The Effectiveness of Mandatory Environmental Regulations: Evidence from Minnesota's Buffer Law

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Abstract

Governments often rely on private landowners to provide environmental public goods, yet evidence on the effectiveness and incidence of mandatory agricultural conservation policies remains limited. We study Minnesota's Buffer Law, which requires agricultural landowners to establish perennial vegetative buffers or adopt comparable alternative practices along public waterways and public drainage ditches. Using imputation-based difference-in-differences designs, we estimate the law's effects on corn and soybean productivity and on two water-quality indicators, nitrate plus nitrite and turbidity. We find little evidence of persistent changes in either corn or soybean yields following treatment. The estimates likewise provide little evidence of persistent changes in either water-quality outcome. Together, the results suggest that the law did not impose a detectable persistent productivity penalty, but also did not generate detectable persistent improvements in the measured water-quality outcomes over the study period.

Keywords: Environmental regulation; Nonpoint source pollution; Water quality; Agricultural productivity

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1 Introduction

Governments frequently rely on private asset owners—through either incentives or mandates—to provide public benefits rather than provide these benefits directly. Yet the economic incidence of these approaches, and whether they generate measurable public benefits, remain unclear. We study these questions using Minnesota's Buffer Law, which requires agricultural landowners to devote land near public waterways to conservation. Specifically, we examine whether a mandatory land-use regulation generates measurable environmental benefits and imposes economic costs on the farmers responsible for providing them.

Agricultural production is associated with negative externalities when landowners' use of private land causes the runoff of nutrients, sediment, and pollutants into publicly shared waterways and ecosystems (Hadachek et al., 2026). Unlike point-source pollution, agricultural nonpoint source pollution largely falls outside the Clean Water Act's primary permitting framework. In the United States, programs designed to reduce agricultural nonpoint source pollution are largely voluntary and incentive-based, offering financial and technical assistance to producers in exchange for adopting conservation practices (U.S. Department of Agriculture, Economic Research Service, 2025a). Many of these programs are administered by the United States Department of Agriculture (USDA) and include eligibility, monitoring, and compliance requirements. However, such voluntary programs may not efficiently allocate resources to places where conservation could generate high social benefits because agencies have incomplete information about landowners' opportunity costs of conservation (Cason and Gangadharan, 2004). Consequently, participation may be concentrated among landowners with relatively low marginal abatement costs, even when conservation on their lands does not generate correspondingly large marginal environmental benefits.

In this study, we exploit Minnesota's Buffer Law as a quasi-experimental setting to estimate the environmental and economic impacts of a mandatory conservation program. Using a difference-in-differences design, we compare changes in the productivity of two major row crops—corn and soybeans—in Minnesota counties along the state border with changes in adjacent counties in neighboring states that were not subject to the law. We complement this analysis by comparing

changes in two water-quality indicators—nitrate plus nitrite and turbidity—at monitoring sites in Minnesota with changes at sites in neighboring states that were not subject to the law. Together, these analyses allow us to examine both the private economic costs of the regulation and the public environmental benefits it was intended to provide.

In doing so, our work relates to several strands of research. The first evaluates the environmental benefits of voluntary federal conservation programs. For instance, Liu et al. (2023), Hsieh and Gramig (2026), and Karwowski and Skidmore (2026) assess the water-quality impacts of the Environmental Quality Incentives Program (EQIP), Conservation Stewardship Program (CSP), and the Wetlands Reserve Program (WRP) and its successor, the Agricultural Conservation Easement Program–Wetland Reserve Easements (ACEP-WRE), respectively. Similarly, Sun et al. (2026) estimate the effects of federal conservation contracts on nitrogen and phosphorus concentrations in the Wabash River watershed. In contrast, our study focuses on the environmental benefits and private economic costs of a mandatory conservation program.

The second is the environmental economics literature examining the environmental impacts of mandatory pollution-control policies. Raff et al. (2026), for example, estimate the water-quality benefits of Wisconsin's phosphorus rule, under which point sources can comply either through treatment technology upgrades or offset trading. While the policy incorporates abatement of agricultural nonpoint source pollution, the mandate primarily applies to point-source discharges. Similarly, Zhang et al. (2026) study the environmental and economic consequences of watershed regulation targeting transboundary pollution, with outcomes centered on industrial water pollution and regional economic growth. In contrast, Minnesota's Buffer Law directly regulates agricultural landowners to address nonpoint source pollution. More broadly, our study provides evidence on whether mandatory agricultural land-use regulation can generate public environmental benefits while limiting the private economic costs borne by regulated producers.

We find little evidence that Minnesota's Buffer Law generated persistent changes in either agricultural productivity or the measured water-quality outcomes. The event-study estimates for corn and soybean yields do not exhibit a consistent post-treatment increase or decrease. Similarly,

the estimates for turbidity and nitrate plus nitrite show no persistent post-treatment changes.

The remainder of the paper is as follows. The next section provides some background on federal conservation programs in the U.S. and the Buffer Law. Section 3 outlines the modeling framework. Section 4 describes the data. In Section 5, we present the estimates. Section 6 concludes the paper.

2 Policy Background

The United States Department of Agriculture (USDA), through the Natural Resources Conservation Service (NRCS) and the Farm Service Agency (FSA), administers many voluntary and incentive-based conservation programs. The Commodity Credit Corporation (CCC), a government-owned entity within USDA, is the primary source of funding for these programs. In addition, the Inflation Reduction Act (IRA) of 2022 appropriated more than $19 billion for federal conservation programs, with funds scheduled to be distributed between 2023 and 2031 (Fuller et al., 2026).

[Insert Figure 1 here]

Figure 1 depicts expenditures on major USDA conservation programs through the CCC in Panel A, while Panel B reports conservation payments as a percentage of total direct government farm payments. The Conservation Reserve Program (CRP), administered by the USDA Farm Service Agency (FSA), is the largest USDA conservation program based on expenditures. It is followed by the Environmental Quality Incentives Program (EQIP), administered by the USDA Natural Resources Conservation Service (NRCS), which also received additional funding through the IRA, unlike CRP. Panel B shows that conservation payments have also represented a sizable share of total direct government farm payments, accounting for roughly 30 percent in 2023. Together, these patterns highlight the importance of voluntary, incentive-based conservation programs within U.S. agricultural policy. However, access to federal conservation funding is often competitive. In fiscal year 2023, only about 25 percent of EQIP applicants and 30 percent of CSP applicants received contracts (National Sustainable Agriculture Coalition, 2024). Enrollment in General CRP, one component of CRP, is also competitive, with offers ranked using an Environmental Benefits

Index (EBI) (Rosenberg et al., 2024). Thus, participation in these programs reflects landowners' decisions to apply and agencies' decisions on how to allocate limited resources.

Unlike the aforementioned federal conservation programs, Minnesota's Buffer Law mandates perennial vegetative buffers of up to 50 feet along lakes, rivers, and streams and buffers of 16.5 feet along public ditches. The initial deadline for implementation was November 1, 2017, for public waters and November 1, 2018, for public ditches. The Minnesota Department of Natural Resources (DNR) developed the Buffer Protection Map, using the Public Waters Inventory (PWI) and public drainage system maps, to identify public waters and public ditch systems subject to these buffer requirements (Minnesota Department of Natural Resources, 2017).[1] Although compliance was mandatory, agricultural landowners could satisfy the requirement by adopting alternative practices that provided water-quality protection comparable to perennial vegetative buffers.

[Insert Figure 2 here]

The law was later amended in 2017. Under the amendment, landowners who submitted a compliance plan could extend the compliance deadline for public waters to July 1, 2018. Panel A of Figure 2 presents the average overall compliance rate across Minnesota counties, along with the average compliance rates for public waters and public ditches. The decline in the compliance rate in 2020 reflects a statewide update to parcel data completed during 2019 and 2020. Panel B reports the first year in which each county surpassed the 80 percent compliance threshold, which provides the basis for the staggered design.

3 Econometric Approach

We use the imputation estimator proposed by Borusyak et al. (2024). Let i denote the observational unit—a county in the yield analysis and a water-quality monitoring unit in the water-quality

[1] Public waters are lakes, wetlands, and watercourses over which the Minnesota DNR has regulatory jurisdiction. The PWI, maintained by the DNR, identifies and maps waterbodies that meet the statutory definition of public waters (Minnesota Department of Natural Resources, a,b).

analysis—and let t index time.[2] Let D_{it} denote an absorbing treatment indicator, let Y_{it} denote the observed outcome, and let G_i denote the first period in which unit i becomes treated. In the yield analysis, treatment timing is staggered because G_i is the first treatment year assigned to county i after the county's observed total compliance rate reaches the 80% threshold. In the water-quality analysis, all treated monitoring units are assigned a common treatment month, denoted by G^{WQ}, while comparison units remain untreated. The common-treatment-date design is therefore a special case of the same imputation framework in which $G_i = G^{WQ}$ for every treated unit.

Let Ω denote the estimation sample. Within this sample, let $\Omega_1 = \{it \in \Omega : D_{it} = 1\}$ denote treated observations, with cardinality N_1, and let $\Omega_\infty = \{it \in \Omega : D_{it} = 0\}$ denote untreated observations, with cardinality N_0. The treatment effect for a treated observation is defined as

$$\tau_{it} \equiv Y_{it} - Y_{it}(\infty), \tag{1}$$

where $Y_{it}(\infty)$ is the untreated potential outcome.[3] Following Borusyak et al. (2024), we consider weighted averages of these treatment effects, with the weights chosen to match the estimand of interest:

$$\tau_\omega = \sum_{it \in \Omega_1} \omega_{it} \tau_{it}. \tag{2}$$

If the target is the average treatment effect on the treated (ATT), then $\omega_{it} = 1/N_1$ for all $it \in \Omega_1$. For event-study analysis, the average effect h periods after treatment, for a given horizon $h \geq 0$, is obtained with $\omega_{it} = \mathbb{I}[K_{it} = h]/|\Omega_{1,h}|$, where $\Omega_{1,h} = \{it \in \Omega_1 : K_{it} = h\}$ and $K_{it} = t - G_i$ is event time. In the yield analysis, h is measured in years, and treatment timing varies across counties. In the water-quality analysis, h is measured in months and treatment timing is common across treated monitoring units.

Because water-quality outcomes are observed monthly, we estimate the underlying water-quality

[2] For the yield analysis, $t \in \{2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023, 2024\}$. For the water-quality analysis, t indexes calendar months over the study period.

[3] Treatment is absorbing, so once a unit is treated it remains treated thereafter. For units that are never treated, $G_i = \infty$.

specification at the monthly frequency. To present the dynamic estimates more parsimoniously, we aggregate the monthly post-treatment effects into annual event-time intervals. Let $\hat{\tau}_h^{WQ}$ denote the estimated treatment effect in event month h, and collect the monthly estimates in the vector $\hat{\tau}^{WQ}$. Let $\widehat{\mathbf{V}}^{WQ}$ denote the estimated variance–covariance matrix of these monthly estimates.

For presentation, we aggregate the monthly estimates to the annual event-time level after estimation. Let $\mathscr{H}_a$ denote the set of monthly event-time estimates available for event year a, and let $M_a = |\mathscr{H}_a|$ denote the number of available months. The aggregated estimate for event year a is

$$\hat{\tau}_a^{WQ} = \frac{1}{M_a} \sum_{h \in \mathscr{H}_a} \hat{\tau}_h^{WQ}. \tag{3}$$

Equivalently, let $\mathbf{q}_a$ be a vector that assigns weight $1/M_a$ to each available monthly estimate in event year a and zero to all other monthly estimates. The variance of the aggregated estimate is calculated using the full variance–covariance matrix:

$$\widehat{\mathrm{Var}}\left(\hat{\tau}_a^{WQ}\right) = \mathbf{q}_a' \widehat{\mathbf{V}}^{WQ} \mathbf{q}_a. \tag{4}$$

Thus, when all twelve monthly estimates are available, each receives weight $1/12$. For event years with fewer available monthly estimates, each available month receives weight $1/M_a$. This procedure leaves the underlying estimation at the monthly frequency and aggregates only the estimated coefficients and their associated variance–covariance matrix.

For identification, we rely on three standard assumptions. The first is that of no interference or spillover (i.e., SUTVA):

$$Y_{it} = \sum_{g \in \mathscr{G} \cup \{\infty\}} \mathbb{I}\{G_i = g\} Y_{it}(g), \tag{5}$$

where $\mathscr{G}$ denotes the set of finite treatment cohorts. That is, we observe the potential outcome associated with unit i's realized treatment timing. In the yield analysis, treated counties enter treatment in the first assigned treatment year after their observed total compliance rate reaches the 80% threshold. In the water-quality analysis, treated monitoring units enter treatment in the

common treatment month G^{WQ}, while comparison units remain untreated.

The second is a conditional parallel trends restriction:

$$\mathbb{E}[Y_{it}(\infty)] = \mathbf{A}'_{it}\lambda_i + \mathbf{X}'_{it}\delta, \qquad \forall it \in \Omega. \tag{6}$$

where $\mathbf{A}_{it}$ may include unit fixed effects and unit-specific trends, and $\mathbf{X}_{it}$ contains observed covariates that are not themselves affected by treatment. In the yield analysis, the covariates include the growing-season Palmer Drought Severity Index (PDSI), temperature and its square, precipitation and its square, and baseline measures of fertilizer use and CRP and EQIP acreage, each interacted with a time trend. For the water-quality analysis, $\mathbf{X}$ includes vapor pressure deficit (VPD) measured seven days before the sampling date and cumulative precipitation over the seven days preceding the sampling date.

The third assumption is no anticipation. For all units i that are eventually treated,

$$Y_{it}(g) = Y_{it}(\infty), \qquad \forall t < g. \tag{7}$$

In the yield analysis, this assumption requires that farmers did not change behavior in ways that affected corn or soybean yields before their county entered treatment under the 80% compliance rule. In the water-quality analysis, it requires that treated monitoring units did not experience treatment-induced changes in water quality before the common treatment date.

Under these assumptions, the estimator proceeds by fitting the untreated outcome model on untreated observations, imputing untreated potential outcomes for treated observations, and then averaging the implied treatment effects using the desired weights. Algorithm 1 summarizes this procedure.

Algorithm 1 Imputation Estimator

Input: $\{Y_{it}, \mathbf{A}_{it}, \mathbf{X}_{it}\}$, untreated set Ω_∞, treated set Ω_1, and weights ω_{it}.

1: **procedure** ESTIMATE

2: Estimate the untreated outcome model on Ω_∞:

$$(\hat{\lambda}_i, \hat{\delta}) = \arg\min_{\lambda_i, \delta} \sum_{it \in \Omega_\infty} \left(Y_{it} - \mathbf{A}_{it}'\lambda_i - \mathbf{X}_{it}'\delta\right)^2.$$

3: For each $it \in \Omega_1$, construct

$$\widehat{Y}_{it}(\infty) = \mathbf{A}_{it}'\hat{\lambda}_i + \mathbf{X}_{it}'\hat{\delta}, \qquad \hat{\tau}_{it} = Y_{it} - \widehat{Y}_{it}(\infty).$$

4: Compute the target estimand:

$$\hat{\tau}_\omega = \sum_{it \in \Omega_1} \omega_{it}\hat{\tau}_{it}.$$

5: **end procedure**

4 Data

County-level data on corn and soybean yields, measured in bushels per acre, for Minnesota, North Dakota, South Dakota, Iowa, and Wisconsin were obtained from the United States Department of Agriculture, National Agricultural Statistics Service (USDA NASS) Quick Stats database.[4] We collect county-level monthly precipitation, measured in inches, and temperature, measured in degrees Fahrenheit, from the National Oceanic and Atmospheric Administration, National Centers for Environmental Information (NOAA NCEI).[5] We obtain Palmer Drought Severity Index (PDSI) data from the GRIDMET dataset.[6] PDSI values range from -15 to 15, with values of 5.0 or higher indicating extremely wet conditions and values of -5.0 or lower indicating extreme drought.[7]

We use the global fertilizer dataset by Coello et al. (2025) to obtain county-level nitrogen fertilizer application rates, measured in kilograms per hectare. Data on federal conservation

[4] USDA NASS Quick Stats can be accessed at https://quickstats.nass.usda.gov/.

[5] NOAA NCEI data can be accessed at https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/county/time-series.

[6] The GRIDMET dataset can be accessed at https://developers.google.com/earth-engine/datasets/catalog/GRIDMET_DROUGHT#description.

[7] We only consider the months from April to October when constructing annual averages of PDSI, precipitation, and temperature, since these months correspond to the growing season for corn and soybean in Minnesota and neighboring states.

programs are obtained directly from the USDA. Specifically, we obtain CRP payments and acreage from the USDA Farm Service Agency (USDA FSA).[8] Similarly, we obtain EQIP payments and acreage from the USDA Natural Resources Conservation Service.[9]

For the water-quality analysis, we use nitrate plus nitrite, measured in milligrams per liter as nitrogen (mg/L as N), and turbidity, reported in nephelometric turbidity units (NTU), from the Water Quality Portal for Iowa, Minnesota, North Dakota, South Dakota, and Wisconsin. The data combine an archived WQX 2.2 profile with WQX 3.0 downloads of U.S. Geological Survey National Water Information System records for calendar year 2024.[10]

Monitoring locations are assigned to 12-digit hydrologic unit code (HUC12) polygons using their reported coordinates and the U.S. Geological Survey's Watershed Boundary Dataset (WBD).[11] We first take the arithmetic mean of all retained measurements for a given outcome within each monitoring-site-month-year. Following Karwowski and Skidmore (2026), we apply the inverse hyperbolic sine transformation and then average the transformed site-month observations within each HUC12, calendar month, and year. The resulting observation unit for the monthly water-quality analysis is therefore a HUC12-month-year.

We match each monitoring-site observation to daily data from the gridMET gridded surface meteorological dataset.[12] We extract daily precipitation and vapor pressure deficit (VPD) at the monitoring-site coordinates. For a sample collected on date t, precipitation is measured as the cumulative precipitation during the seven days preceding sampling, from $t-7$ through $t-1$, in millimeters. VPD is measured as the arithmetic mean during the same seven-day window, in kilopascals. As an alternative weather specification, we use mean VPD over the 30 days preceding sampling.

[8] CRP statistics can be accessed at https://www.fsa.usda.gov/tools/informational/reports/conservation-statistics/crp.

[9] EQIP data can be accessed at https://www.farmers.gov/data/financial-assistance-overview.

[10] The Water Quality Portal is available at https://www.waterqualitydata.us/. The archived WQX 2.2 data are documented at https://www.hydroshare.org/resource/7b4d4e186c6b4e888876bcb713b4dff7/.

[11] The WBD is available at https://www.usgs.gov/national-hydrography/watershed-boundary-dataset. We obtain the HUC12 polygons through the National Map web service at https://hydro.nationalmap.gov/arcgis/rest/services/wbd/MapServer/6/query.

[12] The gridMET dataset is documented at https://developers.google.com/earth-engine/datasets/catalog/IDAHO_EPSCOR_GRIDMET.

For the water-quality analysis, we weight the regression in Equation 6 by baseline cultivated area within the HUC12, measured in thousands of acres and averaged over 2010–2016. For the yield analysis, we instead use baseline county cultivated area, calculated as the mean cultivated area during 2013–2014. We construct the cultivated-area measures from the USDA National Agricultural Statistics Service (NASS) Cropland Data Layer (CDL).[13]

5 Results

5.1 Effect on Productivity

[Insert Figure 3 here]

Figure 3 presents the event-study estimates for log yields of corn (Panel A) and log yields of soybeans (Panel B) in a staggered setting where counties are defined as treated once the compliance rate surpasses 80%. In both panels, the pre-treatment estimates are close to zero and not statistically distinguishable from zero, providing suggestive evidence in favor of the conditional parallel trends assumption in Equation 6.

In Panel A, the post-treatment estimates for corn yields are initially negative, become positive in later years, and subsequently turn negative again. Although some individual estimates are statistically distinguishable from zero, the reversal in signs indicates that these estimates do not represent a persistent decline in corn yields. The post-treatment coefficients are consistently close to zero and statistically insignificant. Similarly, the post-treatment estimates for soy in Panel B are relatively close to zero and are mostly insignificant with no persistent effect. Overall, the event study estimates provide little evidence that the Buffer law caused persistent changes in either soy or corn productivity in Minnesota.

[13]The USDA NASS Cropland Data Layer is available through the Google Earth Engine at https://developers.google.com/earth-engine/datasets/catalog/USDA_NASS_CDL.

5.2 Effect on Water Quality

[Insert Table 1 here]

First, we report summary statistics for the outcome-specific balanced samples from 2010 through 2024 in Table 1. Ever-treated HUC12s have lower average nitrate plus nitrite and turbidity concentrations than never-treated HUC12s. Ever-treated HUC12s also have lower average seven-day vapor pressure deficit, although this difference is smaller in the turbidity sample.

[Insert Table 2 here]

[Insert Table 3 here]

Before turning to the event-study estimates, Table 2 provides a simple comparison of pre- and post-treatment water-quality outcomes for ever-treated and never-treated HUC12s. For nitrate plus nitrite, the resulting two-by-two DID is 0.014, while the corresponding estimate for turbidity is 0.017. Table 3 complements these descriptive comparisons with the corresponding two-way fixed-effects regressions, allowing us to assess their statistical significance. In both cases, the estimates are statistically indistinguishable from zero, providing little evidence of a differential change in either water-quality outcome between treated and untreated HUC12s. We next examine whether the effects vary dynamically following treatment using the event-study specification.

[Insert Figure 4 here]

Figure 4 presents the event-study estimates for nitrate plus nitrite (Panel A) and turbidity (Panel B). Specification I includes HUC12 and year-month fixed effects, while Specification II additionally includes weather controls. Across the two outcomes and specifications, the pre-treatment estimates are statistically indistinguishable from zero at the 5% level of significance, providing suggestive evidence in favor of the conditional parallel trends assumption.

Panel A presents the estimates for nitrate plus nitrite. In both specifications, the estimates are mostly close to zero and statistically insignificant at the 5% level of significance, indicating no

persistent effect of the Buffer Law on nitrate plus nitrite concentration in Minnesota waters. Panel B presents the corresponding estimates for turbidity. The post-treatment coefficients alternate in sign, and their confidence intervals include zero in both specifications. The estimates therefore provide no clear evidence of either a persistent decline or a persistent increase in turbidity following treatment. Overall, the event-study results provide little evidence of persistent changes in either nitrate plus nitrite or turbidity following the implementation of the Buffer Law.

6 Conclusion

This paper examines whether a mandatory agricultural land-use regulation can generate measurable environmental benefits without reducing agricultural productivity. Minnesota's Buffer Law provides an informative setting because, unlike the voluntary and incentive-based programs that dominate U.S. agricultural conservation policy, it requires regulated landowners to establish vegetative buffers or adopt comparable alternative practices. We combine two difference-in-differences analyses: a county-level analysis of corn and soybean yields that exploits variation in the timing at which counties surpassed 80% compliance, and a water-quality analysis of nitrate plus nitrite and turbidity measured at the HUC12-month level. Across both analyses, the results provide little evidence of persistent changes following treatment. Thus, for the outcomes, locations, and period examined, the law does not appear to have caused a detectable sustained productivity loss, but neither do we find evidence of persistent improvements in measured water quality that the regulation was intended to produce.

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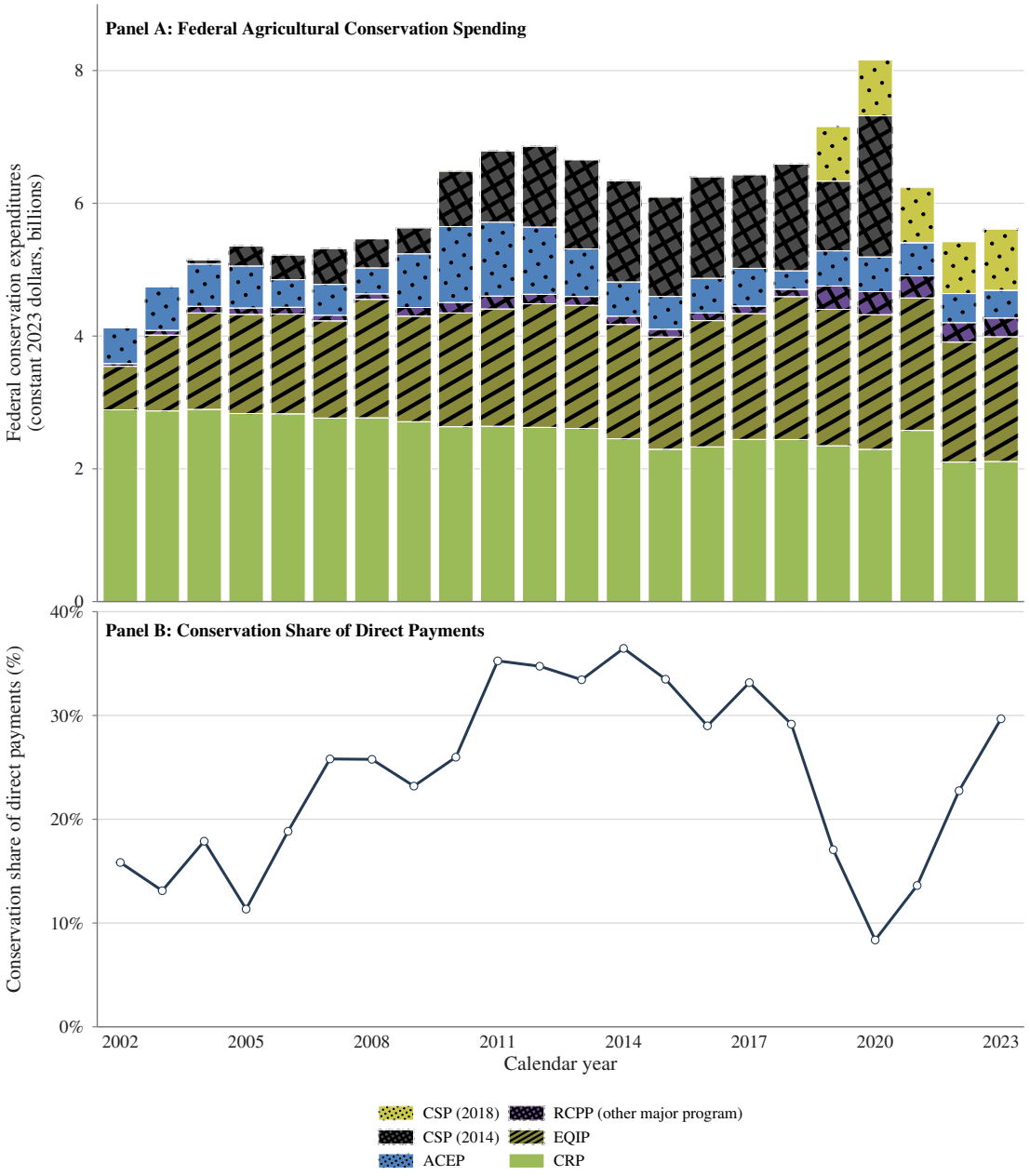


Figure 1. USDA Conservation Spending and Direct Government Payments, 2002–2023

Note: Panel A reports annual federal conservation-program expenditures for major USDA agricultural conservation programs during fiscal years 2002–2023, in constant 2023 dollars (U.S. Department of Agriculture, Economic Research Service, 2025b). The six categories are the Conservation Reserve Program (CRP), Environmental Quality Incentives Program and related programs (shown as EQIP), Regional Conservation Partnership Program (RCPP), Agricultural Conservation Easement Program (ACEP), Conservation Stewardship Program (2014), and Conservation Stewardship Program (2018). The series does not include funding provided under the 2022 Inflation Reduction Act. Panel B reports conservation payments as a percentage of federal direct government payments to agriculture, calculated as 100× conservation program payments divided by total government payments during calendar years 2002–2023 (U.S. Department of Agriculture, Economic Research Service, 2026b,a).

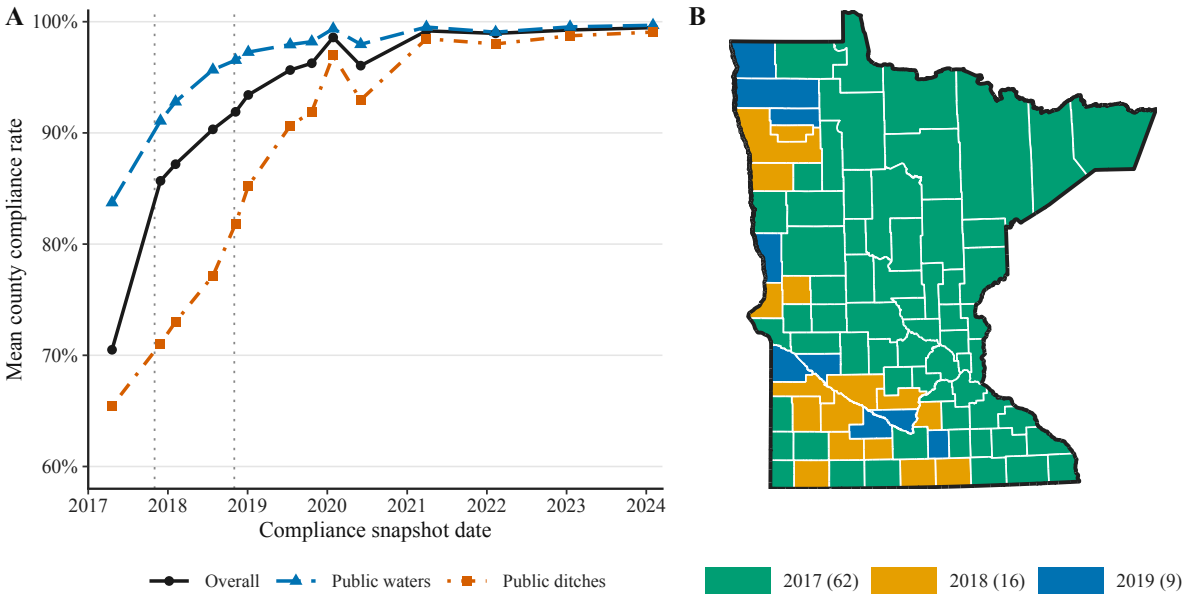


Figure 2. Compliance with the Buffer Law

Note: Panel A presents the compliance rate, defined as the number of parcels compliant with the Buffer Law at time t divided by the total number of state-identified parcels required to comply. Panel B reports the first year in which each county surpassed the 80% overall compliance threshold. We exploit this variation in treatment timing in the yield analysis, which includes three treatment cohorts: 2017, 2018, and 2019.

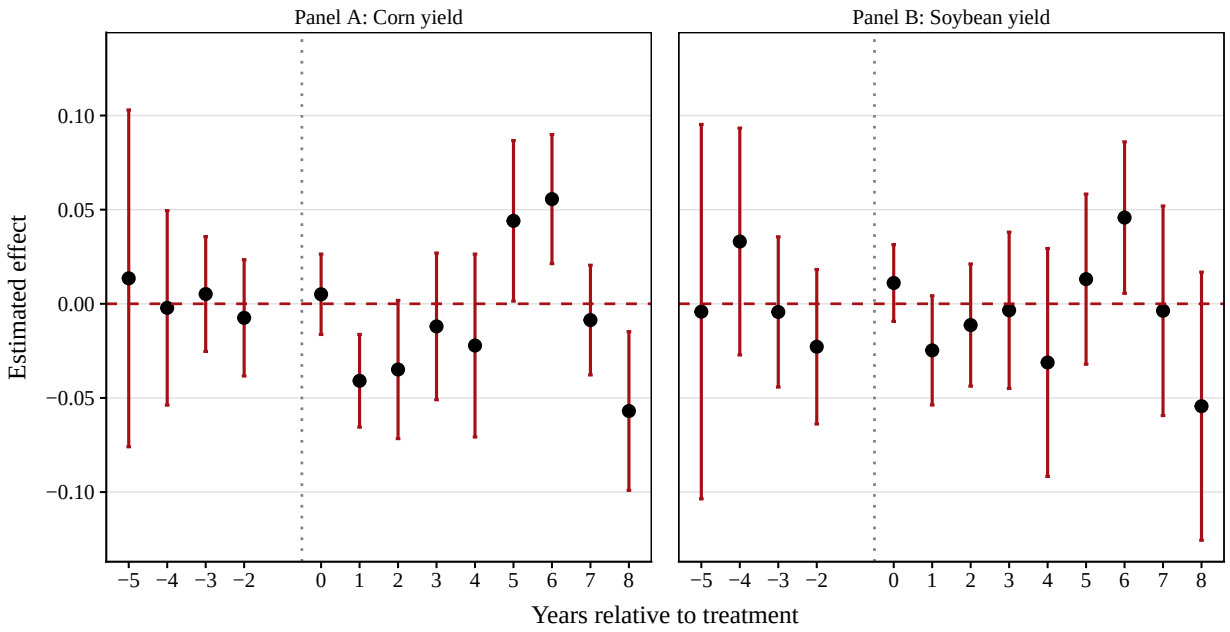


Figure 3. Event-Study Estimates

Note: Panel A reports dynamic treatment effects of Minnesota's Buffer Law on log corn yields, and Panel B reports the corresponding estimates for log soybean yields. Both panels are based on the imputation estimator proposed by Borusyak et al. (2024) in a staggered setting and include the following controls: temperature, temperature squared, precipitation, precipitation squared, PDSI, baseline fertilizer application rate interacted with time, baseline CRP acres interacted with time, and baseline EQIP acres interacted with time. The dots denote point estimates, the vertical bars denote 95 percent confidence intervals, and the horizontal dashed line marks zero effect. The regressions are weighted by baseline cultivated area in each county. Event time is measured in years relative to treatment.

Table 1. Outcome-Specific Water-Quality Summary Statistics by Treatment Status

Variable	All	Ever-Treated	Never-Treated	Normalized difference	p-value
Panel A: Nitrate + nitrite sample					
Nitrate + nitrite (asinh)	0.645	0.221	0.680	-0.873	<0.001
VPD, 7-day prior (kPa)	0.663	0.535	0.674	-0.597	0.009
Precipitation, 7-day prior (mm)	17.818	26.455	17.088	0.851	<0.001
Baseline cultivated HUC12 area (thousand acres)	9.424	2.420	10.015	-1.237	<0.001
Observations	334	26	308		
HUC12s	167	13	154		
Panel B: Turbidity sample					
Turbidity (asinh)	2.717	2.090	2.826	-0.674	<0.001
VPD, 7-day prior (kPa)	0.844	0.800	0.852	-0.166	0.068
Precipitation, 7-day prior (mm)	20.191	19.326	20.341	-0.090	0.284
Baseline cultivated HUC12 area (thousand acres)	7.654	3.056	8.452	-0.859	<0.001
Observations	1,162	172	990		
HUC12s	581	86	495		

Notes: This table reports means across HUC12-month observations. We define treatment as beginning in January 2020. HUC12s with a Minnesota area share of at least 0.80 are classified as Ever-Treated, whereas those with a Minnesota area share below 0.80 are classified as Never-Treated. Nitrate plus nitrite (Panel A) and turbidity (Panel B) are reported on the inverse hyperbolic sine scale. Precipitation and VPD are measured over the seven days preceding sampling. The normalized difference is calculated as $(\bar{x}_T - \bar{x}_{NT})/\sqrt{(s_T^2 + s_{NT}^2)/2}$. p-values are from two-sided two-sample t-tests assuming equal variances, using HUC12-month observations.

Table 2. Pre- and Post-Treatment Water-Quality Outcomes by Treatment Status

	Ever-Treated	Never-Treated	Gap/DID
Panel A: Nitrate + nitrite			
Pre-treatment	0.221	0.688	-0.467
Post-treatment	0.221	0.673	-0.453
Change / DID	0.000	-0.014	**0.014**
Observations		334	
HUC12s		167	
Panel B: Turbidity			
Pre-treatment	2.159	2.904	-0.745
Post-treatment	2.020	2.748	-0.728
Change / DID	-0.139	-0.156	**0.017**
Observations		1,162	
HUC12s		581	

Notes: Panel A reports unweighted averages of nitrate plus nitrite before and after treatment for ever-treated and never-treated HUC12s; Panel B reports the corresponding averages for turbidity. Both outcomes are measured on the inverse hyperbolic sine scale. The first two entries in the final column are treated–untreated gaps, and the final entry is the DID estimate. Pre-treatment covers 2010–2019; post-treatment begins in January 2020.

Table 3. Two-Way Fixed-Effects Estimates of Water-Quality Outcomes

	Estimate
Panel A: Nitrate + nitrite	
Ever-Treated × Post	0.014
	(0.033)
p-value	0.664
HUC12 fixed effects	Yes
Pre/post-period fixed effects	Yes
Covariates	No
Weights	None
Observations	334
HUC12s	167
Panel B: Turbidity	
Ever-Treated × Post	0.017
	(0.138)
p-value	0.900
HUC12 fixed effects	Yes
Pre/post-period fixed effects	Yes
Covariates	No
Weights	None
Observations	1,162
HUC12s	581

Notes: Panel A reports two-way fixed-effects estimates for nitrate plus nitrite, and Panel B reports the corresponding estimates for turbidity. Both outcomes are measured on the inverse hyperbolic sine scale. The reported coefficients are from unweighted regressions with HUC12 and pre/post-period fixed effects. Post-treatment begins in January 2020. Standard errors, shown in parentheses, are clustered by HUC12.

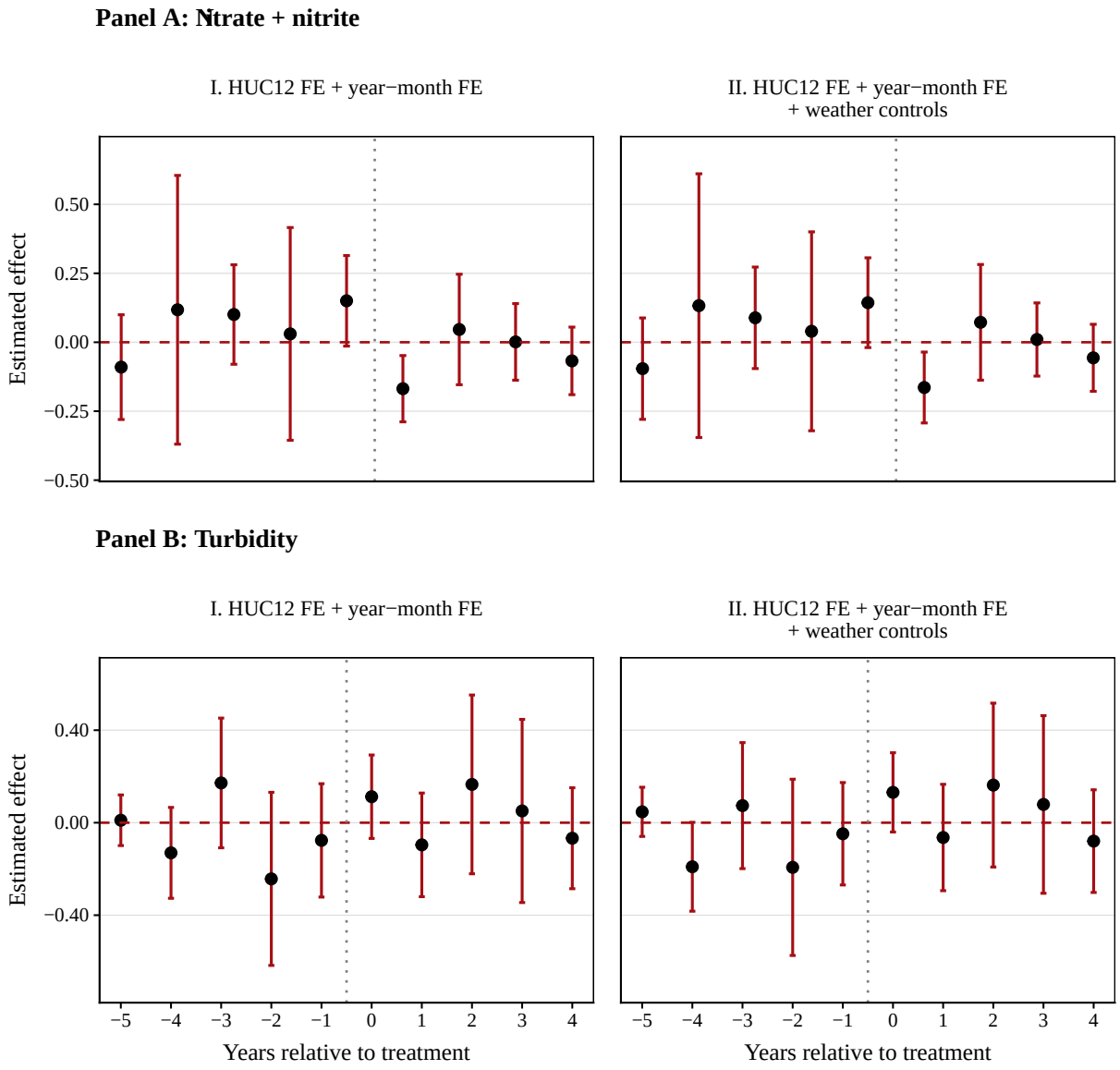


Figure 4. Event-Study Estimates for Water-Quality Outcomes

Note: Panel A reports the dynamic treatment effects of Minnesota's Buffer Law on nitrate plus nitrite, while Panel B reports the corresponding estimates for turbidity. The dependent variables are inverse hyperbolic sine transformations of the water-quality outcomes. The weather controls include average vapor pressure deficit over the seven days preceding the sampling date and cumulative precipitation over the same period, both of which are subsequently averaged at the HUC12-month level. Each specification is weighted by baseline cultivated acreage within the HUC12.