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ARTICLE

The influence of the Environmental Quality Incentives Program on local water quality

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Abstract

The Environmental Quality Incentives Program (EQIP) is the primary conservation program on working agricultural land. The United States Department of Agriculture obligated over $15 billion through EQIP cost-sharing contracts during the fiscal years 2009–2019. The voluntary nature of the program and the lack of performance assessment have led to speculations regarding the effectiveness of the program in delivering environmental benefits, in particular for improving water quality. This study provides quantitative estimates of the influence of EQIP payments on local water quality at a national scale. We link monitoring station level water quality readings with EQIP contract data and exploit the direction of river flow for identification. The estimated effects of EQIP vary across water quality measures. Estimates indicate that EQIP payments have significantly reduced biochemical oxygen demand and nitrogen, indicating improvements in water quality, but increased total suspended solids, fecal coliform, and phosphorus, suggesting that the implementation of certain conservation practices might have increased soil erosion and pathogen transfer, especially in watersheds with more agricultural production.

KEYWORDS

agricultural pollution, best management practices, environmental quality incentives program, water quality

JEL CLASSIFICATION

D24, H41, Q15, Q18, Q53

1 | INTRODUCTION

The degradation of water resources threatens the function of ecosystems and the welfare of our society. The most recent National Water Quality Inventory Report documents that 55% of assessed stream miles in the United States are impaired, and agriculture is the leading source (USEPA 2017). The United States Department of Agriculture (USDA) has employed voluntary conservation programs, such as the Conservation Reserve Program (CRP) and the Environmental Quality Incentives Program (EQIP), as the main mechanism to mitigate water pollution from agricultural activities.[*] Previous economic research on these programs focuses on farmers' participation decision and adoption of various conservation practices (see e.g., Boyer et al. 2016; Cooper 2003; McLean-Meyinsse et al. 1994; Mezzatesta et al. 2013). The voluntary nature of conservation programs and the lack of performance monitoring have led to speculations regarding the effectiveness of these programs in delivering environmental benefits, in particular for improving water quality in impaired watersheds (Osmond et al. 2012; Shortle et al. 2012). This paper provides the first quantitative assessment of the influence of an agricultural conservation program on water quality based on monitoring station level data at a national scale in the United States.

Existing studies have mainly used field-level approaches or watershed-scale modeling to examine the water quality benefits of conservation practices (see e.g., James et al. 2007; Kaspar et al. 2007). Field-level experiments and monitoring have the advantage of isolating the effects of individual management practices, implemented to a specific crop or animal production at a specific geographic location. However, field or farm-level changes in discharges cannot be easily linked to changes in ambient pollution concentrations. The USDA Conservation Effects Assessment Project (CEAP) uses simulation models, such as the Soil and Water Assessment Tool (SWAT), to evaluate the effects of conservation practices on water quality at the watershed scale. These simulation models are useful tools to facilitate landscape-specific water quality assessments because they capture the essential hydrologic and biogeochemical processes of the watershed, which determine the fate and transport of pollutants. However, simulation models rely on many underlying parameters, often estimated in different studies, making it challenging to assess the reliability of the final simulation results (Keiser et al. 2019). Moreover, studies on the impacts of conservation practices using experiments or simulations often do not account for behavioral adjustments that could accompany the implementation of conservation practices (Fleming et al. 2018; Lichtenberg & Smith-Ramirez 2011; Zhang 2018).

This paper uses econometric analysis to examine the average influence of EQIP on local water quality. Established under the 1996 Farm Bill, EQIP is implemented by the Natural Resources Conservation Service (NRCS) of USDA to address natural resource concerns and to deliver environmental benefits by providing financial and technical assistance to farmers and ranchers. Since its inception, EQIP is the primary conservation program aimed at working agricultural land. Under EQIP, agricultural producers are incentivized to adopt conservation practices through cost-sharing contracts with NRCS. During the 2009–2019 fiscal years (FY), NRCS obligated over $15 billion to over 426,000 EQIP contracts, covering 142 million acres.[†]

Despite the scale and importance of EQIP, we lack quantitative evidence on the environmental benefits achieved under the program. One reason is the multiplicity of benefits associated with different types and often even a single type of conservation practices (Liu & Swallow 2016), in addition to the sheer number of practices that have been implemented.[‡] For example, reduced application of nitrogen fertilizer may improve both water quality and air quality.[§] In this study, we mostly bypass

[*]Point sources, such as wastewater treatment facilities, are regulated under the Clean Water Act (CWA). Agricultural nonpoint sources have been largely exempted under the CWA. Large confined animal feeding operations (CAFOs) have been required to obtain National Pollution Discharge Elimination System (NPDES) permits since 2003 (USEPA 2008). Both point sources and nonpoint sources are included in the Total Maximum Daily Loads (TMDLs) for impaired waters.

[†]See the RCA Data Viewer (https://www.nrcs.usda.gov/wps/portal/nrcs/rca/national/technical/nra/rca/text/, last accessed Oct. 2021.

[‡]About 200 practices are offered by NRCS. See the RCA Data Viewer.

[§]Nitrogen fertilizer application leads to emissions of ammonia, which is a precursor of fine particulate matter (Hill et al. 2019).

the details of conservation practices and assess the impact of EQIP on water quality from a program evaluation perspective. Another challenge for econometrically estimating the environmental benefits delivered by conservation programs is to gather detailed measures of environmental quality and spatially link these measures with the corresponding conservation contract information.[¶] For our analysis, we constructed the national river/stream topology network using the U.S. Geological Survey National Hydrography Dataset and spatially linked water pollutant concentrations from monitoring stations with EQIP payment information at the Hydrologic Unit Code 10-digit level (HUC10), referred to as watershed hereafter.

EQIP payments are not randomly distributed across watersheds. It is possible that USDA uses EQIP contracts to target watersheds that offer high marginal benefits, which would threaten the identification of the impact of EQIP payments on water quality. However, the lack of pollution monitoring at the farm level and lack of simulation analysis before program enrollment makes it challenging to target farms that contribute disproportionately to in-steam pollution concentrations (Arabi et al. 2012; Rabotyagov et al. 2014). Some design features of EQIP also make systematic targeting less likely. For example, NRCS must consider a number of statutory requirements when allocating EQIP funds.[**] In fact, U.S. Government Accountability Office (2017) found that the process for allocating EQIP funds to state offices is not based primarily on environmental concerns, and some state offices do not use environmental concerns as the leading factor for allocating funds within their states.

The voluntary nature of EQIP participation makes selection bias a concern in quantifying its environmental benefits using econometric analysis. Many conservation practices provide private gains, for example, increases in yields, in addition to improvements in environmental quality. Asymmetric information between farmers and NRCS officers often precludes achieving a coordinated environmental goal. EQIP payments may be higher in watersheds where private net benefits are larger, and hence conservation practices are adopted with or without financial support. Improvement in water quality can only be attributed to EQIP if farmers would not have adopted these practices without payments. That is, water quality improvement must be "additional" (Claassen et al. 2018; Horowitz & Just 2013; Mason & Plantinga 2013; Mezzatesta et al. 2013). Establishing a credible counterfactual of how water quality would have evolved without EQIP is crucial for evaluating the treatment effect of the program (Zhang 2022).

In this paper, we employ two empirical strategies to address the potential endogeneity of EQIP payments, that is, to remove the potential confounding of unobserved watershed geographical and economic characteristics. We first estimate the impact of EQIP payments using a watershed-fixed effects model. This approach relies on the change of EQIP payments over time and across watersheds to identify the impact of EQIP payments on water quality. In addition, we explicitly consider the geospatial relationship in the river/stream network in our estimation and use the direction of the river flow to assist identification (Duflo & Pande 2007; Keiser & Shapiro 2019). Using this method, we estimate the impact of EQIP payments on downstream water quality by comparing changes in water quality over time, between downstream and upstream of the watersheds, and across watersheds with different EQIP payments.

Our results indicate that EQIP payments have significantly reduced biochemical oxygen demand (BOD) and nitrogen, but increased total suspended solids (TSS), fecal coliform, and phosphorus. Estimates from our preferred specification suggest that a one standard deviation increase in EQIP payments reduces BOD by 0.101 mg/L and nitrogen by 0.041 mg/L, representing 3.03% and 2.89% reductions of the sample means, respectively, and increases TSS by 0.356 mg/L, fecal coliform by 13.30 CFU/100 ml, and phosphorus by 0.003 mg/L, representing 1.31%, 3.95%, and 2.51% increases of the sample means, respectively. Reductions in BOD and nitrogen indicate improvements in water

[¶]Wallander and Hand (2011) use an econometric model to study the impact of EQIP funding on irrigated acreage and water use using farm-level data from the Farm and Ranch Irrigation Survey.

[**]For example, at least 50% of the financial assistance funds must be allocated to livestock operations. NRCS must also direct 5% of EQIP funds to beginning farmers and ranchers and 5% to socially disadvantaged farmers and ranchers.

quality. However, increases in TSS, fecal coliform, and phosphorus reflect the potential deterioration of water quality induced by the implementation of EQIP conservation practices. Estimation results obtained using subsamples with different levels of animal or crop production suggest that the negative effects on water quality happen mainly in watersheds with more agricultural production. The mixed findings across water quality measures are somewhat as expected. Simulation studies have documented the complex interactions of conservation practices and potential perverse consequences (Capel et al. 2018).[††] In addition, behavioral adjustments of agricultural producers could mitigate or even reverse the intended environmental benefits of conservation practices (Fleming et al. 2018).

Our results are robust under alternative specifications and when using different measures of EQIP. Estimates obtained when we consider the influence of lagged EQIP payments suggest that the average impact of EQIP funded projects on water quality is transitory: Lagged payments generally do not affect current water quality. When examining the influence of water quality related EQIP payments, we find that conservation practices directly related to water quality have a slightly stronger influence on BOD and phosphorus, but other practices might have helped with nitrogen reduction but contributed to soil erosion. When we use the number of EQIP projects funded, instead of the amount of EQIP payments, as the variable of interest, our main findings are unchanged.

The paper proceeds as follows. Section 2 provides more background information on EQIP and water quality. Section 3 describes datasets used for econometric analysis. Section 4 details our identification strategies and empirical models. Section 5 summarizes our estimation results, and Section 6 provides additional robustness checks. The last section concludes the paper.

2 | BACKGROUND

In this section, we provide more details about the implementation of EQIP, with a focus on funding allocation. We also introduce the water quality measures used in this analysis and discuss how different conservation practices may affect water pollution.

2.1 | The implementation of EQIP

As a voluntary program, EQIP provides technical and financial assistance to farmers across the country. Since its inception in 1996, the fundamental purpose of EQIP has been to support the implementation of conservation practices, which provide environmental benefits while promoting agricultural production. Water quality improvement is one of the national priorities identified by NRCS under EQIP.[‡‡] The 2002 Farm Bill substantially expanded funding for EQIP, and the subsequent Farm Bills further increased funding to be above $1 billion in each fiscal year from 2008 to 2018 (USDA/NRCS 2014). The most recent 2018 Farm Bill authorized $1.75 billion funding for EQIP in FY 2019 and FY 2020, $1.8 billion in FY 2021, $1.85 billion in FY 2022, and $2.025 billion in FY 2023 (USDA/NRCS 2019). The NRCS headquarter first allocates funds to state offices, and each state office has a process for allocating funds within the state that is consistent with statutory direction and priorities (U.S. Government Accountability Office 2017).

Agricultural or forest landowners engaging in crop, livestock, or forest production on eligible land may apply to participate in EQIP. EQIP applications are accepted throughout the year with a specific deadline for each state. Eligible land types include cropland and hayland, rangeland, pastureland, non-industrial private forestland, and other farm or ranch lands. Eligible applicants include agricultural producers, owners of non-industrial private forestland, Indian tribes, and "those with an

[††]Some practices might have increased soil erosion and pathogen transfer. For example, in tile-drained croplands, conservation tillage can increase infiltration and enhance the risk of liquid manure discharges through subsurface tile drains to surface water (Capel et al. 2018).

[‡‡]Other priorities include water conservation, reducing air pollution, reducing soil erosion, energy conservation, and promoting at-risk species habitat conservation. See https://www.nrcs.usda.gov/wps/portal/nrcs/main/national/programs/financial/eqip/, last accessed October 2021.

interest in the agriculture or forestry operation." Once an application is submitted, the land and applicant's eligibility are first checked before the local NRCS conservation planners schedule an in-person consultation. Different conservation practices will be presented to the landowner and the landowner's chosen conservation practice will be evaluated at a national, state, or local funding pool (U.S. Government Accountability Office 2017). During our study period, 2005–2015, EQIP funded about 42% of the applications received (USDA/NRCS 2014, 2019).

Each state office uses its own ranking tool to assign scores to applications and determines payment rates subject to the available budget. For example, in the EQIP ranking tool implemented in 2017 (the General-Statewide version), the overall scores are based on national priorities, state issues, and local issues, with each category consisting of 15–20 questions with the maximum scores of 500, 400, and 250, respectively. The cost effectiveness of a project is also a ranking criterion. However, the 2002 Farm Bill eliminated bidding down, that is, taking a lower cost share, due to concerns that small or resource-limited farmers cannot compete with larger farmers. NRCS is prohibited from giving a high ranking to an application only because of its cost savings. Initially, EQIP payments were made based on receipts and invoices of actual incurred costs as cost-sharing reimbursements. Since FY2009, payments have been made using "payment schedules," that is, estimated costs. These cost estimates are first developed at the national level and regional adjustments are then made by teams organized roughly according to the USDA Farm Production Regions (USDA/NRCS 2016). EQIP payment rates may be up to 75% of the costs associated with the material and labor of implementing the conservation practice and up to 100% of income forgone.[§§] Contracts are first signed with funds obligated, but payments are mostly made after projects are completed and certified. Contract length varies, depending on the practices, can be up to ten years. For example, for a ten-year contract signed in 2009, funds are obligated in FY 2009, and conservation practices may be implemented using those funds during the FY 2009–2020 time period.

2.2 | Water quality and conservation practices

Depending on the watershed, the primary causes of water quality issues associated with agriculture are sediment, nutrients, pesticides, pathogens, and salinity, contributing to a wide range of water quality measures (Capel et al. 2018; Ongley 1996). We include the eight most important water quality measures in our analysis, based on an extensive review of the literature, to capture changes in agricultural practices on ambient water quality (Hooda et al. 2000; Kato et al. 2009; Keiser & Shapiro 2019; Parris 2011). The selected water quality measures include: (1) pH, which describes the acidity or alkalinity of water and represents the balance between hydrogen ions and hydroxide ions in water. A high or low pH affects the availability of certain chemicals or nutrients in the water for use by plants; (2) water temperature, which affects the rates of biological processes and chemical processes; (3) dissolved oxygen deficit (DOD), defined as 100 minus dissolved oxygen saturation, which is the dissolved oxygen level divided by the maximum oxygen level conditional on the water temperature. When decomposing pollution, dissolved oxygen level in water decreases, and DOD increases; (4) biochemical oxygen demand (BOD)-standard conditions, which is the amount of dissolved oxygen demanded by aerobic biological organisms to break down organic matter in a given water sample at a certain temperature over a specific time period; (5) total suspended solids (TSS), which is the dry weight of particles trapped by a filter; (6) fecal coliform (FC), a kind of bacterium originating in the intestines of warm-blooded animals, serving as a proxy measure for pathogenic bacteria; (7) nitrogen (N); and (8) phosphorus (P).

We include pH, temperature, DOD, BOD, and FC as general measures of water quality; nitrogen and phosphorus as representative measures of nutrient pollution; and TSS as a measure of the

[§§]Historically underserved farmers and ranchers, including limited resource, socially disadvantaged farmers or ranchers, veteran farmers or ranchers, or beginning farmers or ranchers, must be awarded a higher payment rate (U.S. Government Accountability Office 2017).

influence of soil erosion on water quality. DOD and BOD both are affected by the amount of organic matter in the water. The amount of organic matter in the water also affects water pH. Decomposition of organic matter releases carbon dioxide, which combines with water to form carbonic acid.[¶¶] Thus, many manure, nutrient, and soil management practices can affect pH, DOD, BOD, and FC in the water. An increase in water pH or a reduction in the other six water quality measures indicates improvements in water quality. We do not expect any conservation practice to substantially affect water temperature, which is included in the analysis to serve the role of a falsification test (Watanabe et al. 2006).

In 2018, 42,887 EQIP contracts were completed or in action, covering nearly 13.7 million acres of agricultural land, among which more than 7.7 million acres were treated by at least one water quality related practice.[***] Conservation practices related to water quality may be divided into the following categories (Capel et al. 2018). Trapping practices, such as cover crops and buffer strips, and tillage practices, such as no or reduced tillage, are designed to reduce soil erosion and hence protect water quality from sediment and sediment-associated chemicals (Arora et al. 2010). Drainage practices may affect the time for chemical transformation, such as denitrification (Andrus et al. 2014). Wetland construction or restoration practices can remove sediment and chemicals from runoff and drainage water (Locke et al. 2011). Adoption of drip or low-flow sprinklers can also reduce erosion and hence decrease the runoff of sediment and chemicals from cropland (Eisenhauer et al. 2006). Livestock feed, pasture, and waste practices and fertilizer rate and timing management are used to reduce nutrient runoff (Ghebremichael et al. 2007; Jaynes et al. 2004). The set of practices that have been most adopted in terms of the land area includes prescribed grazing, conservation crop rotation, integrated pest management, nutrient management, no-till or strip-till residue management, structure for water control, and access road. In our analysis, we examine the effects of EQIP payments for all conservation practices and payments for conservation practices directly related to water quality.

3 | DATA

We constructed a nationwide, comprehensive dataset to estimate the impacts of EQIP payments on local water quality. We obtained EQIP payments and practices as well as other contract information from NRCS. All contracts are geocoded at both the watershed and the county. However, the exact geolocation of each contract was not provided due to confidentiality concerns. As a result, we do not have any farm- or farmer-specific information. Socioeconomic data were obtained from USDA and the Census Bureau. We collected water quality data at monitoring stations through the Water Quality Portal. In addition, we built the national river/stream topology network using the U.S. Geological Survey (USGS) National Hydrography Dataset. The constructed spatial network links water quality monitoring stations to EQIP payments at the watershed level. Below we describe the data preparation process in detail.

3.1 | EQIP data

Our EQIP dataset includes all contracts that were completed during 2005–2015 with watershed (HUC10) and county information. Compared to a county, a watershed is a more relevant unit for evaluating the impacts of water quality policies. There are over 22,000 watersheds with an average size of 227 square miles, compared to only 3142 counties in the U.S.[†††] Our dataset records the unique contract identifier, practice names and codes, practice units, the contract year, the year of

[¶¶]Nutrients in the water cause plant life and algae to grow quickly. After plants die, the amount of organic waste in the water increases. When bacteria decompose dead plants, they consume dissolved oxygen, which results in high oxygen demand.

[***]See https://www.nrcs.usda.gov/Internet/NRCS_RCA/reports/fb08_cp_eqip.html.

[†††]The average size of a sub-basin (HUC8) is similar to the size of an average county, with a total number of about 2200 in the country.

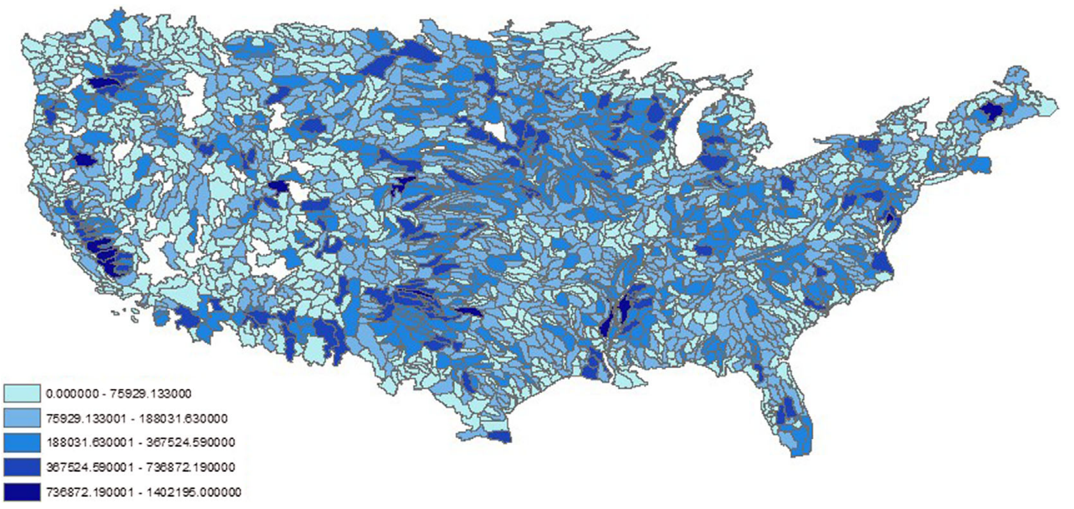


FIGURE 1 Average annual EQIP payments at the River Basin level, 2005–2015. This figure shows the geographical distribution of the average annual EQIP payments at the river basin (HUC 8) level from 2005 to 2015. Darker blue color represents higher payment level. White areas indicate no EQIP payment recorded for the river basin from 2005 to 2015

payment, obligation, and payment. In total, 227 unique conservation practices were implemented during the study period. The year of payment and payment amount document the specific amount paid for a contract in a given year. The dataset only records the year of payment, and we are thus unable to distinguish payments made at the beginning of a year versus at the end of a year. Payments are mostly made as reimbursements after the contracted projects are completed and certified, but advance payments are allowed for historically underserved farmers.[‡‡‡]

Figure 1 shows the distribution of the average annual EQIP payments at the river basin (HUC8) level. Substantial spatial variation exists in EQIP payments. A quick glance at Figure 1 reveals that the Corn Belt and the Central Valley in California received relatively higher annual EQIP payments compared to other regions in the country. Certain regions in the Mountain states received relatively small, and even zero, EQIP payments.

3.2 | Water quality data

We accessed water quality readings at the monitoring-station level from the Water Quality Portal, the most complete water-pollution repository for the U.S.[§§§] We use data for the contiguous United States and obtained for each station its HUC10 geocode, latitude and longitude, and state and county identifiers. The Water Quality Portal is a cooperative service sponsored by the USGS, USEPA, and the National Water Quality Monitoring Council (NWQMC). Because the water quality data were collected by different agencies, extreme care was taken to construct consistent measures of water quality, especially when the units of a measure are different across agencies.[¶¶¶] Also, because nitrogen and phosphorus can exist in many forms in the water, our standardized nitrogen measure includes ammonia-nitrogen, inorganic nitrogen, nitrogen in mixed forms (e.g., nitrate-nitrogen and nitrite-nitrogen), and organic nitrogen. We include inorganic phosphorus and phosphate-

[‡‡‡]See https://www.nrcs.usda.gov/wps/portal/nrcs/detail/national/programs/financial/eqip/?cid=nrcseprd1502414, last accessed Oct. 2021. Note that advance payments must be expended within 90 days of receipt.

[§§§]See https://www.waterqualitydata.us/, last accessed Oct. 2021.

[¶¶¶]For example, the USGS usually records nitrogen in *mg*/*l*, whereas the EPA stations usually record nitrogen in *μg*/*l*.

TABLE 1 Descriptive statistics

Variables	N	Mean	10th Pct.	90th Pct.	Min	Max	Std. dev.
Water quality Measures: Station level							
pH	163,243	7.58	6.62	8.45	5.29	9.09	0.77
Temperature (C)	165,314	16.59	5.56	26.11	−17.7	30.99	8.49
Biochemical oxygen demand(mg/L)	72,218	2.74	0.7	5	0.1	39.8	3.58
Dissolved oxygen deficit(%)	144,538	11.02	−10.3	56.7	−59	97.4	329.13
Total suspended solids(mg/L)	324,033	19.62	2	42.5	0.13	449.2	40.76
Fecal coliform(CFU/100 ml)	170,658	277.43	2	590	0	9530	835.95
Nitrogen(mg/L)	31,963	1.06	0.19	1.70	0.053	21.81	2.29
Phosphorus(mg/L)	63,334	0.176	0.1	0.331	0.004	1.79	4.001
Control variables							
Personal income ($)	34,236	41,620	1698.47	77, 385.85	21.72	5,443,249	151,203
Population (thousand)	34,236	197.77	5.15	200.45	839.1	78,400	2248.41
Agricultural land (thousand acres)	34,236	74.74	0.92	234.43	0.004	1784.48	160.36
Farm income ($million)	34,236	4.738	0.469	11.114	0.001	100.853	5.971
Total animal sales ($million)	34,236	54.53	2.17	125.18	0.06	2225.93	115.19
Cropland operations	34,236	526.68	114.5	1008.5	1	5486.5	420.77
CRP acres	34,236	10,182.47	0	26,844.9	0	129,861.5	24,383.94
Annual mean temperature (C)	68,880	11.52	5.23	18.79	−0.95	26.43	5.12
Annual mean precipitation (cm)	68,880	70.45	22.41	121.98	0.69	390.40	40.81
Payment variable							
Watershed EQIP Payments ($)	68,880	33,026.2	1228.27	81,781	136.5498	2,913,039	62,634

Note: This table reports the summary statistics for water quality measures, control variables, and EQIP payments. Water quality data were obtained from the Water Quality Portal that aggregates the USGS, EPA, and USDA water quality monitoring station data. Socioeconomic control variables were obtained from USDA and the Census Bureau. Annual mean temperature and precipitation were constructed using data from PRISM. Watershed EQIP payments are summation of contract-level payments acquired from USDA/NRCS.

phosphorus for our measure of phosphorus concentration in the water. The other six water quality measures are more straightforward.

For each water quality measure, we collected readings at all monitoring stations from Jan 1, 2005 to Dec 31, 2015, the same period for which we have EQIP payment data. To avoid the influence of extreme readings (i.e., outliers), we drop the values if they are above the 99.5th percentile or below the 0.5th percentile of the distribution for a watershed. Table 1 reports the descriptive statistics for these water quality measures, including the number of observations, mean, the 10th and 90th percentiles, minimum, maximum, and standard deviation. Figure 2 shows the kernel density distribution for each water quality measure. The distributions of pH, temperature, and DOD are close to a normal distribution, whereas the distributions of BOD, TSS, FC, nitrogen, and phosphorus are right skewed.

3.3 | Socioeconomic and weather data

We constructed agricultural production trends using data from the Census of Agriculture.[****] The influence of agricultural production on water quality is represented by the quantity of

[****]Linear interpolation is used to generate values in the years between censuses.

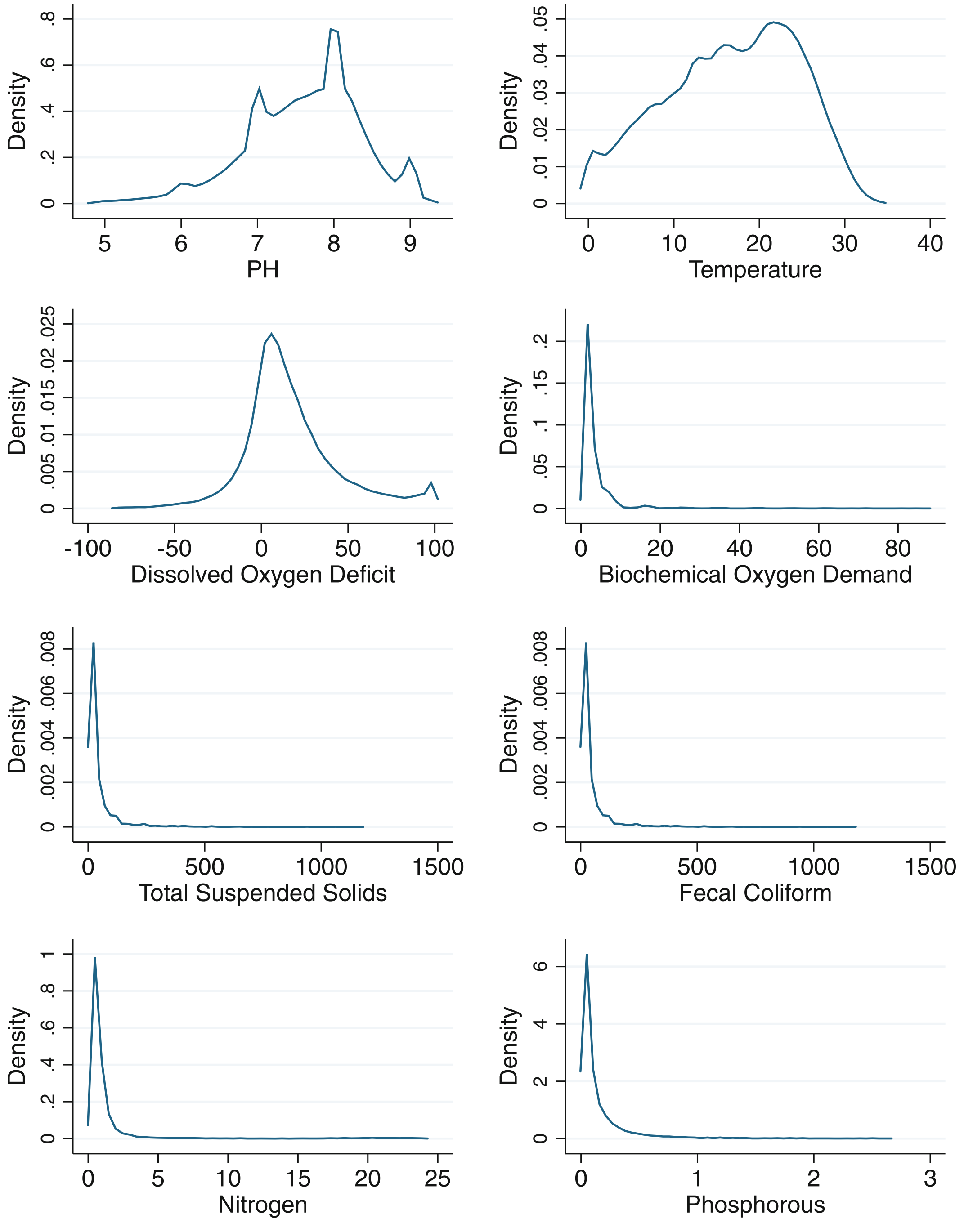


FIGURE 2 Kernel density distributions of water quality measures. This panel of figures shows the kernel density distribution for each water quality measure

agricultural land, numbers of operations on cropland, total animal sales, and farm-related income. Notably, the agricultural land area per county decreased by about 2800 acres from 2007 to 2012, but total animal sales and farm-related income experienced significant increases.[††††] We also obtained county-level CRP enrollment for each year in our study period from the Farm Service Agency.[‡‡‡‡] In addition, we use population and personal income data from the Census Bureau to control for general economic factors that may impact water quality. Because we do not have watershed socioeconomic data, each watershed is matched to its corresponding county socioeconomic data. About a third of the watersheds reside within a county. In cases where a watershed is located across multiple counties, we use the socioeconomic variables from the county that has the largest share of the watershed area.

For each watershed, we also constructed annual mean temperature and precipitation using data from PRISM (Parameter-elevation Regressions on Independent Slopes Model).[§§§§] Table 1 presents the summary statistics for these control variables.

3.4 | Geospatial analysis of water and stream network

To link water quality readings and EQIP payment data, the geographic location of watersheds and water quality monitoring stations are mapped using the geospatial information from the USGS Watershed Boundary Dataset (WBD) and National Hydrologic Dataset (NHD). We constructed panel data at the watershed level of EQIP payments and water quality measures. Monitoring station readings for each water quality measure are averaged to generate water quality measures at the watershed level. Our panel is unbalanced as some water quality monitoring stations do not record data every year.

Because the NHD dataset includes information on the points located along the river, we are able to identify whether a water quality monitoring station is located upstream or downstream of a particular watershed. We first use the variable "fid-point" in NHD (points along the "comid" or the river segment) to construct the flow direction of a river/stream. We also find the nearest point along the river for each monitoring station within a defined distance. In addition, for each watershed, we identify the location that a river flows into the watershed and the location that a river flows out of the watershed by intersecting the NHD dataset with the WBD dataset. The upstream and the downstream segments of a watershed are then recovered using the geolocations of the flow-in and flow-out points.[¶¶¶¶] We then obtain the readings of its upstream and downstream monitoring stations within a defined distance.

4 | IDENTIFICATION AND ECONOMETRIC MODELS

This section discusses the empirical strategies used to identify the influence of EQIP payments on local water quality. By estimating a watershed-fixed effects model, the first empirical strategy relies on changes in EQIP payments over time and across watersheds to identify the impact of EQIP payments on water quality. The second empirical method uses the flow direction of a river as an exogenous variation to estimate the impact of EQIP payments on downstream water quality (Duflo & Pande 2007; Keiser & Shapiro 2019). We compare water quality over time, between downstream and upstream of watersheds, and across watersheds.

4.1 | Fixed effects model

We first use the following fixed effects model to estimate the influence of EQIP payments on water quality of the watershed:

[††††] Changes in agricultural land area capture acreage changes in CRP.

[‡‡‡‡] See https://www.fsa.usda.gov/programs-and-services/conservation-programs/reports-and-statistics/conservation-reserve-program-statistics/index, last accessed Oct. 2021.

[§§§§] The specific PRISM dataset used is AN81m. See https://prism.oregonstate.edu/recent/, last accessed Oct. 2021.

[¶¶¶¶] For example, if a watershed contains fid-points 788,033, 788,034, 788,035, …, 788,056, we can find the corresponding geolocation for the fid-point 788,033, which would be the flow-in point, and the corresponding geolocation for the fid-point 788,056 would be the flow-out point. We can then use the geolocations of the fid-points 788,032, 788,031, 788,030, …, to construct the upstream segment of the watershed and fid-points 788,057, 788,068, 788,059, …, to construct the downstream segment of the same watershed.

$$Q_{it} = \gamma log(Payment)_{it} + \beta X_{it} + \eta_i + \theta_{wt} + \epsilon_{it}, \tag{1}$$

where Q_{it} is the water quality for watershed i in year t. We use both the mean and median of readings from monitoring stations within a watershed year to measure water quality. The $log(Payment)_{it}$ is the log of EQIP payments to farmers in watershed i at time t. In addition to concurrent payments, we also examine in some specifications the impact of payments in the previous two years. In the online supplementary appendix, we explore the influence of the number of EQIP contracts, and our main findings are unchanged by this choice. X_{it} is a vector of economic and weather control variables. η_i is a set of watershed fixed effects, capturing permanent hydrological conditions of the watershed. θ_{wt} is a set of basin-year fixed effects, capturing annual shocks common across all watersheds within a river basin, such as changes in agricultural production, point sources, and water-quality regulations for point sources. ϵ_{it} is the idiosyncratic error term. Standard errors are clustered at the watershed level for all regressions. The identifying assumption of the fixed effects model is $E[log(payment_{it}) \times \epsilon_{it} | X_{it}, \eta_i, \theta_{wt}] = 0$, meaning that after controlling for observable economic and weather variables in X_{it}, unobservable time-invariant watershed characteristics η_i, and unobservable time shocks θ_{wt}, confounders do not exist that affect both EQIP payments and water quality.

The fixed effects model estimates the influence of EQIP payments on water quality by exploiting the variation in payments and water quality over time and across watersheds. The identifying assumption may be violated if EQIP payments are allocated based on some time-varying unobservable factors that correlate with water quality measures. For example, if local NRCS offices use soil testing results as one of the criteria for ranking EQIP applications, our estimate of γ would be biased. However, we are not aware of such targeting mechanism employed by NRCS. Strategic water-quality monitoring could also bias our estimates. Not all monitoring stations work on regular schedules. In an extreme case, if only monitoring stations located in the upstream of the river within a watershed collected samples after EQIP projects in the watershed were implemented, our estimate would be biased. To mitigate these concerns, we consider an alternative empirical strategy that uses the upstream of a watershed as a counterfactual for the downstream of a watershed to identify the influence of EQIP payments on the downstream water quality.

4.2 | Flow direction model

Following Keiser and Shapiro (2019), we use the following flow-direction model to estimate he influence of EQIP payments on downstream water quality:

$$Q_{idt} = \gamma log(Payment)_{it} \times 1\{d = 1\} + \beta X_{it} + \delta_{id} + \tau_{it} + \mu_{wdt} + \epsilon_{idt}. \tag{2}$$

To estimate this model, we construct two water quality observations for each watershed. One observation, Q_{i0t}, measures the mean water quality in the upstream of watershed i at time t, with $d = 0$ indicating the upstream location of the water quality monitoring stations relative to the watershed. The other observation denotes the mean water quality downstream Q_{i1t}, with $d = 1$ indicating water quality monitoring stations downstream of watershed i at time t. As a result, Q_{idt} describes the upstream or downstream water quality for watershed i at time t. We first find all stations that are within a certain downstream or downstream distance of a given watershed and then calculate average water quality from these stations. Our parameter of interest, γ, measures the effect of changes in EQIP payments on downstream water quality. The watershed-downstream fixed effects δ_{id} allow the upstream and downstream of a watershed to have different baseline water quality levels. The watershed-time fixed effects τ_{it} allow each watershed to have different year-to-year variations in water quality, controlling for common annual changes that affect both upstream and downstream of a watershed. These fixed effects address potential concerns arising from the EQIP spatial distribution pattern, as agricultural-intensive watersheds are likely to experience differential changes of EQIP payments over time. The basin-downstream-year fixed effects μ_{wdt} allow for differential annual shocks to the upstream and downstream water quality for watersheds in a river basin, such as changes in point sources and water quality regulations.

Our sample was constructed based on the river/stream network, including the river flowing-in point and flowing-out point, of a watershed. The most common situation is illustrated in Panel A of Figure 3, where we can easily figure out the upstream and downstream for the watershed according to the flow direction and the boundary of the watershed that the river flows in and out. We will start from the flowing-in point and then go upstream up to a certain distance to construct the upstream water quality measure and similarly for the downstream. However, it is possible that a river flows in and out of a watershed more than once, as shown in Panel B of Figure 3. In this case, we consider all flowing-in and out points, and include multiple upstream–downstream water quality pairs for the watershed. We vary the length of "buffer zones" used to include water quality monitoring stations for a watershed. Four distances are considered, 10 miles upstream or downstream of a watershed, as well as 15, 20, and 25 miles.[*****] Note that there is a tradeoff as we increase the buffer distance used to construct water quality measures. A short buffer distance ensures that the constructed measures more accurately reflect the quality of water flowing into and out of a watershed. However, due to the distribution of monitoring stations, some watersheds do not have monitoring stations located within the chosen distance when a short buffer distance is used. A longer distance will allow us to include more watersheds in the analysis, but our estimates will be more prone to biases as the constructed water quality measures are influenced by factors that cannot be adequately controlled by the observed variables and fixed effects. Therefore, we use four buffer distances to see if similar results can be obtained across different distances.

Note that the samples used for estimation differ under the two empirical approaches. For the fixed effects model, the sample is a watershed-year panel and the dependent variable is constructed using readings from monitoring stations within a watershed. Watersheds that do not have any monitoring stations within its boundary are excluded in the fixed effects estimation. However, it is possible that we have water quality measures upstream and downstream of these watersheds. These watersheds will then be included in the final sample for the flow direction model. Similarly, some watersheds are excluded from the flow direction estimation (when monitoring stations do not exist upstream or downstream within a certain distance) but included in the fixed effects estimation (if they have monitoring stations within the boundary). Therefore, the set of watersheds included in the sample and the observations are different under the two approaches.

5 | EMPIRICAL RESULTS

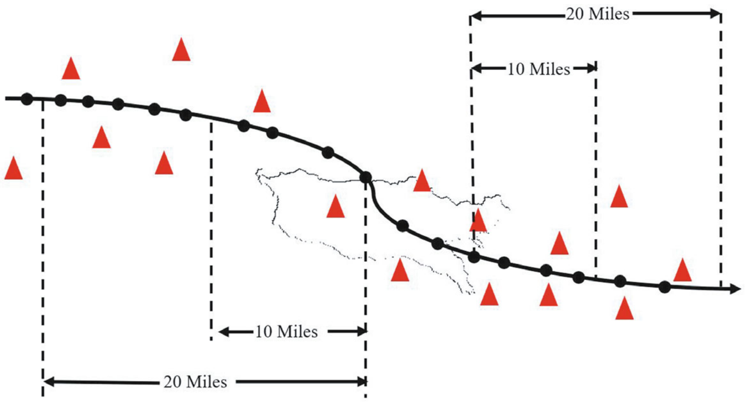
In this section, we first present the estimates from the fixed effects model and the flow direction model, and then compare the estimation results obtained using the two different identification strategies. We regard the flow direction model as more robust and mainly interpret the estimates from the flow direction model.

5.1 | Estimation results using the fixed effects model

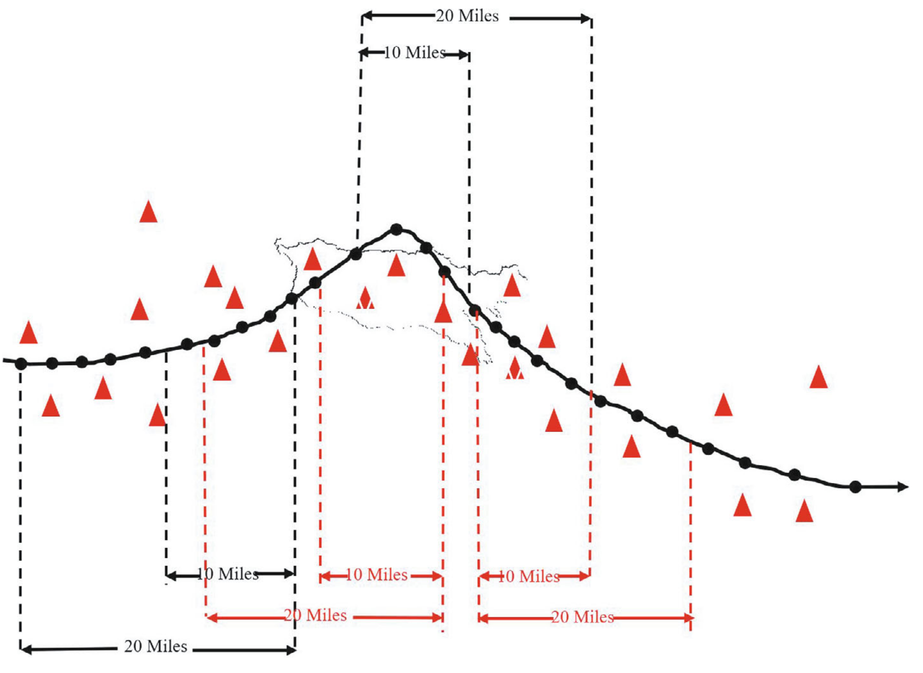
Estimation results using the fixed effects model in Equation (1) are reported in Table 2.[†††††] Columns (1) to (3) use the means of the water quality measures in a watershed as the dependent

*****Keiser and Shapiro (2019) demonstrate that the estimated effects of a Clean Water Act grant to a water treatment plant exist mainly within 25 miles downstream. The impact of agricultural conservation practices on water quality is not likely to be beyond this range.

†††††Considering the length of the table, estimated coefficients of time varying covariates are reported in the online supplementary appendix Table A.1 for water quality measures DOD, BOD, TSS, FC, nitrogen, and phosphorus.



Panel A: River crosses once



Panel B: River crosses more than once

FIGURE 3 Illustration of the flow direction approach. Panel A: River crosses once Panel B: River crosses more than once. This figure illustrates the flow direction approach employed to identify the influence of EQIP payments on water quality. The curve represents the river, and the triangles indicate the locations of water quality monitoring stations. For each watershed, we first locate the upstream and downstream according to the flow direction of the river and the boundary of the watershed that the river flows in and out. We then construct upstream and downstream water quality measures starting from the flowing-in and out points using different buffer distances. Panel A demonstrates the situation where the river crosses a watershed only once and Panel B more than once

variable, whereas columns (4) to (6) use the medians of the water quality measures in a watershed as the dependent variable. Columns (1) and (4) are the baseline models, Columns (2) and (5) add the set of time-varying control variables, and Columns (3) and (6) report estimates with basin-year fixed effects instead of year fixed effects. Different specifications generate consistent findings. The

TABLE 2 The influence of EQIP on water quality: Fixed effects model

	(1) Mean	(2) Mean	(3) Mean	(4) Median	(5) Median	(6) Median
Panel A: pH (7.689-mean, 7.694-median)						
log_pay	0.00123	0.00115	−0.000269	0.00154	0.00129	−0.000103
	(0.00126)	(0.00106)	(0.00120)	(0.00133)	(0.00110)	(0.00125)
N	14,225	14,225	14,225	14,225	14,225	14,225
Panel B: Temperature (16.80-mean, 16.51-median)						
log_pay	0.000688	−0.00515	−0.00554	−0.000344	−0.00666	−0.00833
	(0.0155)	(0.0159)	(0.0160)	(0.0161)	(0.0166)	(0.0167)
N	15,050	15,050	15,050	15,050	15,050	15,050
Panel C: DOD (14.09-mean, 13.56-median)						
log_pay	−0.0850	−0.0539	−0.0566	−0.131*	−0.124*	−0.129*
	(0.0656)	(0.0666)	(0.0674)	(0.0686)	(0.0667)	(0.0707)
N	11,965	11,965	11,965	11,965	11,965	11,965
Panel D: BOD (3.370-mean, 3.205-median)						
log_pay	−0.0266*	−0.0272*	−0.0254*	−0.0293**	−0.0297**	−0.0279**
	(0.0137)	(0.0144)	(0.0143)	(0.0132)	(0.0137)	(0.0136)
N	6472	6472	6472	6472	6472	6472
Panel E: TSS (23.67-mean, 21.34-median)						
log_pay	−0.0490	−0.0723	−0.0655	−0.0518	−0.0836	−0.0743
	(0.0713)	(0.0727)	(0.0723)	(0.0706)	(0.0715)	(0.0707)
N	33,737	33,737	33,737	33,737	33,737	33,737
Panel F: FC (272.99-mean, 227.85-median)						
log_pay	2.375	2.023	1.121	3.263*	2.746	1.916
	(2.009)	(2.051)	(2.060)	(1.953)	(1.996)	(2.014)
N	10,822	10,822	10,822	10,822	10,822	10,822
Panel G: Nitrogen (1.762-mean, 1.726-median)						
log_pay	−0.000826	0.00262	−0.000756	−0.00333	−0.000449	−0.00289
	(0.0136)	(0.0139)	(0.0117)	(0.0136)	(0.0139)	(0.0117)
N	4376	4376	4376	4376	4376	4376
Panel H: Phosphorus (0.143-mean, 0.138-median)						
log_pay	−0.000275	−0.000134	−0.000755	−0.000531	−0.000402	−0.000755
	(0.000521)	(0.000522)	(0.000651)	(0.000519)	(0.000520)	(0.000651)
N	8652	8652	8652	8652	8652	8652
Watershed FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	x	✓	✓	x
Controls	x	✓	✓	x	✓	✓
Basin-Year FE	x	x	✓	x	x	✓

Note: The dependent variables are water quality measures aggregated at the watershed-year level. *log_pay* is the log of the EQIP payments ($2005) to the corresponding watershed. Standard errors in parentheses are clustered at the watershed level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

estimates are also similar in magnitude when we use either the mean or the median water quality measures.

Based on the fixed effects model, we find that an increase in EQIP payments leads to a significant reduction in DOD and BOD, indicating reductions in organic matter in surface water. Specifically, the estimates for DOD are significant at the 10% level when using the median water quality, and the estimates are significant at the 5% level for BOD using the median water quality and significant at the 10% level using the mean water quality.[‡‡‡‡‡] Estimates from the fixed effects model suggest that EQIP payments might have increased FC, but most estimates are statistically insignificant.

5.2 | Estimation results using the flow direction model

Table 3 summarizes the estimated impact of EQIP payments on downstream water quality using the flow direction model in Equation (2).[§§§§§] We compare estimates when using different buffer distances to construct upstream and downstream water quality measures. Our estimation results are consistent in signs across different buffer distances. The biogeochemical processes that determine the fate and transport of pollutants are complex. It is possible that different buffer distances are appropriate for different pollutants. Unfortunately, the literature does not provide a strong prior, and substantial heterogeneity exists across watersheds. From the identification perspective, the shorter the buffer distance is, the better the upstream serves as a counterfactual for the downstream. To be conservative in our findings, we focus only on the statistically significant estimates in the 0–10 mile specification.

Using the flow direction model, we find that holding all other factors fixed, EQIP payments are associated with reductions in DOD, BOD, and nitrogen, but increases in pH, TSS, FC, and phosphorus. EQIP is not expected to have affected water temperature. The estimated effects on BOD, TSS, FC, nitrogen, and phosphorus are significant at the 5% or 1% level in the 0–10 mile specification. Overall, our estimates indicate that a 10% increase in EQIP payments would approximately reduce BOD by 0.008 mg/L and nitrogen by 0.004 mg/L, representing 0.24% and 0.29% reductions of the sample means, respectively, but would increase TSS by 0.027 mg/L, FC by 1.20 CFU/100 ml, and phosphorus by 0.0003 mg/L, representing 0.10%, 0.37%, and 0.23% increases of the sample means, respectively. EQIP payments exhibit substantial variations across watersheds. Depending on the water quality measure, watersheds included in the estimation are also different. We thus calculate the mean and the standard deviation of EQIP payments separately for each water quality measure and then calculate the influence of a one standard deviation increase in EQIP payments on the water quality measure. At the sample means, a one standard deviation increase in EQIP payments would reduce BOD by 0.101 mg/L and nitrogen by 0.041 mg/L, representing 3.03% and 2.89% reductions of the sample means, respectively, and would increase TSS by 0.356 mg/L, FC by 13.30 CFU/100 ml, and phosphorus by 0.003 mg/L, representing 1.31%, 3.95%, and 2.51% increases of the sample means, respectively.

The water quality measures used in the estimation are averages of different numbers of monitoring station level water quality readings. Table A.3 in the online supplementary appendix reports estimates when we weigh each watershed-downstream-year observation using the number of raw water quality readings. The signs of the weighted and unweighted estimates are the same and the magnitudes are statistically equivalent, though the weighted estimates for BOD and nitrogen are statistically insignificant, indicating that the frequency of water quality monitoring affects the precision of our estimates. Considering that our interest is in the influence of EQIP on the average watershed-downstream-year, instead of the average pollution reading, we report the unweighted estimates.[¶¶¶¶¶]

[‡‡‡‡‡]Though not statistically significant, the estimated increases in pH corroborate the finding that EQIP payments are associated with reductions of organic matter in water because decomposition of organic matter increases carbonic acid in water.

[§§§§§]Considering the length of the table, estimated coefficients of time varying covariates are reported in the online supplementary appendix Table A.2 for water quality measures DOD, BOD, TSS, FC, nitrogen, and phosphorus.

[¶¶¶¶¶]Areas with larger population tend to have more monitoring sites and be monitored more frequently. These areas with more water quality data are not necessarily more important when evaluating the influence of EQIP.

TABLE 3 The influence of EQIP on downstream water quality: Flow direction model

	(1) 0–10 miles	(2) 0–15 miles	(3) 0–20 miles	(4) 0–25 miles
Panel A: pH				
log_pay	0.00153	0.00207*	0.00155	0.00177
	(0.00127)	(0.00120)	(0.00114)	(0.00113)
Mean	7.671	7.660	7.652	7.648
N	16,799	18,859	20,300	21,216
Panel B: Temperature				
log_pay	−0.0110	−0.0110	−0.0125	−0.00737
	(0.0103)	(0.00992)	(0.00954)	(0.00943)
Mean	16.064	16.098	16.098	16.121
N	17,187	19,307	20,774	21,706
Panel C: DOD				
D_pay1	−0.0604	−0.0853**	−0.0976**	−0.0961**
	(0.0479)	(0.0448)	(0.0433)	(0.0423)
Mean	15.012	14.747	14.622	14.565
N	20,859	23,046	24,325	25,230
Panel D: BOD				
log_pay	−0.0759**	−0.0697	−0.0636	−0.0948**
	(0.0349)	(0.0467)	(0.0450)	(0.0465)
Mean	3.333	3.593	3.621	3.629
N	10,486	11,823	12,491	13,055
Panel E: TSS				
log_pay	0.268**	0.346***	0.360***	0.265**
	(0.132)	(0.124)	(0.122)	(0.123)
Mean	27.136	27.420	27.441	27.863
N	38,253	42,518	44,947	46,800
Panel F: FC				
log_pay	12.00***	9.201***	8.960***	9.439***
	(3.527)	(3.429)	(3.376)	(3.256)
Mean	336.916	343.202	344.462	344.398
N	17,600	19,330	20,305	21,030
Panel G: Nitrogen				
log_pay	−0.0372**	−0.0212	−0.0173	−0.0150
	(0.0166)	(0.0163)	(0.0164)	(0.0164)
Mean	1.425	1.478	1.482	1.511
N	3278	3947	4362	4688
Panel H: Phosphorus				
log_pay	0.00292***	0.00253***	0.00244***	0.00218**
	(0.000991)	(0.000912)	(0.000884)	(0.000864)
Mean	0.129	0.128	0.126	0.120
N	6443	7544	8322	8938
Watershed-downstream FE	✓	✓	✓	✓
Watershed-year FE	✓	✓	✓	✓

(Continues)

TABLE 3 (Continued)

	(1) 0–10 miles	(2) 0–15 miles	(3) 0–20 miles	(4) 0–25 miles
Basin-downstream-year FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓

Note: The dependent variables are the annual average upstream and downstream water quality measures for a watershed. *log_pay* is the log of the EQIP payments ($2005) to the corresponding watershed. The means of the dependent variables are reported for different buffer distances used to construct the water quality measures. Standard errors in parentheses are clustered at the watershed level. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

5.3 | Comparison of estimates from the two models

Figure 4 summarizes the estimates from both the fixed effects and the flow direction models. Both point estimates as well as the 95% confidence intervals are plotted. Estimates from the flow direction model obtained using water quality readings within different buffer distances to a watershed are all reported.

Despite the differences in model assumptions and the samples used for estimation, results from both approaches show that an increase in EQIP payments significantly reduces BOD, representing a reduction in organic matter in water. Compared to the fixed effects model where the estimated impact of EQIP payments on TSS, FC, nitrogen, and phosphorus are insignificant, the flow direction model generates statistically significant estimates: an increase in EQIP payments significantly reduces nitrogen concentrations but significantly increases TSS, FC, and phosphorus. We regard the estimates from the flow direction model as more robust given the potential concerns over time-varying unobservable watershed conditions. EQIP payments are not estimated to have affected pH and temperature using either approach.

5.4 | Heterogeneous influence across watersheds

The impacts of EQIP payments are likely to differ across watersheds with different agricultural production conditions or geographic characteristics. Here, we explore whether the influence of EQIP payments varies across watersheds with different animal or crop production levels. We divide the dataset into two subsamples according to the median of animal sales or crop sales in 2012 and estimate the flow direction model using each subsample separately. Table 4 reports the estimated heterogeneous impacts of EQIP payments. We observe that EQIP payments have negative impacts on DOD and BOD across all watersheds. On the other hand, EQIP payments to watersheds with high animal sales or high crop sales are associated with statistically significant increases in TSS, FC, and phosphorus. EQIP payments might have also increased FC and phosphorus for watersheds with less agricultural production, but the estimates are less significant and smaller in magnitude. In aggregate, EQIP payments are found to have reduced nitrogen in the downstream of all watersheds except those with high crop sales and have significantly reduced downstream DOD and BOD for watersheds with low crop sales but have made downstream TSS, FC, and phosphorus pollution worse for watersheds with more agricultural production.

6 | ROBUSTNESS CHECKS

Using the flow direction model, we examine whether our estimates are robust under alternative specifications and with different measures of water quality and EQIP. Tables in the online supplementary appendix report the estimates.

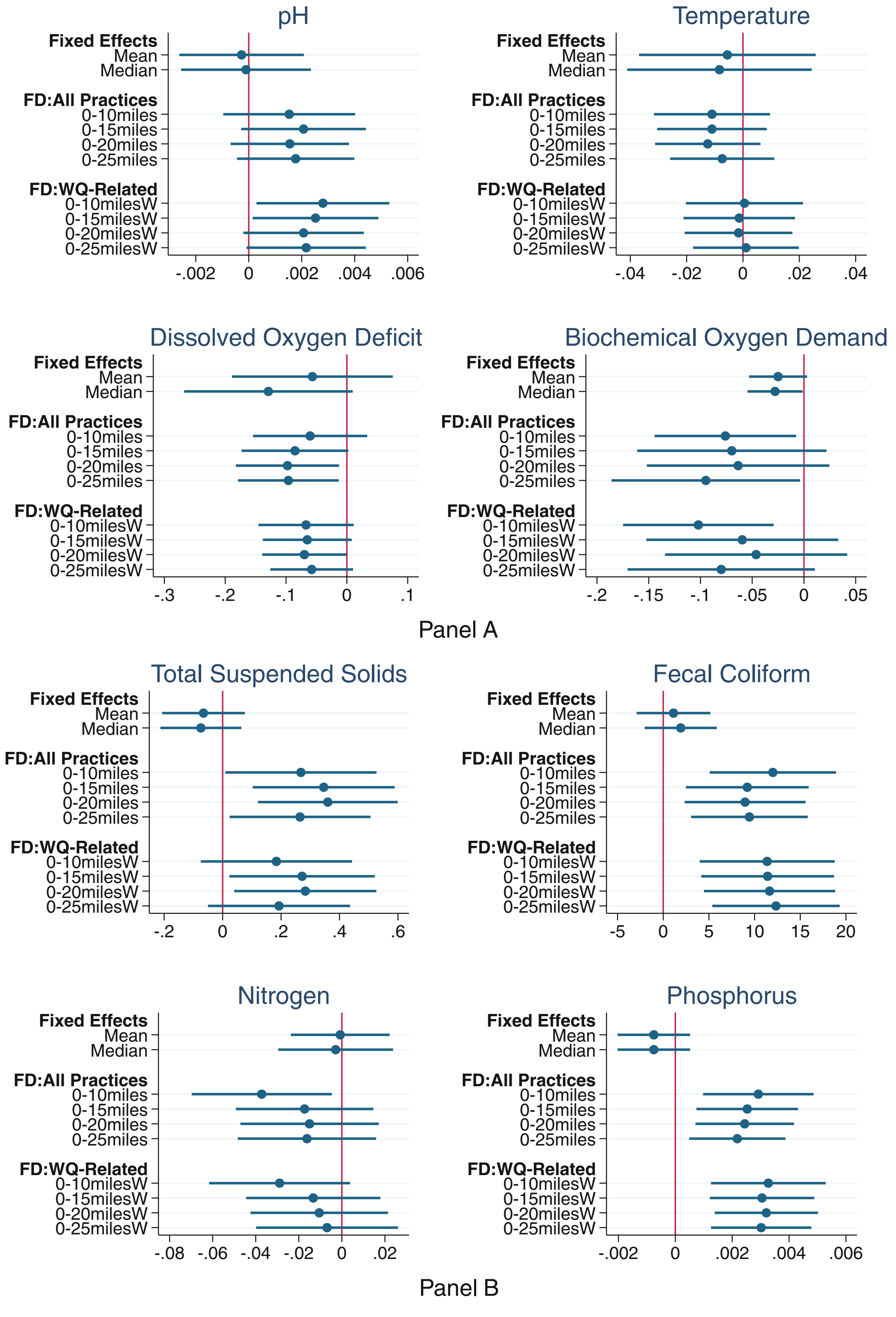


FIGURE 4 Comparison of estimates: fixed effects and flow direction approaches. This figure summarizes the point estimates and 95% confidence intervals obtained from both the fixed effects and flow direction (FD) approaches. Estimates using samples with different buffer distances to the watershed are also reported

TABLE 4 The heterogenous influence of EQIP on downstream (0–10 miles) water quality based on animal and crop sales

	(1) Low animal sales	(2) High animal sales	(3) Low crop sales	(4) High crop sales
Panel A: pH				
log_pay	0.000390	0.000976	−0.00528**	0.00359**
	(0.00210)	(0.00156)	(0.00226)	(0.00150)
Panel B: Temperature				
log_pay	0.00494	−0.00871	−0.0181	−0.00481
	(0.0165)	(0.0130)	(0.0172)	(0.0128)
Panel C: DOD				
D_pay1	−0.0228	−0.0145	−0.109**	−0.0176
	(0.0784)	(0.0588)	(0.0410)	(0.0436)
Panel D: BOD				
log_pay	−0.0654	−0.0745	−0.100**	−0.0419
	(0.0441)	(0.0539)	(0.0481)	(0.0524)
Panel E: TSS				
log_pay	−0.115	0.442**	0.0167	0.473***
	(0.195)	(0.175)	(0.224)	(0.164)
Panel F: FC				
log_pay	4.080	11.16**	8.878*	12.21**
	(4.932)	(4.944)	(4.732)	(5.170)
Panel G: Nitrogen				
log_pay	−0.0479*	−0.0346*	−0.0835***	−0.00399
	(0.0261)	(0.0204)	(0.0205)	(0.0222)
Panel H: Phosphorus				
log_pay	0.00264*	0.00235*	0.00212	0.00312**
	(0.00147)	(0.00129)	(0.00135)	(0.00140)
Watershed-downstream FE	✓	✓	✓	✓
Watershed-year FE	✓	✓	✓	✓
Basin-downstream-year FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓

Note: The dependent variables are the annual average upstream and downstream water quality measures for a watershed. *log_pay* is the log of the EQIP payments ($2005) to the corresponding watershed. The dataset constructed when we use a 10 mile buffer distance is divided into two subsamples according to the median of animal sales or crop sales in 2012 and the flow direction model is estimated separately using each subsample. Standard errors in parentheses are clustered at the watershed level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6.1 | Log dependent variables

Figure 2 reveals that the distributions of BOD, TSS, FC, nitrogen, and phosphorus are highly right skewed. Although skewness is not an issue in terms of bias estimates, we use log dependent variables to see if our main findings are robust to an alternative functional form. We estimate Equation (2) using the log of the water quality measures as the dependent variable, instead of the levels. Table A.4 in the online supplementary appendix reports the estimation results for the five highly skewed water quality measures. Though the magnitudes of the estimated effects are slightly smaller than those obtained using the semi-log specification in Table 3, the signs and the significance levels are the same. Estimates obtained using the log–log specification indicate that a 10% increase in EQIP payments would approximately decrease

BOD by 0.05% and nitrogen by 0.04%, and approximately increase TSS by 0.06%, FC by 0.17%, and phosphorus by 0.02%. The findings of the influence of EQIP payments on water quality are thus consistent between the log–log and the semi-log specifications.

6.2 | Lagged EQIP payments

It is possible that water quality is not only affected by EQIP payments in the current year but also EQIP payments in the previous year or even earlier.[******] As a robustness check, we add one-year and two-year lagged payments in the flow direction model, in addition to concurrent payments. Table A.5 in the online supplementary appendix summarizes the estimates when we add one-year lagged payments or both one-year and two-year lagged payments. Comparing the estimates in Table A.5 to those in Table 3, estimates on concurrent payments are statistically equivalent to those reported in Table 3. Lagged payments do not affect TSS, FC, nitrogen, or phosphorus, suggesting that the average influence of EQIP funded projects on these water pollutants is transitory. One exception is BOD: estimated coefficients of lagged payments are similar in magnitude to those of concurrent payments. Though concurrent payments are not statistically significant when both one-year and two-year lagged payments are added, they are jointly significant, suggesting that the impact of some EQIP practices on BOD could be long lasting. Given that most two-year lagged payments are statistically insignificant, we did not consider further lags.

6.3 | Summer water quality

Both temperature and precipitation affect water quality: for example, higher temperature decreases the amount of dissolved oxygen in the water, and heavy precipitation could lead to more agricultural runoff. We include both temperature and precipitation as controls in all our regressions. In addition, we examine whether EQIP payments affect summer water quality differently. We construct water quality measures by averaging monitoring station readings taken from June to September. The estimated impact of EQIP on water quality during the summer months, reported in Table A.6 in the online supplementary appendix, is largely the same as its impact on the annual average water quality, reported in Table 3.

6.4 | Water quality related EQIP payments

So far, we use payments to all EQIP practices as our variable of interest. Table A.7 in the online supplementary appendix lists the names and the NRCS codes of EQIP practices in our sample as well as an indicator for practices that are directly related to water quality, according to the NRCS definitions. Many practices can affect water quality either directly or indirectly. However, practices directly related to water quality may have a stronger influence on water quality than other practices. Therefore, we estimate Equation (2) using only payments for water quality related EQIP practices. Table A.8 reports these estimates. Water quality related EQIP practices might have a slightly stronger influence on BOD and phosphorus, compared to Column (1) in Table 3, and a statistically significant positive impact on pH, consistent with the fact that a reduction in organic matter in water may reduce water acidity. On the other hand, water quality related EQIP practices might have a weaker impact on TSS and nitrogen: The estimated impact of EQIP payments on TSS is statistically

[******]Note that if a farmer decides to keep implementing some EQIP practices, EQIP supported projects could still be active after contract completion and thus have a long-lasting impact on water quality. However, we were not able to obtain confidential, farm-level EQIP data. Future research can further investigate the potential legacy effect of EQIP payments when new data become available.

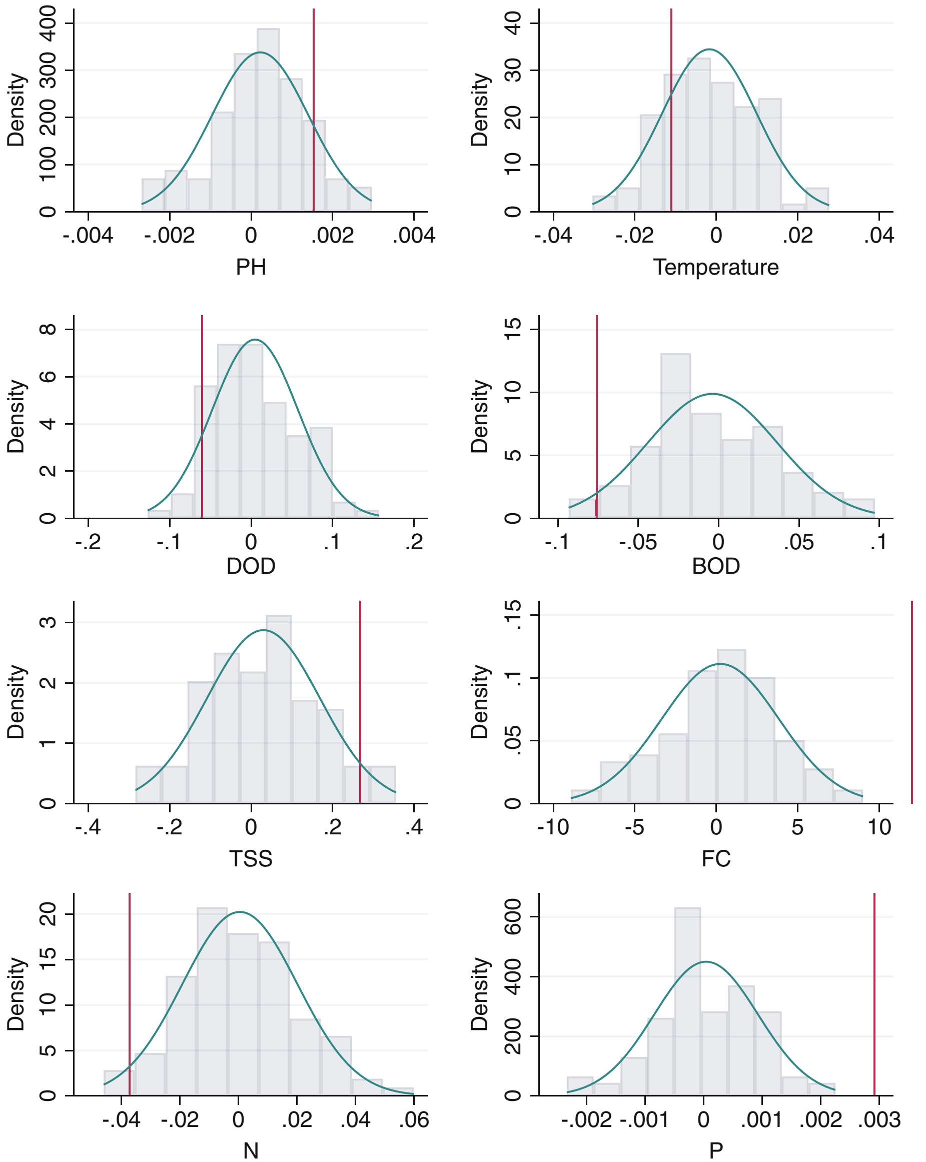


FIGURE 5 Falsification test. This panel of figures shows the distribution of estimates from the falsification test for each water quality measure. We randomize EQIP payments across watersheds 100 times and estimate the flow-direction model after each randomization using water quality measures within 10 miles. The histogram represents the distribution of the estimated coefficients obtained using the randomized samples and the vertical line indicates the corresponding point estimate from Column (1) in Table 3

insignificant now. These estimates suggest that practices not directly related to water quality on average might have helped with nitrogen and phosphorus reduction but contributed to soil erosion.

In addition, we estimate the effects of lagged EQIP payments when considering only water quality related payments. Table A.9 in the online supplementary appendix reports the estimation results when we include one-year lagged payments or both one-year and two-year lagged payments. Results show that the influence of lagged water quality related EQIP payments is similar to that of lagged all EQIP payments reported in Table A.5.

6.5 | Number of EQIP projects

We also use the number of EQIP-funded projects, instead of the amount of EQIP payments, as the variable of interest. Keiser and Shapiro (2019) use the number of EPA grants to wastewater treatment plants to examine the influence of Clean Water Act on water quality. We use both the total number of EQIP projects and water quality related EQIP projects. Tables A.10 and A.11 in the online supplementary appendix report the estimates when we replace EQIP payments with the number of EQIP projects. Compared to the corresponding estimates with payments as the variable of interest shown in Tables 3 and A.8, the directions of the impacts are the same, though the negative impact of EQIP on BOD is no longer statistically significant, and our main findings are unchanged. EQIP projects vary widely in payments and impacts on water quality. From the efficiency perspective, the focus should be on the marginal benefit of EQIP funding. Thus, we use payments as our main variable of interest.

6.6 | Weighting socioeconomic control variables

Socioeconomic control variables are observed at the county level. In our main analysis, when a watershed is located across multiple counties, we use the socioeconomic variables from the county that has the largest share of the watershed area. For a robustness check, we report estimates in the online supplementary appendix Table A.12 using shares of the watershed area weighted county socioeconomic variables as controls. The estimates are almost identical to those reported in Table 3.

6.7 | A falsification test

We conduct a falsification test by randomizing EQIP payments across watersheds. We estimate Equation (2) after each randomization and repeat the process 100 times. Figure 5 plots the estimated effects of EQIP payments on water quality within 10 miles downstream. The histogram in each panel represents the distribution of the estimated coefficients obtained using the randomized samples, and the vertical line indicates the corresponding point estimate from Column (1) in Table 3. The distributions are all centered around zero. As expected, EQIP payments do not have any influence on these pseudo-outcomes, that is, water quality downstream of a different watershed.

7 | CONCLUSION

As the largest conservation program on working agricultural land in the United States, EQIP addresses the most pressing environmental and natural resource concerns of agricultural production. The program has provided substantial financial and technical assistance to farmers and ranchers. However, it is unclear whether and by how much the program has provided environmental benefits. Reducing nonpoint source water pollution in impaired watersheds is one of the national priorities set by NRCS under EQIP. Our paper provides the first econometric estimates of the influence of EQIP on local water quality at a national scale.

We assess the impact of EQIP on local water quality by linking monitoring station level water quality readings with EQIP payment information at the watershed (HUC10) level and by exploiting the direction of the river flow for identification. Our estimates suggest that EQIP payments have significantly reduced organic matter, as indicated by the reductions in BOD, and nitrogen in surface water, both indicating improvements in water quality. However, we also have evidence that EQIP payments have significantly increased total suspended solids, fecal coliform, and phosphorus in surface water, suggesting that the implementation of some EQIP practices might have inadvertently resulted in the deterioration of certain measures of water quality. Better assessment before program enrollment, for example by using simulation tools, should be considered to increase water quality benefits delivered by conservation programs in the future (Arabi et al. 2012; Rabotyagov et al. 2014).

Given that our estimates show that EQIP payments have reduced BOD and nitrogen, it is tempting to compare the estimated benefits of EQIP to its costs. Unfortunately, few studies in the literature have estimated the monetary values of changes in individual water quality measures (Egan et al. 2009; Poor et al. 2007; Leggett & Bockstael 2000; Epp & Al-Ani 1979). Moreover, heterogeneity in the value of a water quality measure across watersheds limits these studies to small geographical regions and makes it challenging to calculate national average benefits (Griffiths et al. 2012). To put our estimates in perspective, we calculate the cost effectiveness of EQIP projects for BOD and nitrogen. Estimates from our preferred specification in Column (1) of Table 3 suggest that a one standard deviation increase in EQIP payments reduces BOD and nitrogen by 0.101 mg/L and 0.041 mg/L, respectively. Using the standard deviation of EQIP payments and the percentiles of water quality measures reported in Table 1, our estimates indicate that $0.27 million (2005 dollars) EQIP payments per year is needed to reduce BOD from the 90th percentile to the 10th percentile for a mile of downstream water and $0.23 million per year is needed to reduce nitrogen from the 90th percentile to the 10th percentile for a mile of downstream water. Though these estimates might be helpful for a back of the envelope comparison across water pollution control programs, we would caution that the impact of EQIP varies widely across watersheds, and such calculations ignore the complex relationships between water quality measures.

Our analysis provides a foundation for further assessment of the efficiency of EQIP. Considering the scale and the scope of the program, an endeavor to systematically evaluate the efficiency of the program across watersheds and conservation practices will be challenging. Future research should strive to use observational data to examine more nuanced aspects of EQIP. For example, considering the complexity of the hydrological processes, as a voluntary cost-sharing conservation program, has EQIP been more efficient in certain types of watersheds than others? Among over 200 conservation practices adopted by farmers participating in EQIP, are some practices more efficient than others in mitigating a certain water quality issue? Studies employing geospatially linked datasets with farm characteristics and ambient pollutant concentrations could prove fruitful in providing insights on the design and implementation of voluntary conservation programs.

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