have been 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.[9] In comparison, in Wisconsin, the NRCS pays farmers $42–$73 per acre for cover crop and $16–$43 per acre for reduced tillage (2023).

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 adop-

[9] Using an alternative estimation based on dollar point estimates from Table 7 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.

tion of key conservation practices, like cover cropping and reduced tillage, four-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. 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: 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	−0.0026**	−0.0022	−0.0029	−0.0019	−0.0033
	(0.0010)	(0.0018)	(0.0037)	(0.0020)	(0.0047)
Upstream % PL Acres			−0.0001		
			(0.0003)		
Upstream % PL Acres (weight=acres)				−0.0001	
				(0.0002)	
Upstream % PL Acres (weight=streamflow)					−0.0001
					(0.0004)
Dep. Var. Mean	0.21	0.18	0.18	0.18	0.18
Observations	38448	23473	23473	23472	23473
F Stat	1178.0	553.1	334.4	305.5	347.1
Year	X	X	X	X	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.

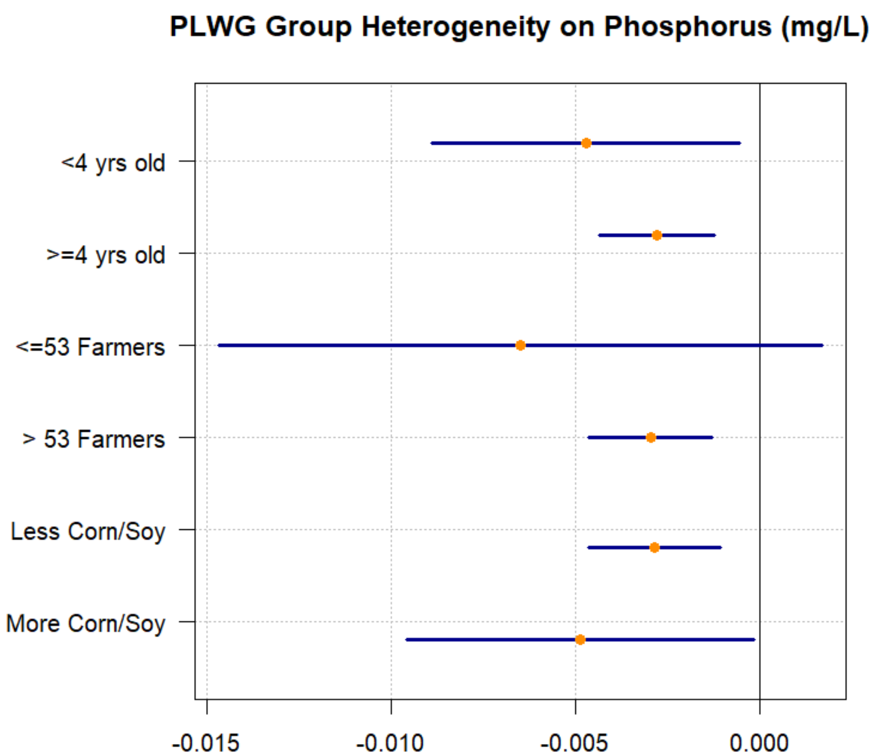


Figure A1: Heterogeneous Treatment Effects by Group Characteristics

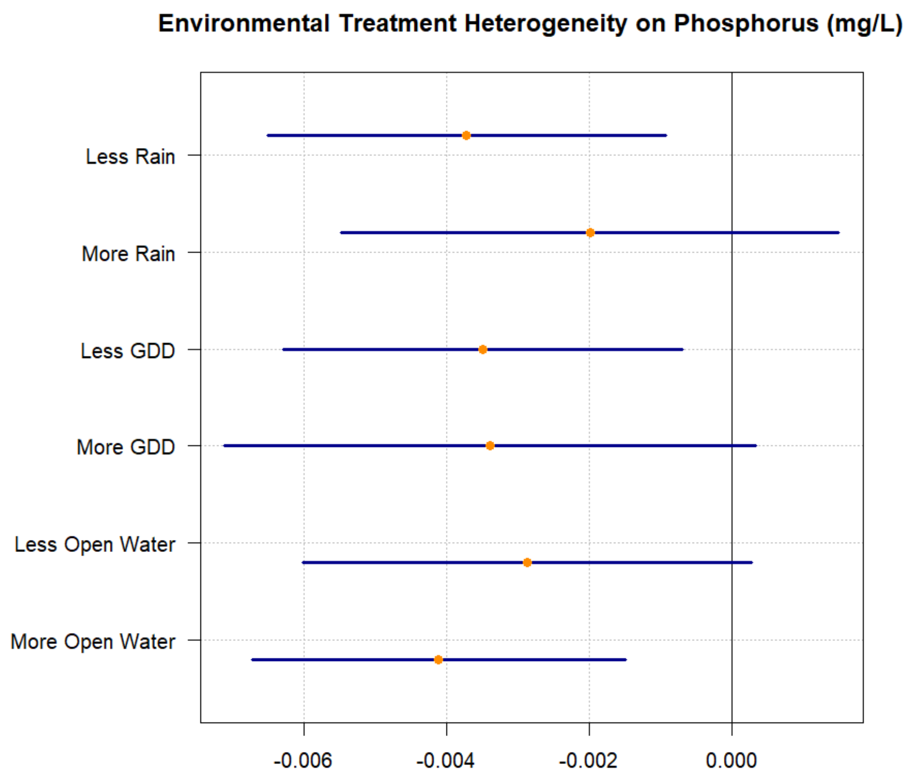


Figure A2: Heterogeneous Treatment Effects by Environmental Characteristics

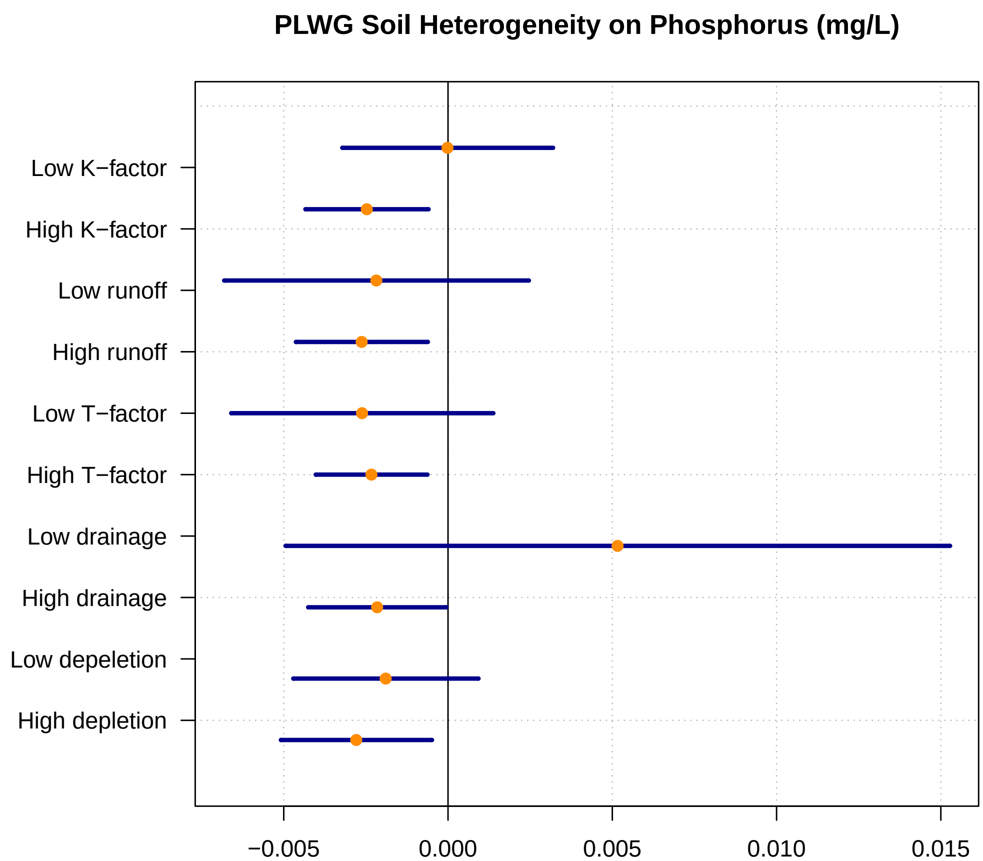


Figure A3: Heterogeneous Treatment Effects by Soil Characteristics

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

	Phosphorus (mg/L)				
	(1)	(2)	(3)	(4)	(5)
% PL Acres	−0.003**	−0.003	−0.004*	−0.003***	−0.002*
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Dep. Var. Mean	0.21	0.22	0.22	0.22	0.21
Observations	38462	20676	18097	32532	38462
F Stat	1194.9	861.8	663.3	1177.8	633.5
Year x Day	X	X	X	X	X
Monitor x Month	X	X	X	X	X
Controls	Co. NMP	EQIP $	CSP $	Dairy Cows	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: 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*	−0.009*	−0.009**
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Dep. Var. Mean	−2.17	−2.17	−2.17	−2.17	−2.17
Observations	38462	38462	38462	38462	38462
F Stat	1248.5	1273.0	1266.8	1211.1	1350.5
Monitor	X	X	X	X	
Year	X				
Month	X				
Year x Month		X	X		
Year x Day				X	X
Monitor x Month					X

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

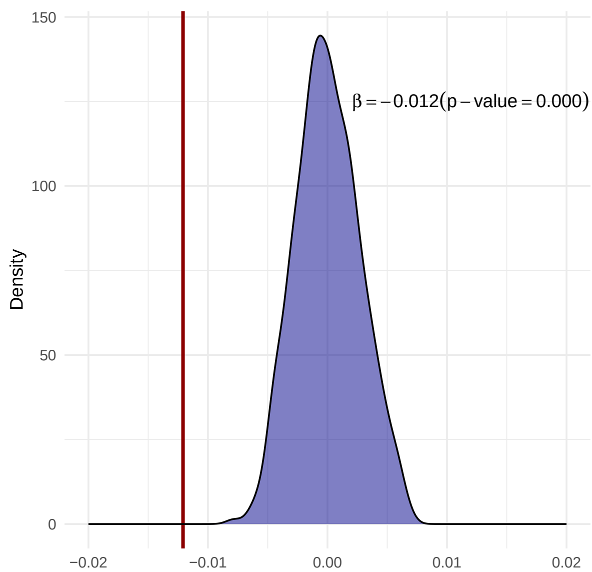
Note: The dependent variable is the phosphorus concentration (mg/L) in levels at the monitor-level. Standard errors are multi-clustered at the HUC10 and Year. Regressions are weighted by 2010 crop acres divided by the number of water quality monitors per watershed per month.

Table A4: Effect of Producer-Led Groups on Phosphorus Concentrations: Aggregated

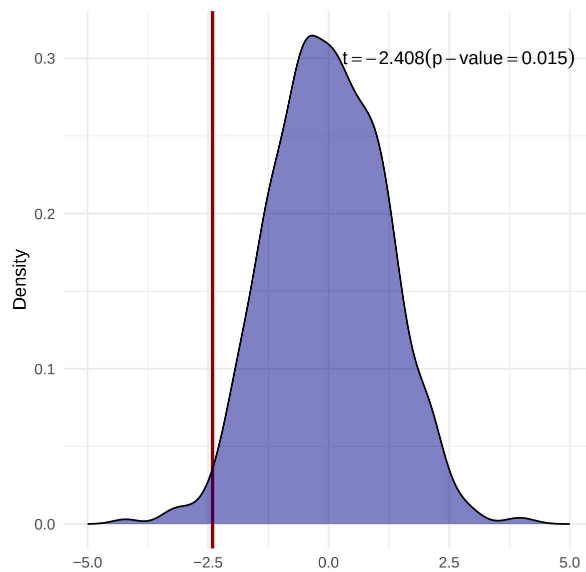
	Phosphorus (mg/L)					
	Spring			All Year		
	(1)	(2)	(3)	(4)	(5)	(6)
% PL Acres	−0.004	−0.004	−0.004	−0.002	−0.002	−0.002
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Dep. Var. Mean	0.15	0.15	0.15	0.14	0.14	0.14
Observations	12514	12514	12514	37035	37035	37035
F Stat	331.6	339.3	292.5	1003.9	1026.7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

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

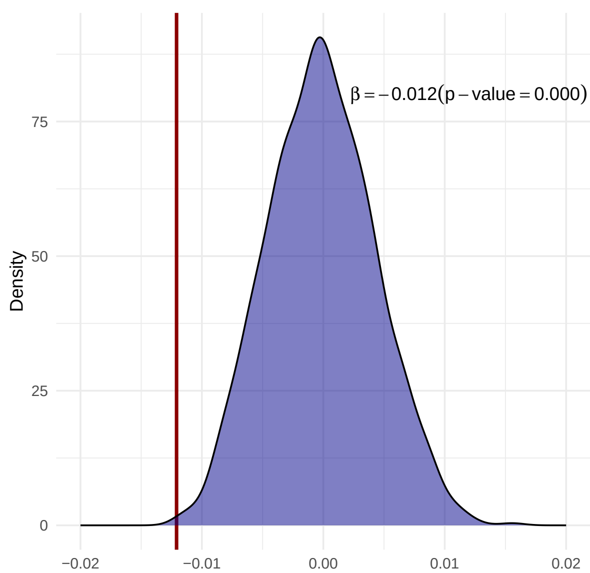
Note: The dependent variable is phosphorus (mg/L) aggregated to the HUC 12 and month level. Standard errors are multi-clustered at the HUC10 and Year. Regressions are weighted by crop acres in the HUC 12.



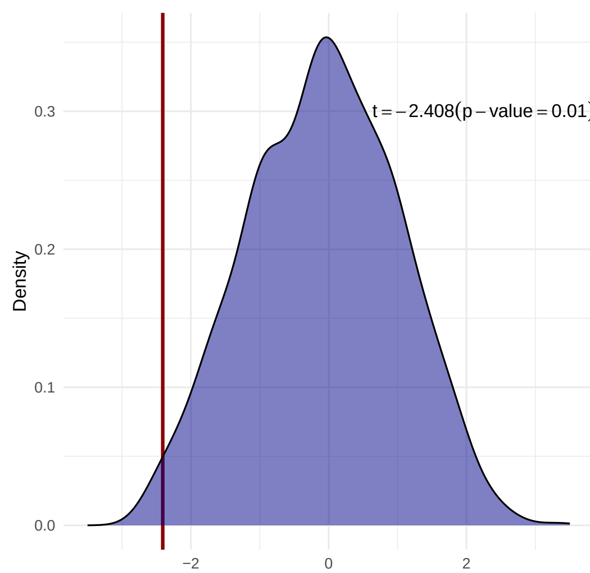
((a)) β: Cross sectional randomization



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



((c)) β: Temporal randomization



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

Figure A4: Placebo Tests for Instrument Validity