Financial Assistance and Environmental Compliance: Evidence from the Clean Water Act and the Clean Water State Revolving Fund

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Abstract

Using the National Pollution Discharge Elimination System compliance and the Clean Water State Revolving Funds (CWSRF) data for wastewater treatment plants in nine states between 2010 and 2018, we examine a) the effect of non-compliance on the distribution and size of awarded CWSRF loans, and b) the effects of the CWSRF provision and award size on post-funding compliance. We observe that funded facilities have poorer compliance records than the unfunded ones and that funded facilities decrease violations within two years after receiving financial support. On average, a $50 million CWSRF loan decreases violations by one count within two post-funding years.

JEL: H40, Q53, H77, Q58

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1. Introduction

Protection of water quality is one of the primary objectives of environmental policy and regulation in the U.S. Passed by Congress in 1972, the Clean Water Act (CWA) has been one of the most prominent federal laws protecting the nation's water resources and environmental quality. Although significant progress has been made, major water quality challenges persist despite more than a trillion dollars spent on abatement initiatives since the CWA (Keiser and Shapiro 2019; Keiser, Kling, and Shapiro 2019). Compliance of wastewater treatment plants with the CWA is a major component of efforts to improve surface water quality in the U.S. Concerns about the adequacy of the wastewater treatment infrastructure, including investment needs, have been documented (USEPA, 2000; USEPA 2016a; Ramseur, 2017)[1].

In 1987, the Clean Water State Revolving Funds (CWSRFs) program was introduced to facilitate compliance with the CWA. The purpose of the CWSRFs program is to provide low-cost loans for a wide range of water quality infrastructure initiatives, including projects aimed at improving compliance with the National Pollutant Discharge Elimination System (NPDES) permits (Copeland 1999; Travis, Morris and Morris 2004; Copeland 2012). NPDES maintains point source discharge permits for a list of regulated water pollutants and corresponding records of reported violations. These permits restrict the discharge of regulated pollutants and specify monitoring and reporting requirements that form the basis for enforcement (Helland 1998a,b; Gaba 2007; Chakraborti and McConnell 2012).

Despite the importance of financial support and the CWSRF program, the distribution and the impact of the CWSRF loans have not been studied. In this paper, we examine the distribution of financial assistance across wastewater treatment plants and the impacts on compliance with the NPDES permits. The objective of this study is twofold. First, we examine the distribution of CWSRF loans across wastewater treatment plants in terms of the likelihood of receiving the award and the size of the awarded loans. In particular, we focus on the role of pre-funding compliance records. Is CWSRF support allocated to poorly performing facilities with more NDPES permit violations? Second, we evaluate the efficacy of CWSRF assistance in mitigating NPDES permit violations. Do CWSRF loans reduce NPDES permit violations in subsequent years? We examine the effects of CWSRF provision and award size on post-award non-compliance.

Adequate wastewater infrastructure financing is critical for compliance with the NPDES permit requirements and protecting water quality (Ramseur 2017). The CWSRF loans provide financial assistance to municipal, state, inter-municipal, or interstate agencies for construction or maintenance of publicly owned treatment works; for construction, repair, or replacement of decentralized wastewater treatment systems; for reduction, treatment, or recapture of stormwater or subsurface drainage water; for implementation of water conservation, efficiency, or reuse measures aimed at reducing the demand for publicly owned treatment works capacity; for implementation of measures to reduce energy consumption needs for publicly owned treatment works; and for measures supporting reuse and recycling of wastewater, stormwater, or subsurface drainage water (Copeland 1999; USEPA 2016a; USEPA 2020). Although CWSRFs can be used for a variety of projects, GAO (2006) reports that most of the funds (96%, approximately $50 billion) are used for wastewater treatment facilities and conveyance projects. States rely heavily on CWSRFs to finance water quality improvement projects (GAO 2006) and allocate funds according to various priorities, including wastewater infrastructure maintenance and replacement needs, population changes, EPA enforcement requirements, and stricter EPA and state water quality standards for temperature, nutrients, and sediments. States are required to match at least 20% of the federal contribution to the CWSRF loans.

The NPDES permits require facilities to sample their discharge and submit the Discharge Monitoring Reports (DMRs), documenting permit violations, to the designated regulatory agency. The EPA and state regulatory agencies also rely on inspections to advance compliance with the NPDES guidelines and procedures. The EPA and the authorized state agencies have various enforcement tools at their disposal against violators of NPDES permit requirements. For example, the regulators may issue administrative orders which require facilities to correct the documented violations. The law also authorizes the regulators to take up civil and criminal proceedings, including mandatory injunctions, penalties, and jail sentences against individuals found to have violated the restrictions willfully.

We use the NPDES discharge violations data from wastewater treatment facilities in nine states between 2010 and 2018 to examine the distribution of CWSRF support and the efficacy of financial support for compliance with CWA. While most recent CWSRF annual reports are available for all 50 states, past reports that include facility-level data are available only for the nine states in this study. The distribution of the CWSRF loans across facilities and over time presents a convenient setting that allows us to compare the performance of funded and unfunded facilities. In particular, we examine the difference between funded and unfunded facilities in terms of pre and post-funding compliance with the NPDES permits. The pre-funding analysis of violations sheds light on the role of non-compliance in the distribution of CWSRF loans, including award counts and magnitudes. The post-funding analysis examines the efficacy of CWSRF awards in improving compliance with the NPDES permits conditional on the award size. We also distinguish the effects of CWSRF awards provided once from the effects of awards provided twice or more times on the post-funding compliance of funded facilities.

Water quality challenges vary across states and watersheds. Similarly, non-compliance of wastewater treatment plants varies across regulated pollutants and regions. Regional authorities may also focus on different pollutants depending on regional priorities and watershed improvement goals. Therefore, we examine the aggregate number of violations instead of focusing on a subset of specific contaminants. Our objective is to examine non-compliance broadly rather than for a particular pollutant. We focus on aggregate violations because the use of particular pollutant violations would be too narrow to make conclusions about the relationship between CWSRF awards and compliance in general. Examination of the aggregate number of violations is more likely to capture the effect of non-compliance on funding and the effect of CWSRF loans on compliance than would an examination of a subset of regulated pollutants.

We observe that the CWSRF loans are allocated to the facilities that appear to be in greater need of support according to the number of cumulative violations. Funded facilities have more violations than unfunded facilities before receiving CWSRF support. Conditional on controls, the results show that violations one year before funding differ significantly across funded and unfunded facilities. Although funded facilities continue to have more violations post-funding than the unfunded facilities, CWSRF loans reduce NPDES violations of funded facilities within two years of receiving support. The lagged effect of loan provision on improved compliance beyond two years is expected because updating wastewater infrastructure and treatment technologies takes some time after loans are provided (Keiser and Shapiro 2019). We also observe that loan size matters for the impacts of one-time but not repeated awards on non-compliance within the first two post-funding years. This result is likely due to a temporal lag in the impact of the awards on non-compliance, especially for larger awards that may require multiple years for project completion.

The remainder of this paper is arranged as follows. Section 2 provides a brief review of the related literature. In Section 3, we review the empirical methodology. Section 4 presents the data used in the analysis. Section 5 presents the empirical results. Discussion and conclusions are provided in the last section.

2. A brief review of related literature

Although water quality in the U.S. has improved significantly since the enactment of the CWA, the law has been one of the most controversial environmental regulations in the U.S. Studies like Harrington and Malinovskaya (2015) and Keiser and Shapiro (2019) find that investments under the CWA have helped reduce water pollution. Other studies document a lack of sufficient improvement in water quality (Adler, Landman and Cameron 1993; Knopman and Smith 1993; Harrington et al., 2009; Hayward 2011; Smith and Wolloh 2012). The EPA reports that over half of stream miles in the U.S. still violate water quality standards (Keiser and Shapiro 2019). In a national assessment of 1.2 million wetland acres, 658 thousand acres were impaired for at least one designated use. Organic enrichment, oxygen depletion, mercury, arsenic and selenium are the top causes of impairment (USEPA, 2016b).

Limited existing literature examines the impact of financial support for water infrastructure. Keiser and Shapiro (2019) assess the effectiveness of the CWA grants in reducing ambient pollution and find that downstream water quality improves after facilities receive financial support. Harrington and Malinovskaya (2015) find that between 2008 and 2012, the CWSRFs were not necessarily allocated to water treatment plants with greater pollutant discharge. However, wastewater treatment plants that receive financial assistance experience a greater reduction in pollutant discharge than unfunded plants. Flynn and Marcus (2021) find that the CWA grants awarded to wastewater treatment plants improve downstream infant health outcomes. Our work adds to the literature by evaluating the effects of the CWSRF on compliance with NPDES permits under CWA. Unlike prior studies, we examine the cumulative violations across all pollutants regulated by the NPDES permits rather than individual regulated pollutants.

Using the data from the EPA's Grants Information and Control System (GICS), Keiser and Shapiro (2019) examine the effects of the CWA investments on ambient pollutant concentrations. Their results indicate that, on average, each CWA grant to municipal wastewater treatment plants decreases downstream dissolved oxygen deficit, fecal coliforms, and the probabilities that downstream waters are not fishable and swimmable. Harrington and Malinovskaya (2015) evaluate the performance of the CWSRF in Iowa, Indiana, Maryland and Texas. Using the Clean Watersheds Needs Survey (CWNS), the Clean Water Benefits Reporting System (CBR) and the Discharge Monitoring Report (DMR) data, they examine the changes in discharge water quality across funded and unfunded wastewater treatment plants. They found that loans awarded between 2008 and 2012 improved plant performance in terms of biochemical oxygen demand (BOD) and organic nitrogen levels relative to the plants in the corresponding states that did not receive the loans. McConnell and Schwarz (1992) also argue that high BOD pollution by wastewater treatment plants is partly due to the lack of federal subsidies.

Previous studies examine the effects of inspection and enforcement on compliance with the CWA (Magat and Viscusi 1990; Earnhart 2004; Shimshack and Ward 2005; Gray and Shimshack 2011). Gray and Shimshack (2011) provide a helpful review of empirical studies on environmental monitoring and enforcement actions and find that monitoring and enforcement activities reduce emissions and violations. Magat and Viscusi (1990) examine compliance with water pollution regulations in the U.S. pulp and paper industry between 1982 and 1985 and find that inspection improves compliance. Sanctions, and especially federal fines, have also reduced pollution by wastewater treatment plants and chemical facilities in the 1990s (Earnhart 2004). Shimshack and Ward (2005) empirically explore the impact of enforcement efforts on biochemical oxygen demand (BOD) and total suspended solids (TSS) in pulp and paper production. They find a two-thirds reduction in statewide monthly violation rates in the years following a fine. On the other hand, non-monetary sanctions, including formal administrative orders, formal notices of non-compliance, and administrative consent orders, have no effect on compliance. Malik (1993) shows that regimes with self-reporting can reduce regulatory costs if less frequent inspections are coupled with more consistent and frequent punishment. However, failures and inconsistencies of the CWA enforcement have been documented in the popular press, government reports, and the law and economics literature (Flatt 1997; Sigman 2005; Duhigg 2009; GAO 2009).

Previous literature also documents the effects of special interests and corruption on compliance with the NPDES permit system (Flatt 1997; Grooms 2015). Using the Permit Compliance System (PCS) and Integrated Compliance Information System (ICIS) data, Grooms

(2015) finds that more corrupted states report larger decreases in documented violations than less corrupted states after oversight transitions from federal to state control. Helland (1998a) examines the NPDES permit violations and special interest groups' influence on state-level regulation using data from 232 pulp and paper plants from 1989 to 1993. He finds that state regulatory agencies are responsive to national and local interest groups. The extent of state residents' involvement in environmental organizations affects violations and the probability of inspection. Grant and Grooms (2017) empirically examine nonprofit environmental groups' influence on compliance with environmental regulations under the NPDES permit system. Their results suggest that the presence of nonprofit environmental organizations reduces the number of violations. They also find that nonprofit groups reduce government inspections and severe effluent violations.

The EPA authorizes states to pursue enforcement actions under the CWA, which leads to inconsistencies in CWA enforcement across states (Grooms 2015). Unique environmental, financial, and cultural settings lead to enforcement heterogeneity (Travis, Morris and Morris 2004). Flatt (1997) argues that without the threat of federal oversight, states are left to their own devices with no mechanism for uniform enforcement of the CWA laws. Lack of federal efforts to ensure the consistency of enforcement has been documented (GAO 2009). We consider the data from nine states with different environmental, regulatory and fiscal contexts. We control for state heterogeneity using fixed-effects specifications and defer a detailed examination of particular state-level differences to future studies.

3. Methods

Our empirical approach takes advantage of the variation in NPDES non-compliance and CWSRF loan provision across wastewater treatment plants. We start with a t-ratio comparison of facility violations before versus after receiving financial support, and across funded and unfunded facilities. Next, for the pre-funding violation analyses, we evaluate the difference between pre-funding compliance of funded and unfunded facilities. The pre-funding analysis examines the differences in violations of funded and unfunded facilities one, two and three years before CWSRF provision. We use Heckman's two-stage estimation to examine the effect of non-compliance on funding outcomes and award sizes. We also use a difference model with violations as the dependent variable and future funding as the independent variable for pre-funding compliance analysis. Last, we examine post-funding compliance of funded and unfunded facilities using multiple period difference-in-difference (DiD) techniques (Kirkpatrick and Bennear 2014; Yamazaki 2017). Post-funding analyses are repeated on a matched group of funded and unfunded facilities using the propensity score matching technique. We include binary funding outcomes and award sizes in pre-funding and post-funding analyses.

T-ratio analysis

The temporal variation in the provision of CWSRF loans across treatment plants enables a comparison of violations within and across funded and unfunded groups before and after funding. We start with a t-ratio comparison of a) mean annual violations of funded and unfunded facilities after each funding year, b) mean annual violations of funded and unfunded facilities prior to each funding year, c) mean annual pre and post-funding violations of funded facilities, and d) mean annual violations of unfunded facilities before and after specific years.

Funded facility treatment groups include only the facilities funded in the respective year but not in the previous two years. Each of the corresponding control groups includes facilities that are not funded in the corresponding year, the preceding two, or the subsequent two years. For example, the 2014 treatment group, comprised of the facilities financed in 2014 but not before, is compared to the control group with facilities not funded between 2012 to 2016. The comparisons are made using the average number of annual violations from three pre-funding years and three post-funding years to assess differences between the funded and unfunded groups as well as changes within each group pre- versus post-funding. Each treatment year comparison excludes the violations from the corresponding year because the relative timing of the CWSRF award and violation occurrence is difficult to establish. Furthermore, violations documented in the same year as the CWSRF award are unlikely to be important determinants of CWSRF awards or to reflect the effects of loan provisions on compliance.

Pre-funding compliance

We explore the effect of pre-funding violations on CWSRF loan allocation by comparing the pre-funding violations of funded facilities with corresponding violations of unfunded facilities. The pre-funding analyses use violations as the independent variable to examine the effects on funding decisions and award sizes. Heckman's 2 stage model includes first stage binary funding outcomes and second stage award magnitudes conditional on receiving CWSRF support. For funded facilities, we include CWSRF provision observations from 2010 to 2018 and compliance data from the corresponding three pre-funding years. For example, to examine the distribution of CWSRF support in 2010, we use compliance data from 2007 to 2009. Hence, our group of funded facilities includes those that received CWSRF support between 2010 and 2018. It would be preferable to ensure that those facilities did not receive support before 2010. Unfortunately, we do not have data on CWSRF prior to 2010. For treatment years 2012 through 2018, we ensure that neither treatment nor control facilities received CWSRF since 2010.

The Heckman model is used to examine the likelihood and magnitude of CWSRF in two stages. Selection bias occurs when certain facilities are systematically included in the second stage based on the first stage selection process. This can lead to biased and inconsistent estimates in the second stage because the analysis is based on a censored sample. Heckman two-step selection model is a standard approach in these types of circumstances (Little and Rubin 2019; Brounen and Kok 2011). In the first stage, a probit model with state and year controls is used to examine whether facilities receive CWSRF support.

$$\Pr(F_{ist} = 1) = \Phi(q_s + \lambda_t + \beta_1 y_{i,t-1} + \beta_2 y_{i,t-2} + \beta_3 y_{i,t-3} + \boldsymbol{\pi}\, \boldsymbol{X}_{it} + \delta \mathrm{RF}_{ist} + \varepsilon_{it}) \qquad [1]$$

where, $\Phi(\cdot)$ is the cumulative density function of the standard normal distribution. F_{ist} takes the value of 1 when a facility *i* in state *s* receives CWSRF loan in year *t*. Q_s and λ_t are state and year fixed effects. $y_{i,t-1}, y_{i,t-22}$, and $y_{i,t-3}$ are annual violations by facility *i* in state *s* in one, two and three years before *t*. β_1, β_2 and β_3 show the effect of lag violations on funding decisions. To account for the possibility of some facilities receiving CWSRF loans in more than one year, repeated funding binary control, *RF*, is included that takes value of 1 if the awarded loan is one of several loans and zero otherwise. This variable is excluded from the second stage formulation because it is statistically insignificant and inclusion of at least one explanatory variable only in the selection equation is recommended (Sartori 2003). ***X*** represents a vector of facility, county and state level time-variant controls. ε_{it} is the standard idiosyncratic disturbance term.

In the second stage, linear specification is used to examine the magnitude of assistance as follows:

$$Z_{ist} = \alpha_s + \lambda_t + \beta_1 y_{i,t-1} + \beta_2 y_{i,t-2} + \beta_3 y_{i,t-3} + \boldsymbol{\pi}\, \boldsymbol{X_{it}} + \vartheta\psi + \varepsilon_{it} \qquad [2]$$

where, Z_{ist} is the magnitude of the loan awarded to facility *i* in state *s* and period *t*. α_s and λ_t are state and year fixed effects. The inverse of Mills ratio, ψ , is obtained from the first stage probit model. All regressors from the first stage are used in the second stage regression except for repeated funding dummy *RF*.

We also examine the prefunding compliance using panel count models including Poisson and logit with violations as the dependent variable and CWSRF support in the future three years as explanatory variables. Poisson regressions use facility annual number of violations, while logit models use transformed binary annual violation occurrence as dependent variables. Clearly, the purpose of these regressions is not to imply a causal inference in terms of the effect of future funding on violations in the preceding years. Instead, these regressions shed light on whether the facilities that are funded in the future have more violations in the present. In other words, these models quantify differences in the present, pre-funding violations between funded and unfunded facilities in the future. Although these "difference" models are not very intuitive in terms of causal inference, they offer an additional insight for the difference in prefunding compliance of funded and unfunded facilities. Therefore, the results from these models are provided in the appendix.

We examine Heckman as well as count models because they use different empirical specifications and data. The methods use different data because the dependent variable in the count difference models is violations in year t (2009-2015) and control variables, including facility size and county income in year t, and future funding in t+1, t+2, and t+3. On the other hand, the dependent variable in the Heckman models is funding in years 2010-2018 with lag violations, county income, facility size and repeated funding dummy as control variables. Hence, the dependent variable and the controls for flow and income in the Poisson models are for 2009-2015.[2]

On the other hand, the dependent variable and the controls for flow and income in the Heckman models are for 2010-2018. As a result, the data and the number of observations differ across the two approaches. Hence, some differences in findings are possible. Since the conclusions can differ, we feel that reporting the results from both approaches is helpful for robustness' sake.

Post-funding compliance

The difference-in-difference (DiD) technique has been widely used to study similar intervention effects, where outcomes are compared over time and between treatment and control groups (Angrist and Pischke 2008; Brent, Cook and Olsen 2015; DeAngelo and Hansen 2014; Finkelstein 2007; Lavaine and Neidell 2017). Post-funding analysis exploits the DiD estimation techniques to compare the NPDES permit violations across funded and unfunded facilities and across pre and post-funding periods. Provision of the CWSRF loans cannot be assumed to be random, as would be required for a randomized experimental study with treatment and control groups. This is common in most social science research based on observational data. Nevertheless, the DiD framework enables the analysis of loan provision and non-compliance conditional on the parallel trends in violations of funded (treatment group) and unfunded (control group) facilities prior to providing CWSRF loans. We confirm that the pre-treatment violation trends of funded and unfunded facilities do not differ significantly in most cases based on the parallel trends tests. We also present the results from the matched DiD analyses based on the nearest neighbor propensity score matching.

We proceed with the multiple-period (Kirkpatrick and Bennear, 2014 Yamazaki 2017) analysis of combined funding year treatments. We employ DiD models to compare the violations within and across funded and unfunded groups before and after CWSRF awards. The control group includes facilities that are not funded within the corresponding pre-treatment, treatment, and post-treatment periods, while the treatment groups include facilities that receive CWSRF in the corresponding year but not in the preceding years. The treatment group facilities are funded in one or more years in the relevant window.

The regressions use data from several pre-funding and two post-funding years and exclude the data from the corresponding funding year for funded facilities. Observations for treatment facilities in treatment years are not included in our analyses because relative timing of violations versus awards could not be established within the treatment years. For the control group, all observations are included. We ensure that none of the facilities in our treatment or control groups receive CWSRF support in pre-funding years.

We perform the DiD analysis using two samples: one includes only one-time funded facilities between 2014 and 2016 as a treatment group, and the other includes facilities that received one or more loans between 2012 to 2016 as a treatment group. Between 2014 and 2016, only ten facilities received multiple awards. Therefore, we focus on singular awards in these models and ensure that pre-treatment (2010-2013) funding is not provided to any of the included facilities. This analysis disregards repeated funding and examines the effect of singular CWSRF awards. To account for multiple awards, we use the second sample (2012-2016), which includes 105 facilities funded more than once. However, the 2012-2016 analyses use observations from only two pre-funding years (2010 and 2011) for parallel trend tests. Hence, the advantage of the 2014-2016 analysis focusing on singular awards is that these models include four rather than two pre-funding years to confirm parallel trends of treatment and control groups pre-treatment. On the other hand, 2012-2016 analysis includes repeatedly funded facilities but uses only two pre-treatment years for parallel trend confirmation. We confirm the parallel trends of treatment and control facilities for both approaches. Also, conventional and propensity score matching-based DiD specifications are used for both (Chabé-Ferret and Subervie 2013).

The effects of CWSRF loans on post-treatment compliance are examined in terms of discrete funding and in terms of loan magnitude effects. First, we examine funding decisions disregarding the magnitudes of the loans. Subsequently, we include the effects of the loan magnitudes.

Dynamic estimation with lagged dependent variable as a regressor can result in a correlation between the unobserved effect and the dependent variable (Deininger et al., 2011). Therefore, we estimate our models conditional on both the initial value of the dependent variable and the facility level average of the time-varying exogenous variables (Wooldridge 2005; Vesterberg 2018; and Deininger et al. 2011). All models are estimated using the standard facility level random effects Poisson model.

Parallel Trend Assumption

The DiD analysis relies on the assumption that the control group serves as an adequate proxy for the counterfactual outcome that would have been observed in the treatment group if the treatment was absent (Ryan et al. 2015; Chan et al. 2017; Lai 2017; Oakes and Kaufman 2017). As is common in observational data, we cannot test this assumption directly because we do not observe the treated group in the absence of support from CWSRF. The identifying assumption in such a situation rests on the parallel trends of outcomes in the treatment and control groups in the pre-treatment period (Wrenn, et al. 2016). This assumption holds if trends are similar across the treatment and control groups in the absence of the treatment (Beatty and Shimshack 2011).

The validity of the parallel trend assumption can be assessed by testing whether the differences in pre-funding trends of violations between treatment and control facilities are statistically and economically indistinguishable from zero. We use equation (3) to test differences in trends during four pre-treatment years in the models for the singular awards made between 2014 and 2016 as follows (Autor 2003; Agarwal and Qian 2014; Kearney and Levine 2015; Cerulli and Ventura, 2019):

$$y_{ist} = \alpha_s + \lambda_t + \beta_1 F_{i,t+2} + \beta_2 F_{i,t+3} + \beta_3 F_{i,t+4} + \beta_4 F_{i,t-1} + \beta_5 F_{i,t-2} + \varepsilon_{it} \qquad [3]$$

where, y_{ist} is the violation of facility i in state s at time t, λ and α are time and state fixed effects. We include an indicator for the three out of four pre-treatment periods and leave out the indicator for the last pre-treatment period (t+1). $F_{i,t+2}$, $F_{i,t+3}$, $F_{i,t+4}$ are 1 if facility i is funded 2, 3, or 4 years after. Hence, the corresponding beta coefficients represent the prefunding difference in violations. Pre-treatment indicators (β_1, β_2 and β_3) are expressed relative to the omitted period, which serves as the base period for the parallel trends tests. If the trends in pre-treatment violations between treatment and control facilities are similar during the pre-treatment periods, then β_1, β_2 and β_3 should be statistically insignificant (Kearney and Levine, 2015). $F_{i,t-1}$ ($F_{i,t-2}$) are 1 if facility i receives CWSRF one (two) year(s) before t, and 0 otherwise. β_4 (β_5) indicate the difference in violations between treatment and control facilities one (two) years after receiving the CWSRF support relative to the benchmark control group (Agarwal and Qian, 2014).

A similar formulation is used to evaluate two pre-treatment years' violation differences in the models that include singular and repeated awards made between 2012 to 2016 (equation 4). In this formulation β_1, β_4, and β_5 is analogous to the corresponding coefficients in equation 3. β_2 and β_3 are absent from equation (4) because this model includes only two pre-funding years for parallel trend analysis. However, this model includes β_6 for repeated funding effect pretreatment and β_7 and β_8 for repeated funding effects post-treatment.

$$y_{ist} = \alpha_s + \lambda_t + \beta_1 F_{i,t+2} + \beta_4 F_{i,t-1} + \beta_5 F_{i,t-2} + \beta_6 RF_{i,t+2} + \beta_7 RF_{i,t-1} + \beta_8 RF_{i,t-2} + \varepsilon_{it} \quad [4]$$

Binary funding treatment DiD

The DiD strategy is applied in a setting with multiple periods and treatments (Imbens and Wooldridge 2009). First, we focus on the effects of binary funding decisions disregarding the magnitudes of the loans and account for repeated awards using equation (5). Multiple indicator variables reflect the heterogeneity in the lagged effects of funding provision on non-compliance in subsequent years. The multi-period regression model for the combined treatment analysis examines the difference in violations in the post-treatment years across treatment and control facilities.

$$y_{ist} = \alpha_s + \lambda_t + \beta_{11} F_{i,t-1} + \beta_{12} F_{i,t-2} + \beta_{21} RF_{i,t-1} + \beta_{22} RF_{i,t-2} + \boldsymbol{\beta_3} \boldsymbol{X_{it}} + \varepsilon_{it} \quad [5]$$

where y_{ist} is the violation by facility *i* in state *s* in year *t*. F and RF are the dummies for one-time funding and for repeated funding respectively. $F_{i,t-1}$ ($F_{i,t-2}$) is 1 for facility-year observations with one and only loan provided one (two) year(s) ago. Similarly, $RF_{i,t-1}$ ($RF_{i,t-2}$) is 1 for facility-year observations with the last of the repeated awards provided one (two) year (s) ago. Hence, β_{11}, and β_{12} show the effects of receiving a one-time award in treatment year t-1 and t-2 on violations in year t. Similarly, β_{21}, and β_{22} respectively show the effect of receiving awards in multiple years in treatment years t-1 and t-2 on compliance in year t. α_s is state fixed effect and λ_t is the year fixed effect. $\boldsymbol{X}$ is a vector of facility and county level time-variant variables. ε_{it} represents the standard idiosyncratic disturbance term.

Continuous funding treatment DiD

Next, the effects of the award size are examined using the following model, which expands the previous specification by adding an interaction term for loan size.

$$y_{ist} = \alpha_s + \lambda_t + \beta_{11}F_{i,t-1}CWSRF_{i,t-1} + \beta_{12}F_{i,t-2}CWSRF_{i,t-2} + \beta_{21}\,RF_{i,t-1}CWSRF_{i,t-1} + \beta_{22}\,RF_{i,t-2}CWSRF_{i,t-2} + \boldsymbol{\beta}_3\,\boldsymbol{X}_{it} + \varepsilon_{it} \quad [6]$$

where the notation is consistent with the notations in equation 5, except that this model also includes interaction terms between binary funding variables and corresponding award magnitude, CWSRF. $CWSRF_{i,t-1}$ ($CWSRF_{i,t-2}$) indicates the magnitude of the loan provided to facility *i* one (two) year(s) prior to year t. For the facilities that receive multiple loans, the repeated funding amount is the total across multiple awards. β_{11} shows the magnitude effect of receiving support a year ago when funding was made only once. Similarly, β_{12} shows the magnitude effect of receiving support two years ago when funding was made only once. Interpretations for β_{21} and β_{22} are analogous except that they respectively show the cumulative effects of multiple loans provided to facility i up to one and two years before t.

Propensity score matching DiD

The DiD estimator is most suitable when treatment is random. However, treatment is often not randomized in observational data. In such cases, matched control groups can be used to reduce selection bias (Rubin 2008). We use the propensity score matching (PSM) technique (Rosenbaum and Rubin 1983) to control for unmeasured differences between the treatment and the control groups (Heckman et al. 1997). The DiD-PSM approach relies on matching treatment and control subjects in terms of observed characteristics to identify best match counterfactuals, making the common trend assumption more plausible (Gebel and Voßemer 2014).

We use a logit model to estimate the propensity score, which is the probability of receiving support from the CWSRF depending on several observable characteristics. The covariates include all available control variables that can influence the probability of obtaining the CWSRF loans. Propensity score matching entails forming matched sets of treatment and control subjects that share a similar value of the propensity score. We use the nearest neighbor matching technique to pair each treatment facility with the twenty closest control facilities in terms of the propensity score (Caliendo and Kopeinig 2008). After matching, the observable characteristics should be balanced between treatment facilities and matched control facilities. We formally test for the significance of differences in observable characteristics between the treatment and the matched control facilities samples using t-tests.

4. Data

We use data from 6,921 facilities in 9 states, including Arkansas, Arizona, California, Indiana, Nebraska, Oklahoma, Texas, Vermont and West Virginia, from 2010 to 2018. The time frame of the analysis is based on the availability of the CWSRF loan data. Table 1 shows the annual summary statistics for the funded and unfunded facility-year observations. The funded group includes 3,362 facility-year observations, while the unfunded group includes 21,016 observations. The unfunded group includes observations for the facilities which were verifiably not funded between 2010 and 2018. Observations for the facilities that have no recorded funding but have missing data at least for one of the years during this time frame, are excluded from Table 1. On the other hand, all available observations for the facilities that are funded at least once are included in Table 1 even if data for these facilities are missing in some years. Rationale for this construction is to make sure that the funded group includes facilities funded at least once, while the unfunded group includes only the facilities that were never funded in this time frame.

The states included in our analysis vary in size, violations, and funding. Table A1 in the appendix provides summary statistics for violations, facility size, and funding broken down by state. For example, West Virginia has the largest average violation count of 17 per facility per year, while Nebraska has the lowest at 2.2. Such variation across states in our sample can be helpful for generalizing our findings. Still, generalization of the results requires caution. The mean violation in the U.S. (2) is comparable to the mean violations in some of the states in our sample. However, the range of annual facility violations in our sample is between 0 and 166, while for the U.S. sample it is between 0 and 246. Similarly, the facilities in our sample are smaller than some of the facilities in other states.

[Insert table 1 here]

Wastewater treatment plants' violations data are obtained from the EPA's ICIS-NPDES database. The Effluent Limit Exceedances database provides discharge monitoring self-reported data, including violations of the NPDES permit effluent limits. The violations are reported per permit holding facility. We use the aggregate number of annual violations across different pollutants rather than focus on individual effluents. The use of annual data mitigates the timing problem with violations and associated reporting (Grant and Grooms 2017). The quality of the data varies from state to state (GAO 2005; GAO 2009).

The data on the CWSRF support received by the individual wastewater facilities are obtained from the State Departments of Environmental Quality. The state environmental protection agencies publish annual reports that identify all disbursements of financial support under the CWSRF program in the respective year. We rely on these reports to identify the facilities that receive assistance.

We include two years' lagged violations, annual wastewater flow, annual numbers of inspection activities, and county per capita income as facility-level covariates. Data on facility controls are obtained from the EPA's ICIS-NPDES database, while the per capita income is obtained from the Bureau of Economic Analysis (BEA).

5. Results

The results are presented in the following order. We first compare the compliance records of funded and unfunded facilities using t-tests. Next, we report results from the pre-funding analysis and from the post-funding DiD models. Post-funding DiD results include unmatched and matched sample models for robustness check. The unmatched models include all data, while the matched models include nearest neighbor-based propensity score-matched data to address concerns about the non-random funding treatment.

T-ratio analysis

Table 2 shows the mean annual violations of funded and unfunded facilities two years before and two years after each CWSRF assistance treatment year. The estimates in Table 2 are organized across columns A, B, and C and rows 1, 2 and 3. Block A1 shows the mean annual numbers of violations by the funded facilities during the two years before receiving support from the CWSRF in the respective years. Block B1 shows the corresponding non-compliance of the unfunded facilities. For example, in 2013, 92 funded facilities[3] had 6.4 violations per facility per year during 2011- 2012, while the 5914 unfunded facilities had 3.5 annual violations per facility. Block C1 (C2) shows t-statistics for the hypothesis that there is no significant difference in the mean annual violations during the two years prior to (following) the loan provision year across funded and unfunded facilities. Blocks A3 and B3 show the t-test statistics for the hypothesis that no statistically significant difference exists between the mean annual violations before and after the treatment years for funded and unfunded facilities, respectively.

[Insert Table 2 here]

The results in block C1 show that the funded facilities have significantly higher numbers of pre-funding violations than the unfunded facilities in two out of five loan provision (treatment) years. These results support the hypothesis that in 2013 and 2014, CWSRF was provided to the facilities that performed worse in terms of NPDES violations in the preceding years. However, block C2 shows that the mean number of annual post-funding violations is also higher for the funded facilities than for the unfunded facilities in two of the four treatment years. Based on these statistics, the efficacy of CWSRF in reducing non-compliance is ambiguous because the funded facilities have more violations than the unfunded facilities before as well as after funding. Block

A3 shows a significant difference in mean annual pre-funding and post-funding violations of the funded facilities in 2014. Similarly, block B3 suggests a significant difference in mean annual pre-funding and post-funding violations of the unfunded facilities from 2013 to 2016.

Conclusions about the efficacy of CWSRF loan provision are difficult to reach. First, it is difficult to assess whether the CWSRF reduced the violations of the funded facilities relative to the violations that would have been observed in the counterfactual case because non-compliance by the funded facilities is not observed in the absence of funding. Second, the t-tests do not take into account the confounding effects of other factors. Third, Table 2 comparisons of funded and unfunded facilities before and after funding disregard the effects of repeated CWSRF provision. Therefore, we turn to the multivariate regression analysis for a more detailed examination. Next, we present the results from the pre-funding analysis, followed by post-funding parallel trend analysis and multi-period DiD results.

Pre-funding compliance

We examine the role of non-compliance for CWSRF distribution by comparing pre-funding violations of funded and unfunded facilities. Table 3 presents the results from the Heckman 2-stage selection models, including first step binary funding outcome (selection) and second step award magnitude (OLS) analysis. These models include all available observations regardless of whether a facility has missing data in some of the years. Unlike Table 1 and the forthcoming post funding analysis results, no observations are excluded from these regressions.

[Insert table 3 here]

Results of selection models 1 and 2 show pre-funding violation differences between funded and unfunded facilities. The estimates suggest that facilities with more violations are more likely to receive CWSRF assistance in a subsequent year. There is a statistical difference in violations of funded and unfunded facilities one year before receiving support. Facilities with more violations in t-1 are more likely to be funded in year t than facilities with fewer violations in t-1. These results suggest that perhaps prior non-compliance attracts the attention of regulators and signals the need for financial support.

While the probability of a facility being funded depends on NPDES violations in the previous year, Stage 2 results show that the magnitude of the award is not associated with non-compliance. There is no statistical effect of non-compliance on the magnitude of the awards. Table 3 suggests that funding decisions depend on facilities' compliance in the previous year, but the magnitude of the award may depend on other factors like the size of the facility. Our results show a statistically significant association between facility size and the award's probability and magnitude. Larger facilities are more likely to receive the awards and tend to receive larger grants. Larger treatment plants may be prioritized because such facilities tend to be located in more populated areas (Keiser and Shapiro 2019).

The Poisson and logit regressions results with violations as the dependent variables and future funding as explanatory variables are provided in appendix table A2. We put these results in the appendix because these models are not intuitive in terms of causal inference. Clearly, we do not mean to imply that future funding outcomes influence non-compliance in the preceding years. Instead, these results represent an additional angle of view on whether compliance of facilities funded in future periods differs from compliance of future unfunded facilities. Statistical significance of funding in years t+1, t+2 and t+3 support the hypothesis that facilities with poorer compliance records receive CWSRF assistance. The results consistently show a statistical difference in violations of unfunded and eventually funded facilities 1, 2, and 3 years before the funding was received. These results hold even when controlling for repeated provision of CWSRF awards in the preceding one or two years.

Post-funding compliance

The results for the effect of CWSRF provision on facility violations are presented as follows. First, we report the results from parallel trend analysis (Table 4), followed by the results from binary funding treatment DiD (Table 5) and continuous funding treatment DiD (Table 6). All results are presented for matched and unmatched samples. Also, the results are presented for one-time funding treatment in 2014-2016 and repeated funding treatment in 2012-2016. We include both of these results in all tables because 2014-2016 treatment analysis has a longer pre-treatment period (2010-2013 as opposed to 2010-2011) for parallel trend analysis, while the 2012-2014 treatment model accounts for repeatedly funded facilities. The 2014-2016 treatment regression models exclude repeated funding because only ten facilities received CWSRF support more than once in 2014-2016. Hence, Table 4 shows four models, and Tables 5 and 6 show eight models, half of which (models 2, 4, 6 and 8) include control variables like facility's size, previous compliance record and county income. The rest (models 1, 3, 5 and 7) do not include additional controls. We include these models because, on the one hand, the regressions without control variables have more observations. On the other hand, the regressions with additional controls account for additional factors besides the fixed effects and the treatment variables. Based on the DiD requirements, some of the available observations have to be excluded from the post-funding regressions. First, the facilities funded in the pre-treatment periods have to be removed from the regressions because neither treatment and not control facilities can be funded pre-treatment. Second, facilities with missing data in the pre-treatment years have to be removed from the regressions to ensure that pre-treatment period includes only the facilities that were not funded pre-treatment.

Parallel trend analyses for post-funding DiD

Although the pre-funding year compliance results indicate that funded facilities tend to have more violations in the pre-funding years than the unfunded facilities, the parallel trend assumption requires a separate assessment. In particular, the results of pre-funding violations show that funded facilities have more violations than unfunded facilities but do not necessarily reveal whether the trends in violations differ between treatment and control facilities.

We report the results of the formal parallel trend analyses in Table 4. The insignificance of lead indicators in most models (with and without matching) indicates that the difference in treatment and control group's violations in the base year (one year before receiving support) is not significantly different from other pre-funding years. This suggests that the difference in violations over time between funded and unfunded facilities does not change prior to funding. We have one exception in model 1 (2014 to 2016 treatment), where the pre-funding violation differences 4 and 3 years before receiving support are significantly greater than the difference in the base year. However, the matched results (models 3 and 4) show no significant differences. Hence, the unfunded groups represent a reasonable benchmark counterfactual for the funded groups in terms of the trends in CWA violations pre-treatment.

[Insert Table 4 here]

Binary funding treatment

We report the results from the multiple-period DiD models to examine the effects of binary funding (Table 5) and award sizes (Table 6) on non-compliance in the post-funding years. Funded groups in models 1, 2, 5 and 6 (Tables 5 and 6) include facilities funded only once between 2014 and 2016. In models 3, 4, 7 and 8, some facilities receive CWSRF support more than once between 2012-2016. These models separate treatment facilities into one-time and repeatedly funded groups.

Models 3, 4, 7, and 8 have more facilities than models 1, 2, 5 and 6 because the latter models exclude facilities that received support in 2012 and 2013, which are the pre-treatment years in these models. Neither treatment nor the control facilities can receive support in the pre-treatment years in the DiD approach. Observations for treatment facilities in treatment years are not included in any of the models because relative timing of violations versus awards could not be established within the treatment years. However, all observations from the control group are included in the regressions.

The 2014-2016 treatment year analyses (models 1 and 2 in Table 5) show negative effects of receiving a one-time CWSRF support on non-compliance of the funded facilities in the subsequent two years. Estimates in models 3 and 4 with the extended treatment period of 2012-2016 suggest that receiving a one-time CWSRF support helps the funded facilities reduce violations two years after receiving the awards relative to the unfunded facilities. Model 4 also suggests that multi-funded facilities decrease their violations two years after receiving their last award. However, model 3 indicates that violations increase one year after receiving the last

CWSRF award. This may be due to the magnitude of projects associated with repeated funding, which may take longer to complete, producing more violations in the meantime. This effect is not statistically significant in our preferred model 4, which includes facility and county covariates.

[Insert Table 5 here]

Overall, Table 5 shows that the loans provided in 2012-2016 had the intended effect of reducing non-compliance. Post-funding violations decline two years after receiving support. Models 1 and 2 also suggest that facilities funded only once between 2014 to 2016 experienced a reduction in violations one year after receiving the loans. On the other hand, facilities that receive multiple loans may be pursuing larger projects, which take longer to complete and improve compliance. As a result, one-year lagged violations are statistically insignificant, while two-year lagged violations show a decrease relative to the unfunded facilities. These results are consistent with the matched sample regression results in models 5-8 in terms of signs and statistical significance of the estimated coefficients.

Table 5 shows that violations in the previous three years have a significant and positive coefficient. This suggests that NPDES violations are persistent as the facilities with more violations before receiving CWSRF continue to experience more violations in later years. The size of the facility (water flow) does not appear to correlate with non-compliance. Per capita income in the county where the facility is located is positively correlated with reported violations. One reason for this result may be that facilities in wealthier counties may follow more rigorous reporting practices than those in poorer counties. In such cases, facilities in wealthier counties may show more violations. Regulatory actions in terms of the number of lag inspection actions also help reduce non-compliance[4].

Continuous funding treatment

Table 6, structured similarly to Table 5, reports the effect of award size on post-funding compliance. Interaction terms between binary funding variables and the corresponding CWSRF award size show the effects of award size on the number of violations. The results show that the size of one-time awards does not have a statistically significant effect on violations one year after funding. However, according to models 3, 4, 7, and 8, which account for repeat provision of CWSRF, the larger the one-time provided loans, the fewer the violations two years after funding. This result suggests that the one-time award's magnitude has a lagged effect two years after funding on compliance, which is consistent with the results in Table 5. On the other hand, the results in Table 6 show no statistical effect of the size of the repeat awards on non-compliance within two years of receiving the last award. Repeated loans are likely awarded to facilities with larger projects that may take longer to complete. Therefore, reduction in non-compliance may take longer than two years. Replacing or updating treatment technologies and operations that improve compliance can take longer than two years after loans are provided (Keieser and Shapiro 2019).

[Insert Table 6 here]

We also estimate marginal effects for funding provision and award size. Table A3 in the appendix shows marginal effects at means corresponding to Poisson regressions results of models 4 from Tables 5 and 6, respectively. Marginal effect estimates suggest that each one-time award reduces violations by 0.139, and repeated awards reduce violations by 0.209. It takes, on average, seven one-time loans (1/0.139) and five (1/0.209) multi-awards to reduce violations of funded facilities by one count within two years after funding. The effects of CWSRF provision on non-compliance can be compared to alternative non-compliance interventions. For example, our results show that each inspection reduces violations by .005. Hence, it takes 200 inspections to reduce violations by one count.

Marginal effect estimates for the effects of award size indicate that a dollar of one-time CWSRF award decreases violations by 2.61*10-8 per facility two years after funding. This implies that, on average, it takes a $50 million CWSRF loan to decrease violations by one within two years of award provision. In our sample, an average one-time grant is $7.6 million. Hence, it takes roughly seven awards to decrease violations by one. It is important to recognize that our post-funding compliance examination is limited to two post-award years. Improvements in compliance from CWSRF investments can take longer than two years (Keiser and Shapiro 2019). Therefore, limiting the analysis to only the first two years after funding provision is likely to undervalue the efficacy of CWSRF in improving long-term compliance.

Consistent with the results in Table 6, the marginal effect for the magnitude of the repeated CWSRF award is not statistically significant. Although the provision of multiple awards has a statistically significant and negative effect on violations (Tables 5 and A3), the magnitude of the repeated awards has no statistically significant effect on violations within two years from the last loan provision. Large repeated CWSRF loans may require multiple years to complete. As a result, the impact of these awards may not be observed within the first two years after funding. Instead, one may need to look at longer time periods after funding to detect a change in non-compliance. This is consistent with Keiser and Shapiro (2019), who document a positive effect of CWA grants on downstream water quality attributes several years after the grant is provided.

6. Conclusions

Compliance with the Clean Water Act is an important public health and environmental quality objective. The U.S. has spent over $1 trillion to control water pollution, and the economic efficacy of these investments remains debated (Keiser and Shapiro 2019; Keiser, Kling and Shapiro 2019). Wastewater treatment facilities are responsible for treating wastewater before it is discharged into public water bodies. Pursuant to the CWA, all wastewater discharge facilities are issued permits that specify the type and the amount of the regulated pollutants each facility can discharge. Compliance with discharge permits depends on operational procedures and on technological infrastructure at the treatment facilities. Adequacy of operational procedures and especially technological infrastructure depends on the availability of finances. Clean Water State Revolving Funds program was set up in 1987 in part to address this investment need. This study examines the allocation of CWSRF assistance across wastewater treatment facilities and the impacts of these investments on compliance with the CWA in recent years.

While prior studies examine downstream water quality in terms of dissolved oxygen deficit, fecal coliform, and organic nitrogen (Earnhart 2004; Shimshack and Ward 2005; Earnhart and Harrington 2014; Harrington and Malinovskaya 2015; Chakraborti 2016; Keiser and Shapiro 2019), we focus on the CWA compliance using cumulative discharge violations of NPDES requirements across all regulated pollutants. The analysis of cumulative discharge violations of NPDES permits covering all regulated pollutants enables a broader evaluation of CWSRF loans, which can be used for various projects aimed at improving discharge water quality with respect to various pollutants. The limitation of using a cumulative number of violations is that the reporting quality can vary across different pollutants (Harrington and Malinovskaya 2015), which can mask the effects that may be present for particular pollutants. The disaggregated analysis of particular pollutants and financial support would be useful and should be pursued in future studies.

The NPDES violations by wastewater treatment plants in nine states between 2010 and 2018 reveal that funded facilities have poorer compliance records before receiving CWSRF support than the unfunded facilities. This result is in contrast with Harrington & Malinovskaya (2015), who observe that financial support is generally not allocated to the facilities in greatest need in terms of compliance. Our results show a statistically significant difference between funded and unfunded facilities in pre-funding compliance. We also document that larger loans are awarded to larger facilities. Since larger facilities tend to be located in more populated areas, this result is consistent with Keiser and Shapiro (2019), who observe that larger loans are awarded to facilities located in more populated areas.

We examine the effects of provision and magnitude of financial support on post-award compliance. We find that the CWSRF loans awarded between 2012 and 2016 reduced violations of funded facilities within two years after funding. This result is consistent with previous literature documenting a positive effect of financial support on water quality. Harrington and Malinovskaya (2015) find that CWSRF loans improve biological oxygen demand and organic nitrogen discharge of treatment plans in four states. We extend their results by considering the cumulative number of violations rather than focusing on particular pollutants and by explicitly examining the effects of single versus multiple awards and the effects of award magnitude. Keiser and Shapiro (2019) use a longer time horizon and a broader scope of analysis to show that Clean Water Act grants have a statistically significant and positive effect on downstream water quality several years after the grant is provided and continue to have a positive effect for many years after. The lagged effect of the grants is expected because some of the grants support projects that can take multiple years to complete. Our study differs by examining cumulative NPDES compliance rather than particular water quality attributes and focusing on the short-term impacts on compliance within the first two years after funding. We find a qualitatively similar positive effect of CWSRF support even within the first two years post-funding.

We observe some evidence of larger singular CWSRF awards having greater impacts on reducing non-compliance than smaller awards two years after funding. We also estimate that, on average, a $50 million one-time award decreases non-compliance by one violation two years post-funding. On the other hand, the cumulative size of repeated CWSRF awards is not statistically significant for reducing non-compliance within the first two years post-funding. Statistical insignificance of the value of multiple CWSRF awards is likely due to the data limitations. Our data include only two post-treatment years. Facilities that receive multiple CWSRF awards are likely to be engaged in larger infrastructure upgrades that take several years to complete after funding is provided. The average size of one-time awards in our sample is $7.6 million, while the average combined value of repeated awards is $28.7 million. Since projects funded by larger grants may take longer to complete, our results may not capture improvements in compliance that take more than two years to materialize. In this respect, our focus on the first two years of compliance post-funding undervalues the efficacy of CWSRF in improving compliance in the long run. Future examinations that use longer time horizons may detect longer-term impacts of CWSRF support, similar to Keieser and Shapiro (2019).

It is important to acknowledge that the NPDES permits can be relaxed or tightened over time in response to changes in the water quality of the receiving watershed (Chakraborti and

McConnell 2012). Hence, changes in compliance records can depend on the availability of adequate investments and management of the water treatment plants as well as on the changes in the requirements of the NPDES permits. Since the NPDES permit requirements can change over time, our results should not be interpreted in terms of the effect of the CWSRF support on water quality in general. Instead, the results in this study apply strictly to compliance with the CWA in terms of the NPDES violations rather than to water quality.

Our results are limited by the temporal and spatial scope of the analysis. Although CWSRF has been in place since 1987, facility level funding data are publicly available only from 2010 and only for a subsample of states. As a result, we cannot assess the effectiveness of the CWSRF prior to 2010 or generalize the result for the U.S. as a whole. Limited data availability prevents us from evaluating the long-run effectiveness of CWSRF support. We consider the effects of the CWSRF support on compliance with the CWA for only up to two years following the provision of the loan. It is, however, possible that improvements in compliance may be observed in the longer run. The lagged effect is expected as infrastructure improvement projects can take time to complete. Nevertheless, this study provides important evidence supporting the efficacy of the CWSRF in improving compliance with CWA even within a couple of years after the provision of financial assistance.

Our results are also subject to the quality of the data used in the analysis. Although all point sources are required to obtain an NPDES permit under the CWA, not all facility, permit, or discharge monitoring data are provided in ICIS-NPDES, and reporting quality differs across states, facilities, and over time. In this regard, the inconsistency of the NPDES violation reports is a significant caveat. While this study offers a valuable initial assessment of the CWSRF program's role in compliance with the CWA, possible strategic underreporting by wastewater facilities should be considered in the extrapolation and interpretation of our results.

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Table 1. Summary statistics for wastewater treatment plants, 2010-2018

	VARIABLES	Mean	Std. Dev.	Min	Max
Unfunded[5] (N= 21,016)	Annual Violations per facility	5	10.4	0	183
	Water Flow [Mgal/ Year]	507	2597	1	81452
	Annual Number of Inspections	2	4	0	48
	County Per Capita Personal Income ($)	39820	10603	17078	134275
Funded (N= 3,362)	Annual Violations per facility	6	12	0	166
	Water Flow [Mgal/ Year]	1775	6433	1	150881
	Annual Number of Inspections	3	5	0	28
	County Per Capita Personal Income ($)	42093	13498	21423	134275

Table 2: T-tests for mean annual violations

		Year	**A.** Funded	**B.** Unfunded	**C.** t-ratios Funded vs. Unfunded
1	Mean annual violations in prior two years	2012	3.3	3.9	-0.46
			N= 47	N= 5243	(1.23)
		2013	6.4	3.5	2.42***
			N= 92	N= 5914	(0.90)
		2014	7.65	3.9	3.59***
			N=80	N=6555	(1.04)
		2015	4.23	3.88	0.25
			N= 42	N= 6701	(1.39)
		2016	3.2	4.1	0.07
			N= 54	N= 6674	(1.19)
2	Annual mean violations in subsequent two years	2012	7.69	4.37	2.59***
			N= 59	N= 5981	(1.27)
		2013	6. 2	3.5	1.1
			N= 96	N= 5,323	(0.98)
		2014	10.6	4.3	5.66***
			N= 77	N=5269	(1.10)
		2015	5.3	4.4	-1.27
			N= 42	N= 6468	(1.77)
		2016	5.36	4.4	-0.44
			N= 51	N= 5849	(1.36)
3	Pair-wise t ratio for before minus after treatment	2012	-0.63	0.807	
			(1.30)	(1.30)	
		2013	0.26	-10.75**	
			(1.50)	(0.04)	
		2014	-1.4**	-10.29***	
			(1.79)	(0.39)	
		2015	1.86*	-3.69***	
			(1.70)	(0.04)	
		2016	-0.38	2.29**	
			(1.10)	(0.02)	

Asterisks (*,**,***) indicate 10% , 5% and 1% significance.
Block A3, B3, C1 and C2 show t-statistics and standard errors in parenthesis.

Table 3. Pre-funding violations

VARIABLES	Model 1		Model 2	
	Stage 1 (Selection)	**Stage 2 (OLS)**	**Stage 1 (Selection)**	**Stage 2 (OLS)**
Lag1 Violation	0.0153***	463,738	0.0177***	113,240
	(0.00501)	(305,291)	(0.00465)	(152,868)
Lag2 Violation	0.00111	-17,554	0.00198	10,092
	(0.00535)	(176,040)	(0.00517)	(166,062)
Lag3 Violation	0.00371	40,617	0.00315	-13,202
	(0.00525)	(201,703)	(0.00500)	(180,608)
Water Flow			6.60e-05***	2,073***
			(1.03E-05)	(247.4)
Rep. Fund Lag1			1.504***	
			(0.184)	
Rep. Fund Lag2			0.757***	
			(0.201)	
Per. C. Income			-0.000101***	-217.3
			(5.82e-06)	(261.6)
Mills ratio		2.479e+07		3.931e+06*
		(1.799e+07)		(2.326e+06)
Year Fixed Effect	Yes	Yes	Yes	Yes
State Fixed Effect	Yes	Yes	Yes	Yes
Observations	35,463	604	32,773	582
Number of Facilities	7,353		7,166	

Asterisks (*,**,***) indicate 10% , 5% and 1% significance.

Table 4. DiD parallel trend test

	Unmatched		Matched	
	Model 1	**Model 2**	**Model 3**	**Model 4**
	Treatment Years 2014 to 2016	**Treatment Years 2012 to 2016**	**Treatment Years 2014 to 2016**	**Treatment Years 2012 to 2016**
Two year lead treatment effect (funded once)	0.0469	-0.0069	0.0425	(0.01)
	(0.0826)	(0.058)	(0.159)	(0.06)
Three year lead treatment effect (funded once)	0.236**		0.202	
	(0.0922)		(0.232)	
Four year lead treatment effect (funded once)	0.453***		0.379	
	(0.0846)		(0.260)	
One year lag treatment effect (funded once)	-0.206**	0.068	-0.223	0.05
	(0.0871)	(0.056)	(0.185)	(0.06)
Two year lag treatment effect (funded once)	-0.132	-0.144**	-0.186	-0.175***
	(0.0861)	(0.058)	(0.204)	(0.06)
Two year lead treatment effect (Repeated funding)		-0.0201		-0.0309
		(0.057)		(0.06)
One year lag treatment effect (Repeated funding)		0.0223		0.0304
		(0.049)		(0.05)
Two year lag treatment effect (Repeated funding)		-0.147***		-0.135***
		(0.05)		(0.0504)
Controls	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
State Fixed Effect	Yes	Yes	Yes	Yes
Observations	18,538	18,977	6,342	13,793
Number of Facilities	2,411	2,542	822	1,864

Asterisks (*,**,***) indicate 10% , 5% and 1% significance.

Table 5. Post-funding violations and CWSRF loan provision

	Unmatched				Matched			
	Treatment Years 2014-2016		**Treatment Years 2012-2016**		**Treatment Years 2014-2016**		**Treatment Years 2012-2016**	
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
Funded Once Lag1	-0.284*** (0.0698)	-0.347*** (0.0740)	0.031 (0.0473)	0.0716 (0.0499)	-0.286 (0.184)	-0.344 (0.177)	0.0257 (0.0474)	0.0628 (0.0500)
Funded Once Lag2	-0.227*** (0.0711)	-0.275*** (0.0727)	-0.201*** (0.0505)	-0.142*** (0.0521)	-0.240 (0.253)	-0.308** (0.198)	-0.202*** (0.0506)	-0.139*** (0.0523)
Repeated Fund lag1			0.0864** (0.0436)	0.0299 (0.0441)			0.0914** (0.0438)	0.0420 (0.0443)
Repeated Fund Lag2			-0.0286 (0.045)	-0.139*** (0.045)			-0.0175 (0.0452)	-0.123*** (0.0452)
Lag Mean Violation		0.0120*** (0.000323)		0.0118*** (0.000317)		0.0143*** (0.00246)		0.0116*** (0.00036)
Initial Violation		0.0531*** (0.00312)		-0.00349*** (0.001)		0.0472*** (0.00829)		0.0516*** (0.00343)
Lag Inspection		-0.00345*** (0.00102)		-0.0054*** (0.001)		-0.00884** (0.00449)		-0.00387 (0.00108)
Mean Water Flow		6.83e-06 (1.22e-05)		5.49E-07 (1.14E-05)		2.36e-05 (1.47e-05)		-3.20e-05** (1.27e-05)
Water Flow		7.14e-07 (2.60e-06)		1.65E-06 (2.48E-06)		-1.99e-05** (1.01e-05)		5.71e-06** (2.86e-06)
Per C Income		1.04e-05*** (1.53e-06)		9.15e-06*** (1.50E-06)		-1.88e-07 (7.41e-06)		5.84e-06*** (1.62e-06)
Mean Per C Income		-2.14e-05*** (2.83e-06)		-2.02e-05*** (2.79E-06)		-1.01e-05 (7.98e-06)		-1.46e-05** (6.72e-06)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,790	18,538	21,222	18,977	7,001	6,342	15,325	13,793
No. Facilities	2,759	2,411	2,891	2,542	895	822	2,080	1,864

Asterisks (*,**,***) indicate 10% , 5% and 1% significance.

Table 6. Post-funding violations and magnitudes of CWSRF awards

	Unmatched				Matched			
	Treatment Years 2014-2016		Treatment Years 2012-2016		Treatment Years 2014-2016		Treatment Years 2012-2016	
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
Funded Once Lag1*Award size	-1.20E-08	-1.30E-08	4.92E-09	6.92E-09	-2.04E-08	-2.13e-08*	4.68E-09	6.51E-09
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Funded Once Lag2*Award size	-1.60e-08*	-1.51E-08	-3.03e-08***	-2.48e-08***	-2.40E-08	-2.32E-08	-3.03e-08***	-2.47e-08***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Repeated Award lag1*Cumulative Award size			-1.57E-10	-1.70E-10			-1.33E-10	-1.53E-10
			(0.00)	(0.00)			(0.00)	(0.00)
Repeated Award Lag2 *Cumulative Award size			1.70E-10	1.22E-10			1.79E-10	1.32E-10
			(0.00)	(0.00)			(0.00)	(0.00)
Initial Violation		0.0527***		0.0511***		0.0471***		0.0516***
		(0.00)		(0.00)		(0.01)		(0.00)
Mean Lag Violation		0.0120***		0.0118***		0.0142***		0.0116***
		(0.00)		(0.00)		(0.00)		(0.00)
Inspection Lag1		-0.00336***		-0.00331***		-0.00874*		-0.00366***
		(0.00)		(0.00)		(0.00)		(0.00)
Mean Flow		7.99E-06		3.64E-07		2.35E-05		-3.23e-05**
		(0.00)		(0.00)		(0.00)		(0.00)
Water Flow		6.04E-07		1.86E-06		-1.97e-05*		5.98e-06**
		(0.00)		(0.00)		(0.00)		(0.00)
Per C Income		1.04e-05***		9.07e-06***		-1.47E-07		5.77e-06***
		(0.00)		(0.00)		(0.00)		(0.00)
Mean Per C Inc		-2.15e-05***		-2.01e-05***		-1.01E-05		-1.46e-05***
		(0.00)		(0.00)		(0.00)		(0.00)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,790	18,538	21,222	18,977	7,001	6,342	15,325	13,793
No. Facilities	2,759	2,411	2,891	2,542	895	822	2,080	1,864

APPENDIX

Table A1. Summary statistics

		Mean	Std. Dev.	Min	Max
AR (# of grants =17)	Annual Violations per facility	6	10	0	120
	Daily Water Flow [Mgal/Year]	374	2353	1	69446
	CWSRF Size [10^6 $ per year per facility]	16.9	32.9	0.35	140
AZ (# of grants = 4)	Annual Violations per facility	7	10	0	49
	Daily Water Flow[Mgal/Year]	115	175	3	741
	CWSRF Size [10^6 $ per year per facility]	1.5	1.5	0.035	3.233
CA (# of grants =112)	Annual Violations per facility	2	5	0	26
	Daily Water Flow [Mgal/Year]	5820	12620	50	56856
	CWSRF Size [10^6 $ per year per facility	33.5	80	0.5	600
IN (# of grants =111)	Annual Violations per facility	3	7	0	45
	Daily Water Flow [Mgal/Year]	2455	4793	2	38261
	CWSRF Size [10^6 $ per year per facility]	9.96	18.5	0.227	139
NE (# of grants =87)	Annual Violations per facility	5	12	0	63
	Daily Water Flow [Mgal/Year]	971	2861	2	21416
	CWSRF Size [10^6 $ per year per facility	4.09	7	0.1	40
OK (# of grants =73)	Annual Violations per facility	9	10	0	46
	Daily Water Flow [Mgal/Year]	1042	2044	7	16190
	CWSRF Size [10^6 $ per year per facility	5.7	7.6	0.2	39.9
TX (# of grants =109)	Annual Violations per facility	4	7	0	39
	Daily Water Flow [Mgal/Year]	4572	12336	10	57074
	CWSRF Size [10^6 $ per year per facility	8.3	15	0.2	107
WV (# of grants =98)	Annual Violations per facility	15	26	0	166
	Daily Water Flow [Mgal/Year]	371	2293	2	21554
	CWSRF Size [10^6 $ per year per facility	3.4	5.3	0.007	26.5
Other States	Annual Violations per facility	2.02547	7.15493	0	246
	Daily Water Flow [Mgal/Year]	1168	16683	1	1353815

Table A2. Poisson and logit difference models for pre-funding violations

VARIABLES	Pre funding violations			
	Panel-Poisson		Panel-Logit	
	Model 1	**Model 2**	**Model 3**	**Model 4**
Fund t+1	0.486***	0.426***	0.804***	0.682***
	(0.0959)	(0.0911)	(0.185)	(0.182)
Fund t+2	0.427***	0.379***	0.753***	0.682***
	(0.0972)	(0.0927)	(0.209)	(0.206)
Fund t+3	0.462***	0.379***	0.909***	0.684***
	(0.0991)	(0.0952)	(0.241)	(0.241)
Water Flow		-1.65E-06		9.25E-06
		(2.60E-06)		(1.10E-05)
Rep. Fund t-1		0.139***		0.139***
		(0.04)		(0.039)
Rep. Fund t-2		0.008		0.008
		(0.06)		(0.05)
Per C Income		4.15e-06***		-2.19e-05***
		(1.60E-06)		(4.26E-06)
Year Fixed Effect	Yes	Yes	Yes	Yes
State Fixed Effect	Yes	Yes	Yes	Yes
Observations	22,012	20,243	22,012	20,243
Number of Facilities	3,059	3,045	3,059	3,045

Table A3. Marginal effect at means from panel Poisson models 4 in Tables 5 and 6

Variable	Model 4 (Table 5) Award	Model 4 (Table 6) Award size
Only Fund Lag1	.0766411	
	(.05)	
Only Fund Lag2	-.139**	
	(.05)	
Rep. Fund Lag1	.0609	
	(.04)	
Rep. Fun Lag2	-.209***	
	(.05)	
Only Fund Lag1* CWSRF Lag1		6.78e-09
		(8.53e-09)
Only Fund Lag2* CWSRF Lag2		-2.61e-08 ***
		(5.53e-09)
Repeated Lag1* CWSRF Lag1		-1.93e-10
		(3.86e-09)
Repeated Lag2* CWSRF Lag2		-1.16e-10
		(3.86e-09)
Inspection lag1	-.005***	-.005***
	(.003)	(0.001)
Year FE	Yes	Yes
State FE	Yes	Yes
Observations	17470	17470
No. of Facilities	2,538	2,538
Controls	Yes	Yes

[1] By some estimates, wastewater treatment plants in the US will need $271 billion to meet CWA objectives over the 20 years, and infrastructure affordability will remain to be an issue of great concern (Ramseur, 2017; USEPA, 2016a)

[2] 2009 is the earliest violation we include because our funding variable starts from 2010 and we include 1, 2, and 3 years of future funding as independent variables.

[3] Some of the facilities have missing compliance information in some years. If there is also no other information including pollutant specific permit limits, enforcement, or inspection, then the observation is treated as missing. Otherwise, we treat the observation as a zero as compliance is mostly reported when violation exists. Missing data for some of the facilities in some of the years is the reason why the numbers of observations for the same treatment and control groups differ across pre-treatment (row 1) and post-post treatment (row 2) in Table 2.

[4] Funding may come with regulatory activities like inspection and enforcement, which in turn may influence compliance. To consider this line of reasoning following reviewer's suggestion, we examined whether funding triggers additional inspection or enforcement actions. Using the techniques similar to equations 5 and 6, we found no evidence of increased inspection or enforcement after funding. This results is available upon request. We thank the reviewer for the suggestion.

[5] We have an unbalanced panel data set because not all facilities have data in each year.