The Impacts of the "Right to Know": Information Disclosure and the Violation of Drinking Water Standards*

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ABSTRACT

Information disclosure regulations are increasingly common, but their effects on the behavior of regulated firms and consumers are unclear. The 1996 Amendments to the Safe Drinking Water Act mandated that community drinking water systems issue to customers annual consumer confidence reports (CCRs), containing information on violations of drinking water regulations and on observed contaminant levels. We examine whether mandatory information provision induced reductions in violations using panel data collected by the Commonwealth of Massachusetts on drinking water violations by 517 community water systems from 1990-2003. We find some evidence that the requirement to compile a CCR lowered violations, but much stronger evidence that utilities required to mail CCRs directly to customers reduced violations.

***Journal of Economic Literature* Classifications: L51, Q53, Q58, D80**

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1. Introduction

Over the past two decades there has been significant growth in the use of information disclosure programs in regulatory policy. The oldest such regulation in the United States may be the requirement that firms disclose financial information to investors. Other examples include food safety and nutrition labeling, as well as a growing number of environmental information disclosure regulations. Although they are implemented frequently, the effects of such programs on environmental quality are unclear. A fuller understanding of how regulated entities respond to environmental information disclosure is critical in any economic assessment of these initiatives.

Drinking water quality is one area in which information disclosure regulations have been used in concert with traditional command-and-control regulations. In the United States, nearly 270 million people obtain piped water from 53,000 community drinking water systems.[1] The federal government regulates water quality in these systems under the Safe Drinking Water Act (SDWA). During the early 1990s, the number of contaminant regulations with which systems had to comply under the SDWA rose sharply, from 31 in 1990 to 83 in 1995, raising compliance costs significantly. Partly in response to concerns regarding "unfunded mandates," the federal government heavily subsidizes compliance with the SDWA. Between 1995 and 2003, Congress appropriated $1 billion each year for the drinking water state revolving loan program, which authorizes the Environmental Protection Agency (EPA) to make annual capitalization grants to states, against which systems may borrow at below-market rates for treatment and distribution infrastructure improvements. Nonetheless, U.S. community water systems incur tens of thousands of violations of SDWA regulations each year (Tiemann 2006).

[1] The remainder obtain drinking water from unregulated private wells, or from very small, "non-community" systems. A community drinking water system serves at least 15 connections, or at least 25 people, year-round. (U.S. Environmental Protection Agency Office of Water 2002).

The 1996 Amendments to the SDWA mandated that community drinking water systems issue annual consumer confidence reports (CCRs) to their customers. The CCRs summarize information regarding the source of drinking water, any detected contaminants, and any violations of both health-based drinking water regulations and procedural regulations (e.g., requirements for timely testing). The CCRs were first issued in 1999, reporting violations from the 1998 calendar year.

In this paper we evaluate whether this mandatory information disclosure regulation altered the behavior of water suppliers, using panel data for 517 water suppliers in Massachusetts from 1990-2003. We exploit two main sources of variation in information disclosure. First, disclosure varies over time – the reporting requirement is only in place for the last six years of the 14 years in our data. Second, while all systems must compile a CCR beginning in 1998, the method of disclosing information to consumers varies by system size. In particular, suppliers serving 10,000 or more people must mail their CCR directly to households, and smaller community suppliers must post the CCR in a public place and make it available on request, but may waive the mailing requirement. We will exploit this second source of variation in the "intensity" of information disclosure, as well.

We find some evidence that the requirement to compile a CCR lowered violations, and much stronger evidence that utilities required to mail CCRs directly to customers had lower violations after the CCR rule took effect. This result is intuitive in light of the likely pathways through which information disclosure is thought to affect utility behavior. Because utilities were already required to report violations to the state, the utility itself does not learn much by compiling the data for the CCR. The CCR may have a much stronger effect on utility behavior if there is a political response to the findings, which is more likely when the public is made directly aware of the violations through the annual mailing of the CCR.

2. Policy Background

The SDWA Amendments of 1996 included four principal components. The first component involved procedures for establishing new drinking water standards. Since 1986, EPA had been required to promulgate an additional 25 drinking water standards every three years. The 1996 Amendments revoked this requirement and also required EPA to consider costs in establishing new drinking water standards.[2] The second component of the Amendments addressed funding for water quality improvements. The Amendments established the Safe Drinking Water State Revolving Fund funded at $1 billion annually through 2003, designated for drinking water improvements and pollution prevention. The third component of the amendments established new procedures for source water protection.[3]

The final component of the 1996 Amendments established the CCR program. The Amendments required community water systems to publish annually their violations of drinking water standards, any detectable amounts of regulated contaminants in their drinking water (even if below the statutory limit), and detectable levels of some unregulated chemicals if systems are testing for them. They must make these data available by July 1, reporting violations and contaminant levels for the previous calendar year. Violations of all types must be reported, including so-called “paperwork violations” in which water suppliers fail to submit violation information in appropriate formats, fail to test on a timely basis, etc. Our research design allows us to test the impact of information disclosure on total violations, as well as the more severe

[2] Since 1996, EPA is required only to evaluate five contaminants every five years and then use risk assessments to determine which, if any, of those contaminants should be regulated.
[3] Community water systems were required to conduct a source water assessment that highlights potential vulnerabilities in drinking water sources.

health violations, which include instances in which water suppliers actually exceed one or more federal Maximum Contaminant Levels (MCLs), as well as procedural drinking water treatment violations considered by EPA to raise the probability of an MCL violation.

The method of releasing CCRs to the public differs with the size of the water system. Systems serving more than 100,000 users must mail CCRs directly to consumers and post them online. Systems serving between 10,000 and 100,000 users must mail the reports directly to consumers but may forgo online posting. Systems serving between 500 and 10,000 users can, with the permission of the Governor of their state, publish the CCR in a local newspaper in lieu of direct mailing. Systems serving fewer than 500 users, with permission of the Governor, can simply provide notice to their customers that the report is available upon request.

Because some contaminant testing is done at the point of entry into the system, while some testing must be done in the water distribution system (for example, suppliers must test for lead in the distribution system because water pipes are the primary source of lead), there are also some differences in CCR requirements for utilities that purchase water from other sources. Water wholesalers must conduct all point-of-entry testing and provide information on violations and detectable contaminant levels to purchasing systems by April 1 (for data covering the previous calendar year). Purchasing systems must then supplement these data with information on their own tests from the distribution system, and all violations (at both the wholesale and retail level) are reported to consumers in the CCR. The entity responsible for billing generally handles the mailing of the CCR to all customers.

Two issues arise in thinking about the effect of the CCR rule as a regulatory treatment. First, to what extent did utilities anticipate the requirements for public disclosure before the rule took effect? The amendments authorizing the CCRs were passed in August 1996. The first

CCRs were issued by July 1, 1999 for violations and detections during the 1998 calendar year. Utilities may have anticipated and responded to the requirements prior to January 1, 1998. However, we do not believe that the anticipation effect was strong, and evidence suggests that utilities were not anticipating the disclosure rule much before the Amendments were passed and signed in 1996.[4] In our primary models we use 1998 as the first "treatment" year. If systems anticipated the requirements in advance and made treatment choices to lower violations before 1998, then we will underestimate the CCR's effect by assuming it begins in 1998.

The second issue is whether other changes in the SDWA or in enforcement may have coincided with the CCR rule, potentially inflating our treatment effect estimate. However, the bulk of the legislative changes contained in the 1996 amendments addressed procedural issues on how EPA set new drinking water standards. The requirement to do source water assessment was unlikely to have immediate impacts. States were first required to develop a plan to conduct their source water assessments. These plans had to be submitted and approved by EPA by 1999. States then had until 2003 to complete the source assessments. We do not expect the existence of the state revolving loans to have had a significant impact on drinking water violations as the vast majority of money (96%) from state revolving loans went to fund improvements in waste water treatment rather than treatment that directly improves drinking water quality (GAO 2006). Furthermore, we have engaged in discussions with regulators regarding whether significant changes in enforcement or penalties occurred during this time frame, particularly in 1998, and they have assured us that no major changes took place.[5]

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[4] Legislative debate over amending the SDWA began as early as 1993, but there is no mention of a "right to know" provision (either in the Amendments' legislative history, or in industry publications or press releases) until Rep. Waxman's May 1996 proposal. It appears to have been a "surprise" move by opponents of the Amendments' requirement for benefit-cost analysis of new MCLs – this, and not the information disclosure requirement, is the provision on which water suppliers are clearly focused leading up to the passage of the Amendments.

[5] Damon Guterman, Massachusetts Department of Environmental Protection, personal communication, July 27, 2006. Penalty information specific to individual violations is not publicly available.

3. Related Literature

The literature on information as a policy instrument covers widely disparate types of information disclosure regimes. We categorize information disclosure programs by the nature of the good about which information is being disclosed.

3.1 Information disclosure about public goods

Many information disclosure programs have been developed to inform consumers about the *public* benefits of particular actions. For example, green marketing and eco-labeling programs have been developed to help consumers recognize private products that are bundled with public goods provision such as species preservation (dolphin safe tuna), ecosystem benefits (organic food and clothing), and hazard reductions (toxics release inventory). Consumers may have preferences over how their consumption choices affect the provision of these public goods, and an information program helps them tailor their consumption patterns to match those preferences. The key, however, is that the private goods they are consuming are of essentially the same quality regardless of whether those private goods are bundled with public goods.

The literature on public benefit disclosure programs includes a number of theoretical explorations (Kotchen 2006, Sedjo and Swallow 2002, Swallow and Sedjo 2000, Kirchhoff 2000, Kennedy *et al*. 1994). Empirical studies of the effects of such programs include analyses of the labeling of "dolphin-safe" tuna (Teisl *et al*. 2002) and "shade-grown" coffee (Loureiro and Lotade 2005), as well as disclosure of the percent of renewable sources comprising total energy supply by electric utility providers (Delmas *et al*. 2006). The findings from the literature on this class of information disclosure problems suggest that mandatory information disclosure can change consumer behavior and can result in improvements in environmental performance, particularly among larger firms that produce goods sold directly to consumers.

Many analyses have focused on the requirement that manufacturing facilities publicly disclose toxic chemical releases under the U.S. Toxics Release Inventory (TRI) program (Karkkainen 2001, Wolf 1996).[6] From the TRI's inception, total releases of reportable toxic chemicals have fallen by nearly 50 percent, but the observed decrease in toxic releases has not been causally attributed to the TRI. Data are not available on chemical releases before the program began, or for unregulated facilities, making it difficult to test the hypothesis that TRI actually decreased toxic releases (Bennear and Coglianese 2005). Analysts of the TRI have performed event studies on outcomes other than environmental performance, examining the effect on stock prices of the annual release of TRI data.[7] Other researchers have tried to address the causality questions surrounding the TRI by testing for alternative explanations for the observed decreases in releases of listed chemicals. For example, facilities may have shifted to unlisted chemicals, or to chemicals with lower volume but higher toxicity (Greenstone 2003, Gamper-Rabindran and Swoboda, ongoing), or they may have reduced their use of listed chemicals below reporting thresholds (Bennear 2006).[8]

3.2 Information disclosure about private goods

Information disclosure programs also have been developed to inform the public about *private* benefits and costs of their actions – the health effects of direct consumption of a good, for example. The SDWA information disclosure regulation that we assess here falls into this category. The provision of information about tap water quality is a public good, but the benefits

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[6] Unless consumers or investors with an interest in this information live in the immediate vicinity of a reporting facility, the benefits of using this information to change consumption or investment activity contribute to a public good, thus we place the TRI in this first category of information disclosure programs.

[7] Findings suggest that firms whose TRI releases received media coverage experienced abnormal stock returns (Hamilton 1995) and that firms in turn responded to these abnormal returns by reducing pollution (Khanna *et al*. 1998).

[8] Still others have examined the characteristics of facilities and firms that make them more likely to reduce toxic chemicals in response to information mandates (King and Lenox 2001, Konar and Cohen 1997).

received from the information accrue to households in private fashion.[9] Other examples in this category include nutritional labeling, cigarette warnings, and organic food labeling when consumers perceive private health benefits of consumption.

The oldest strain in the literature on *private* benefit disclosure programs concerns the effects of mandated disclosure of firms' financial information to investors on market returns (Greenstone *et al*. 2006, Healy and Palepu 2001, Benston 1973, Stigler 1964). Mandatory food safety labeling, such as mercury advisories for fish consumption (Shimshack *et al*. 2006), nutrition labeling (Brown and Schrader 1990, Foster and Just 1989), the surgeon general's tobacco warning label (Sloan *et al*. 2002, Fenn *et al*. 2001), and HIV/AIDS education (Duflo *et al*. 2006) are other examples that have been examined empirically.[10]

Two recent studies link drinking water quality information disclosure to impacts on consumer behavior. Madajewicz *et al*. (2005) estimate the response of well water users in Bangladesh to information provided by the researchers on the level of arsenic in the well. Jalan and Somanthan (2004) randomly assign households in Delhi, India to receive information on whether their drinking water tested positive for fecal contamination and test for any effect of this information.[11]

The findings from the literature on these types of information disclosure programs indicate that consumers who will receive private benefits from quality or hazard labeling react rationally to such information in many, but not all, cases (reducing consumption of "bads" and

[9] An exception would be a case in which a regulated supplier managed a surface water supply, and took steps due to information disclosure to improve source water quality. Such an effect could have positive externalities of a public nature, like improvements in species habitat.
[10] See also Adler and Pittle (1984) and Viscusi *et al*. (1986).
[11] Johnson (2003) examines consumers' comprehension of information provided in the drinking water quality reports that are the subject of this paper. He finds that consumers are not sensitive to the design or format of the consumer confidence report.

increasing consumption of "goods"). To our knowledge, there is no previous research linking these kinds of regulations to producer behavior.

3.3 Ways in which information disclosure might influence firms' behavior

The mechanisms through which information is expected to influence behavior can be grouped into three broad categories. The first category is the market mechanism (Sunstein 1999). If information about a firms' environmental performance is known and market participants (such as consumers, investors, and employees) have preferences over environmental performance, firms can face market pressure to improve performance (Reinhardt 2000). The second category is the political mechanism; people may use the political system to lobby for more stringent regulation, or to protest particular production practices (Sunstein 1999, Wolf 1996, Fung and O'Rourke 2000, Denicolo 2000). Finally, information disclosure programs can affect the internal decision making of an organization. The act of measuring and reporting data on environmental performance may itself lead to internal changes at the firm that improve environmental performance (Karkkainen 2001, Banks and Heaton 1995).

It is useful to examine these three potential mechanisms with regard to the SDWA policy we assess here. The market mechanism is likely not relevant in this case, as there is essentially no market through which consumers can respond to information provided by their water supplier. The only potential response that would be reflected in a market is if customers moved to an area served by a different water supplier and we do not anticipate this reaction to be significant.[12] The internal mechanism is also unlikely to play a large role for the CCR rule because water suppliers are already required to monitor and report any violations to the state DEP. So compiling these data for their customers should not be providing the *water supplier* with

[12] Households could, of course, switch to bottled water for drinking, but drinking water comprises such a small portion of total water use by households in Massachusetts that the market "pressure" exerted by this activity would be very small. We may explore this question and other potential consumer reactions in future research.

information it did not already have. Of the three potential pathways for information disclosure to influence the behavior of regulated entities, the political mechanism is the most likely in this case. We will address this issue when we interpret results of our econometric models, but will not formally model the mechanism through which disclosure may affect water suppliers' behavior.

3.4 Information disclosure and social welfare

We end this section with an important caveat about social welfare. The literature on eco-labeling suggests that providing information about the provision of a public good can, in theory, have either positive or negative effects on both environmental quality and, more generally, social welfare (Kotchen 2006, Sedjo and Swallow 2002). Analysts have only recently begun to explore the welfare implications of the class of information disclosure that we analyze here (Cohen and Santhakumar 2006), but implications thus far are similar to that in the eco-labeling case – it depends. It is certainly possible that the costs of such programs exceed their benefits.

In the particular case addressed in this paper, environmental compliance under the SDWA, some environmental standards might not pass a strict benefit-cost test – the drinking water contaminant standards may be set low enough that their social costs exceed their social benefits.[13] To be concrete, if the standards in place under the SDWA already have social costs that exceed social benefits, and information disclosure about violations and contaminant levels causes regulated suppliers to further reduce contaminant levels below the inefficient standards,

[13] In addition to requiring information disclosure by regulated suppliers, the 1996 SDWA Amendments require benefit-cost analysis of all new MCLs. The first two new MCLs promulgated after the Amendments, a stricter MCL for arsenic and a new MCL for radon, by EPA's own estimates, had net costs. These standards came into force after our observation period, and without retrospective analyses of historic MCLs, we have no information about the relative benefits and costs of standards with which suppliers had to comply between 1990 and 2003 (with one exception – EPA's analysis of the new arsenic standard suggested that the "old" standard – the one relevant to our data – had net benefits).

the marginal costs of each such reduction exceed the marginal benefits, and the program as a whole may diminish social welfare. [14]

A full exploration of the welfare implications of the SDWA information disclosure requirement is beyond the scope of this analysis. However, we achieve what would be the necessary first step in performing a benefit-cost analysis of the regulation – measurement of its impacts on the compliance behavior of regulated water suppliers. Further work on the regulation's impact on consumers and other factors is an intended area of future research.

4. Econometric Models

Our econometric approach to assessing the impact of information disclosure on drinking water violations is a set of panel data models that exploit variation in disclosure over time, examining data before and after the implementation of the regulation to identify its effect, and also spatial variation created by the system size threshold for mailing CCRs. We use linear and count-data panel models to estimate the effect of the CCR on the number of violations suppliers incur annually. We also use logit models to estimate the effect of the CCR on the probability of positive violations. Alternatives to our panel data approach are discussed in Section 6.3.

The first equation to be estimated is (1), where *V* is the number of violations by supplier *i* in year *t*:

$$V_{it} = \alpha CCR_t + \theta CCR\_mail_{it} + \delta CCR\_size_{it} + \psi CCR\_size_{it}^2 + \omega K_t + \gamma Z_i + u_i + \varepsilon_{it} \qquad (1)$$

We also estimate each of the panel data models with *V* equal to annual health violations, rather than total violations. On the right-hand side, *CCR* is an indicator variable set equal to 1 in years in which consumer confidence reporting is required; *CCR_mail* is set equal to 1 if a supplier is

[14] See Dinan *et al*. (1999) for a discussion of the welfare losses from uniform national drinking water standards, in comparison to local standards.

required to mail the report; *CCR_size* is *CCR* multiplied by the number of people a supplier serves (in thousands); *K* is a vector of covariates that vary over time but not by supplier, such as the number of MCLs with which suppliers must comply; *Z* is a vector of supplier characteristics including the source basin and county, type of primary source (surface v. groundwater), system ownership (public v. private), system size, and whether the supplier purchases some or all of its supply from another drinking water purveyor. The error structure comprises u, a supplier heterogeneity parameter, and ε, the residual.

The model parameters to be estimated are α, θ, δ, ψ, ω, and γ, with α and θ of greatest interest. In most models, u_i will be a supplier fixed effect, so we will not directly estimate γ. In some models, K_t will be a set of yearly dummy variables, so we cannot directly estimate α.

Violations are discrete, infrequent events; V is equal to zero most of the time and cannot be negative. Thus, we also estimate panel Poisson models (2), obtaining parameter estimates by maximizing the corresponding log-likelihood function. Negative binomial models are also estimated, relaxing the Poisson's assumption that the conditional mean is equal to the conditional variance.[15]

$$\begin{aligned} &\Pr(V_{it} = v_{it}) = \frac{e^{-\lambda_{it}} \lambda_{it}^{v_{it}}}{v_{it}!}, v_{it} = 0,1,2,... \\ &\ln \lambda_{it} = \alpha CCR_t + \theta CCR\_mail_{it} + \delta CCR\_size_{it} + \psi CCR\_size_{it}^2 + \omega X_t + \gamma Z_i + u_i + \varepsilon_{it} \end{aligned} \qquad (2)$$

We also estimate a set of logit models, with a binary dependent variable equal to one if we observe one or more violations for supplier *i* in year *t* and zero if not. We estimate the parameters in (3) by maximizing the corresponding log likelihood function.

[15] The adaptation of the Poisson and negative binomial models to accommodate fixed and random effects is due to Hausman *et al*. (1984).

$$\Pr(v_{it} \neq 0 \mid CCR, CCR\_mail, CCR\_size, K, Z) =$$
$$\frac{\exp(\alpha CCR_t + \theta CCR\_mail_{it} + \delta CCR\_size_{it} + \psi CCR\_size_{it}^2 + \omega X_t + \gamma Z_i + u_i + \varepsilon_{it})}{1 + \exp(\alpha CCR_t + \theta CCR\_mail_{it} + \delta CCR\_size_{it} + \psi CCR\_size_{it}^2 + \omega X_t + \gamma Z_i + u_i + \varepsilon_{it})} \quad (3)$$

For the panel model estimates of α to be causal effects, it must be the case that nothing else occurred in 1998 among community water suppliers that affects violations and is not controlled for in the estimation. For the estimates of θ to be causal effects, it must be the case that nothing else occurred in 1998, specific to suppliers over the mailing threshold, that is correlated with violations. Inclusion of the quadratic function of *CCR_size* helps to ensure that anything captured by *CCR_mail* is not simply a result of larger suppliers reacting differently to the requirement to compile a CCR, but is in fact a result of being over the mailing threshold.

5. Data

Drinking water violations are observed for 517 Massachusetts drinking water suppliers between 1990 and 2003. We observe the start and end dates for each violation, and have aggregated violations to an annual level. Data on violations and supplier characteristics were obtained from the Massachusetts Department of Environmental Protection (DEP), the state environmental regulatory agency.[16] These characteristics include: the number of service connections, primary water source (groundwater v. surface water), city/town and county in which suppliers are located, source basin (watershed) from which water is drawn, type of water system ownership (public v. private), and whether or not a system purchases water from another

[16] We chose Massachusetts after consultation with staff at the U.S. EPA, who suggested that this state's record-keeping for drinking water regulation was particularly accurate. EPA does have data on SDWA violations for all 50 U.S. states, but an independent audit of the federal database suggests numerous problems. For example, it is estimated that only 68 percent of national violations of the total coliform rule (and only 15 percent of other MCL violations) are reported accurately (U.S. Environmental Protection Agency 2002).

purveyor. In addition, the DEP has provided us with the number of federal MCLs in place in each year, an important measure of "exposure" to the probability of a violation.

Descriptive statistics are provided in Table 1. Massachusetts water suppliers incur, on average, about one violation every two years between 1990 and 2003. For suppliers serving more than 10,000 people, violations occur more frequently before the information disclosure regulation (on average, 0.47 violations per year) than after (on average, 0.33 violations per year), a difference in raw means that is significant at the one percent level. Raw mean total violations increase for smaller suppliers after information disclosure, and the difference is significant at the five percent level. The probability of non-zero total violations in a supplier-year is 0.26.

Health violations are the sum of: (1) actual MCL violations; and (2) procedural violations (in drinking water treatment, for example) deemed by EPA to raise the probability of an MCL violation. Like total violations, mean health-based violations are lower after the regulation than before for suppliers serving more than 10,000 people (significant at the five percent level). For smaller suppliers, the observed increase is also significant at the five percent level. The probability of non-zero health violations in a supplier-year is 0.09.

Figures 1 and 2 describe trends in violations among Massachusetts community water suppliers over time and by system size. Figure 1 describes violations per MCL by system size, splitting systems at the 10,000-person CCR mailing threshold. Even adjusted for the steep increase in MCLs in the early 1990s, violations rise significantly over this period, followed by a decline beginning in 1996, the year the SDWA Amendments were passed. The changes are less dramatic for smaller systems than for larger systems. There is no obvious change in 1998, the first year for which violations were reported to consumers (in the 1999 CCR), for systems either above or below the CCR mailing threshold.

What if we examine the time series and the cross-section in combination? In Figure 2, we graph the average number of violations in 1997 and 1998 by 25 "bins" of water suppliers, each comprising approximately 4 percent of systems (about 20 systems). Each dot graphs the average number of violations for a bin in one year. The bin containing the 20 largest systems is excluded so that it is possible to see any apparent change in violations between the two years around the 10,000-person mailing threshold.[17] In 1997, the year immediately preceding mandatory disclosure, violations trend upward for systems serving between 4,000 and 15,000 people. In 1998, violations rise from 4,000 to 10,000, then drop quite steeply at the CCR mailing threshold, staying below or approximately equal to 1997 violations for larger systems. Though we cannot draw any causal inference from the graph, visually it appears as though violations for systems near 10,000 may be affected by information disclosure. This is consistent with the observed drop in mean violations for larger systems in Table 1, and it is the effect we will seek to identify econometrically.

The independent variables of greatest interest identify supplier-years in which information disclosure is required, and supplier-years in which information must be mailed directly to consumers. An annual CCR is required in about 45 percent of supplier-years in our data. Mailing a CCR directly to customers is required in about 14 percent of supplier-years.

The average Massachusetts water supplier serves about 3,500 people. Most are publicly-owned (although about one-third are private), and 19 percent purchase some or all of their water supply from a wholesale water provider, in many cases from the Massachusetts Water Resources Authority (MWRA). Surface water is a primary source for almost one-third of the regulated community suppliers; the rest obtain water primarily from groundwater sources.

[17] There are 20 suppliers (out of 517) in this last bin, and the midpoint population served is 1,030,500.

6. Results

6.1 Models of total violations

Table 2 reports results from the estimation of linear panel data models, in which the dependent variable is total annual violations. We begin by estimating equation (1), in which u_i is a supplier fixed effect, with results reported in the first column.[18] We estimate that, for suppliers large enough to trigger the mailing requirement, those serving 10,000 or more people, disclosure reduced annual drinking water violations by about 0.21, about one-fifth of a violation and just under half of mean violations in the sample. The pattern of violations over time is approximately what we see in Figure 1 – little change between 1990 and 1991, an increase beginning in 1992 becoming very steep, and then dropping (somewhat more slowly) beginning in 1996. If we use a quadratic time trend, rather than yearly dummies (column 2), we can also identify the independent effect of compiling the CCR, and the effect of an increase in the number of MCLs with which suppliers must comply. The coefficient on CCR is –0.09, but statistically insignificant. The effect of mailing CCRs remains about –0.21 violations annually. An additional MCL increases violations by less than 0.01 per year.

Table 2 also reports results from the estimation of a panel Poisson model and a panel negative binomial model for total violations. We report incident-rate ratios (IRRs), or exponentiated coefficients, for the count data models. These indicate that the requirement that suppliers mail annual CCRs to households reduces violations by between 30 and 38 percent. As in the linear model, the year dummies describe the hill-shaped pattern of violations between

[18] The results of a Hausman test reject the specification of u_i as a supplier random effect.

1990 and 2003. The data are slightly overdispersed, so the negative binomial model is the correct model, though the differences in parameter estimates are not very large.[19]

Table 3 provides an additional layer of detail, first regressing the year dummies from column 1 of Table 2 on CCR and the number of MCLs with which suppliers must comply, and then regressing the (unreported) supplier fixed effects from column 1 of Table 2 on supplier characteristics.[20] Even with a very small number of observations on the dependent variable (14 years), the number of MCLs increases violations, and the requirement to produce a CCR reduces violations. Supplier characteristics may also play a role. Controlling for a supplier's source basin, publicly-owned suppliers on groundwater violate less often than their private counterparts; the opposite is true for suppliers on surface water. All else equal, surface water suppliers violate (weakly) less often than groundwater suppliers, and this effect is more pronounced for suppliers with a larger number of service connections. This seems anomalous, since surface water sources are significantly more vulnerable to bacterial and other types of contamination (from runoff), but the surface water dummy variable may be collinear with source basin and other covariates in the model.

6.2 Models of health violations

We also estimate the panel data models with the more severe "health violations," rather than total violations, as the dependent variable. Health violations are infrequent; about 92 percent of supplier-year observations on this variable are zeros, and another 6 percent are ones. The linear models in Table 4 suggest that mailing CCRs directly to customers results in reduced

[19] In addition, by estimating the model with supplier fixed effects, we have removed the most significant source of overdispersion – supplier heterogeneity.

[20] With supplier and year fixed effects, we cannot identify the impact of these covariates on violations in the models reported in Table 2. To produce unbiased estimates, the second-stage models reported in Table 3 require independence of CCR, Number_MCL, and the first-stage time dummies (for the model in row 1), and independence of Z_i and u_i (for the supplier characteristics model in row 2). Thus, these second-stage models provide some of the detail that would appear in a random-effects model, but they are not free from *all* of the assumptions of a random-effects model.

violations (by about 0.08 per year), and there may be a "pure" CCR effect on health violations, as well (the model with a quadratic time trend, reported in column 2, suggests that the requirement to compile a CCR and make it available on request reduced violations by about 0.06 per year). The Poisson model suggests a reduction in violations of 57 percent when CCRs must be mailed.[21] The time dummies in all models capture the annual trend in health violations we see in Figure 1 – peaking in 1995, and falling thereafter with the exception of increases in 2000 and 2002. This is captured in the Poisson model by dummies representing pairs of years, due to the prevalence of all-zero outcomes with annual dummies. The prevalence of all-zero outcomes also explains the drop in the number of observations from the linear to the Poisson model.

As we did for total violations, we also estimate second-stage models to explain some of the variation in supplier and year fixed effects. Table 5 reports the results from these regressions. For health violations, compiling a CCR and making it available to consumers (without mailing) has no statistically significant impact, but an increase in the number of MCLs does increase violations. Publicly-owned suppliers violate more frequently (the opposite of the effect of system ownership on total violations). For every 1,000 service connections, suppliers incur 0.02 additional health violations per year, though this effect is negated for suppliers on surface water.

6.2 Models of the probability of positive violations

Our final set of panel data models allow us to estimate the effect of the CCR rule and the requirement to mail CCRs on the probability of positive violations.[22] Table 6 reports results of four fixed-effects logit models, in terms of odds ratios. We report two models for total

[21] The negative binomial fixed effects model for health violations does not converge.
[22] This may be a particularly good model for health violations, since health violations are equal to zero in 92 percent of supplier-years and equal to one in 6 percent of supplier-years (thus, modeling violations as 0/1 comes very close to capturing all of the variation).

violations, one with a quadratic time trend (column 1) and one with annual dummies (column 2). We also include the results of two health violations models, one with a quadratic time trend (column 3) and one with dummies for each pair of years (column 4).

In each of these four models, the requirement to mail CCRs directly to households has a negative and significant effect on the probability of positive violations, reducing the probability of nonzero violations (and of nonzero health violations) by about one-half. The requirement to compile a CCR and make it available on request has no significant impact. The number of MCLs with which suppliers must comply increases the probability of a violation, and of a health violation, and estimates of variables capturing the time trend follow the expected patterns.[23]

6.3 Alternative approaches

There are a variety of other approaches that are potentially suitable for identifying the effect of information disclosure through the CCR on water suppliers' regulatory compliance behavior. We have considered many of these approaches, tried many, and rejected others outright.

One initially promising approach was a differences-in-differences model, in which the community water systems (which are subject to the CCR rule) serve as the treatment group and so-called "non-community" systems (not subject to the CCR, but still subject to compliance with the SDWA's contaminant rules) as controls. Early analysis revealed the non-community systems, serving fewer than 15 connections or 25 people, to be simply too different from the community systems to serve as reasonable controls.

[23] In order to account for the prevalence of utilities with zero violations, we have also estimated a zero-inflated Poisson model for total violations. In this model, neither the CCR rule, itself, nor the requirement to mail CCRs appears to have any significant effect on either positive counts of violations or on the probability of having zero violations. This model included a quadratic time trend and basin fixed effects, but treated observations within the same supplier as independent (except in the estimation of standard errors, robust to clustering by supplier).

A second quasi-experimental approach would exploit the system size threshold for CCR mailing, but not the time series, in a regression discontinuity (RD) design. An RD model would assume that water systems very near 10,000 are similar in all respects except for the requirement to mail the CCR above the threshold. Suspecting that the CCR mailing threshold was not deterministic, we collected data on whether suppliers actually mailed their CCR in each year, 1998-2003, available in paper and microfiche files at the Massachusetts DEP.[24] We then implemented a fuzzy RD model, using the 10,000-person mailing threshold as an instrument for actual mailing. Results are reported in Table 7.

There are a number of weaknesses to this approach. Most obvious is the loss of power in comparison to the panel data models. The fuzzy RD model must drop all systems except those in the neighborhood of 10,000 customers, since the instrument is valid only for these systems. In Table 7, we offer two different assumptions about the breadth of this neighborhood, but even using the most generous assumption, [6,000, 14,000], there are so few suppliers in this group that none of the parameter estimates are significant. Given the inclusion of a quadratic function of distance to the threshold, we are not able to estimate a model with supplier fixed effects; instead we estimate annual models, 1998-2003, further reducing statistical power. The panel model in column 7 is a random-effects model – a specification rejected earlier by a Hausman test.

These RD results do not contradict the panel model results, but they do not support them, either. While we would have been pleased with quasi-experimental results that support the panel model results, we prefer the panel models for three reasons related to research design. First, as is obvious in Figure 2, the effect of the CCR is likely to be identified only by exploiting the combination of time-series and cross-sectional variation in reporting. The RD model, by design,

[24] About 18 percent of suppliers below the threshold chose to mail the CCRs over this period. In rare instances, larger suppliers failed to comply with the mailing requirement.

focuses only on the cross-section. Second, even if we were to estimate significant parameters with the RD model, the coefficient on *CCR_mail* would amount to an effect at the mailing threshold; it would not generalize to an average treatment effect. With systems in Massachusetts serving from 21 to 2 million customers, this interpretation would be much less satisfactory than the results from our panel models. Third, in the panel data models we borrow one of the auspicious aspects of the RD approach. Recall that we include a quadratic function of *CCR**system size in each panel model (and tested higher-order polynomials with no significant results). This allows the *CCR_mail* coefficient in these models to zero in on what is happening around the mailing threshold in identifying θ, rather than on other potential interactions between reporting and system size (say, for example, related to administrative sophistication).

We might also have chosen other panel data models. Quantile regression is one option, focusing on the upper quantiles of the distribution of violations, where disclosure is likely to have the greatest impact. While results are not reported here, we estimated quantile regressions for the 95th quantile of total violations, and the 98th for health violations – the full set of parameters was only identified for these far upper quantiles. Both the requirement to make a CCR available upon request and the requirement to mail a CCR diminish total violations for the 95th quantile. For health violations, the CCR reduces violations for the 98th quantile, and mailing appears to increase them. The quantile regressions do not exploit the full range of variation in the data, and they pool what is clearly a panel, treating observations within a supplier over time as independent. For these reasons, we prefer the panel data models reported in Sections 6.1-6.2.

Finally, we have also estimated a zero-inflated Poisson model for total violations, explicitly modeling zeros as the result of a separate data-generating process from that which creates positive counts of violations. In this model, neither the CCR nor the requirement to mail

CCRs has any significant effect on either positive counts of violations or on the probability of zero violations. Like the quantile regressions, the zero-inflated Poisson model treats observations within a supplier as independent. The IRR for *CCR_mail* in the Poisson portion of the model is 0.683, consistent with the Poisson results reported in Table 2, but the p-value is 0.110. Were it possible to estimate a panel version of this model, the efficiency gain may have tipped the scales in support of the other panel data models. We have no reason to believe that instances of zero violations and positive counts result from different data-generating processes, but we report this result for completeness.

7. Conclusions

Taken together, the panel data models we estimate suggest that the requirement to disclose information on drinking water violations by mailing information directly to households on an annual basis reduced violations by Massachusetts water suppliers. Our findings suggest that there may also be some impact of the CCR among smaller utilities, required to compile the CCR and make it publicly available but not to mail it, but the evidence for this impact is considerably weaker.

In order to understand these findings we reflect on the various mechanisms through which information disclosure can affect environmental performance. As noted earlier, there are three primary mechanisms: the market mechanism, the political mechanism, and the internal mechanism. We would not expect the market mechanism to contribute much to our understanding of how community water systems respond to information disclosure requirements as there is essentially no market through which consumers can respond to information provided by their water supplier.

The remaining two mechanisms – the political and internal mechanisms – operate quite differently. The internal mechanism suggests that the act of gathering and compiling information about violations alerts the water supplier to issues of which it was previously unaware and changes the internal dynamics of the utility in ways that lead to reductions in violations. This mechanism is unlikely to play a large role for the CCR rule because water suppliers are already required to monitor and report any violations to the state. So compiling these data for their customers should not be providing the *water supplier* with information it did not already have.

That leaves the political mechanism, which we expect is the dominant mechanism for this particular information disclosure regime, and perhaps many others. In order for the political mechanism to work, however, the information disclosure program must make customers aware of violations about which they were previously unaware. This effect is more likely if reports are mailed directly to consumers. While placing the CCR in a local paper may trigger some small political response, readership of newspapers, in particular local newspapers, is on the decline (The State of the News Media 2006). So it is not surprising that water suppliers required to directly mail their CCRs either experience, or expect to experience, a larger political response and, thus, are more likely to respond by lowering violations.

This work adds considerably to the evolving understanding of the effects of information disclosure on environmental quality. There is significant movement in regulation at all levels toward "regulation by information". For the SDWA example we analyze, mandatory information disclosure complements, but does not supplant, existing pollution control regulations. This is not always the case, especially in developing countries. Further work analyzing the effects of information disclosure on regulated firms, consumers, governments and other institutions is an important area for future research.

Table 1. Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Dependent variable					
Total violations (annual)	6830	0.452	1.051	0	17
1990-1997	3781	0.451	1.059	0	16
Systems serving ≥10,000	1272	0.465	0.929	0	8
Systems serving <10,000	2509	0.444	1.120	0	16
1998-2003	3049	0.452	1.041	0	17
Systems serving ≥10,000	956	0.326	0.749	0	9
Systems serving <10,000	2093	0.510	1.145	0	17
Health-based violations (annual)	6830	0.116	0.436	0	7
1990-1997	3781	0.117	0.455	0	7
Systems serving ≥10,000	1272	0.200	0.603	0	7
Systems serving <10,000	2509	0.075	0.350	0	6
1998-2003	3049	0.115	0.411	0	5
Systems serving ≥10,000	956	0.151	0.444	0	3
Systems serving <10,000	2093	0.098	0.393	0	5
Pr(violations>0)	6830	0.261	0.439	0	1
Pr(health violations>0)	6830	0.086	0.280	0	1
Independent variables					
CCR	6830	0.446	0.497	0	1
CCR_mail	6830	0.140	0.347	0	1
Service connections (000)	6315	3.495	6.577	0.001	87.16
Number of MCLs	6830	73.697	17.534	31	90
Publicly owned	6315	0.667	0.471	0	1
Purchase water	6830	0.190	0.392	0	1
Surface water source	6830	0.336	0.472	0	1

Notes: Health-based violations are violations of maximum contaminant levels (MCLs), or violations of procedural regulations that would increase the probability of an MCL violation. Total violations include health-based violations, as well as paperwork violations.

Table 2. Linear and Count Data Model Estimates				
	Linear FE Models		*Count Data FE Models*	
Variable	**Year Effects (1)**	**Time Trend (2)**	**Poisson IRRs (3)**	**Negative Binomial IRRs (4)**
CCR		-0.094 (0.066)		
CCR Mailed	-0.211*** (0.060)	-0.211*** (0.059)	0.622*** (0.067)	0.703*** (0.089)
CCR_Size	0.001 (0.001)	0.000 (0.001)	1.000 (0.002)	0.997 (0.003)
CCR_Size^2	0.000 (0.000)	0.000 (0.000)	1.000 (0.000)	1.000 (0.000)
Number_MCL		0.006*** (0.002)		
Time		0.186*** (0.034)		
Time^2		-0.011*** (0.002)		
Year 1991	0.003 (0.004)		1.993 (2.440)	1.992 (2.440)
Year 1992	0.076** (0.015)		34.798*** (35.292)	31.327*** (31.827)
Year 1993	0.515*** (0.043)		231.803*** (232.282)	190.348*** (190.877)
Year 1994	0.643*** (0.048)		290.426*** (290.904)	236.278*** (236.820)
Year 1995	0.891*** (0.079)		403.319*** (403.794)	289.061*** (289.644)
Year 1996	0.756*** (0.055)		341.368*** (341.835)	268.663*** (269.214)

Table 2. Linear and Count Data Model Estimates				
	Linear FE Models		***Count Data FE Models***	
Variable	**Year Effects (1)**	**Time Trend (2)**	**Poisson IRRs (3)**	**Negative Binomial IRRs (4)**
Year 1997	0.646***		290.682***	217.915***
	(0.054)		(291.141)	(218.458)
Year 1998	0.648***		300.434***	245.321***
	(0.051)		(301.041)	(246.002)
Year 1999	0.595***		272.463***	203.309***
	(0.058)		(273.051)	(203.999)
Year 2000	0.572***		260.962***	196.537***
	(0.058)		(261.543)	(197.211)
Year 2001	0.476***		213.595***	168.696***
	(0.050)		(214.154)	(169.333)
Year 2002	0.442***		196.357***	142.392***
	(0.054)		(196.906)	(143.023)
Year 2003	0.226***		92.568***	67.096***
	(0.038)		(93.073)	(67.647)
Number of Obs.	6830	6830	6315	6315
Number of Groups	517	517	473	473

Notes: Dependent variable is annual violations. Coefficient estimates are reported for linear model, and incident-rate ratios for Poisson and negative binomial models. Standard errors are in parentheses, and are robust to heteroskedasticity and serial correlation in columns 1 and 2. Asterisks denote statistical significance: *** at α=.01; ** at α=.05; and * at α=.10. All models include supplier fixed effects, and linear models (columns 1 and 2) include a constant. CCR=1 in 1998-2003, and CCR Mailed=1 in 1998-2003 for water systems serving more than 10,000 people. Year effects are relative to 1990.

Table 3. Regressions of Fixed Effects on Explanatory Variables

Model and Variables	Coefficient Estimate	Standard Error
Dependent variable: time effects from linear model		
CCR	-0.216**	(0.092)
Number_MCLs	0.015***	(0.002)
N=14 R^2=0.73		
Dependent variable: supplier FEs from linear model		
Purchaser	0.571	(0.576)
Publicly owned	-0.269***	(0.072)
000 service connections	-0.015	(0.023)
Surface water primary source	-0.533**	(0.220)
Purchaser*Public	-0.504	(0.404)
Purchaser*000 service connections	0.001	(0.005)
Purchaser*Surface	-0.110	(0.350)
Public*000 service connections	0.029	(0.022)
Public*Surface	0.638***	(0.236)
Surface*000 service connections	-0.019**	(0.009)
N=464 R^2=0.18		

Notes: Dependent variable in first row is year parameter estimates from column 1 of Table 2. Dependent variable in second row is supplier fixed effects (unreported) from column 1 of Table 2. Robust standard errors reported in column 2. Asterisks denote statistical significance: *** at α=.01; ** at α=.05; and * at α=.10. Row 2 model also includes fixed effects for 50 source basins, jointly significant (F (38, 404) = 1125.29) but not reported here. Both models include a constant.

Table 4. Linear and Count Data Model Estimates, Health Violations Only			
Variable	**Linear Year Effects (1)**	**Linear Time Trend (2)**	**Poisson IRRs (3)**
CCR		-0.058** (0.028)	
CCR Mailed	-0.081** (0.034)	-0.080** (0.034)	0.439*** (0.118)
CCR_Size	0.000 (0.000)	0.000 (0.000)	1.016 (0.016)
CCR_Size^2	0.000 (0.000)	0.000 (0.000)	1.000 (0.000)
Number_MCL		0.000 (0.001)	
Time		0.080*** (0.015)	
$Time^2$		-0.004*** (0.001)	
Year 1991	0.003 (0.002)		
Year 1992	0.003 (0.002)		57.557*** (58.051)
Year 1993	0.127*** (0.018)		
Year 1994	0.144*** (0.020)		182.791*** (183.283)
Year 1995	0.259*** (0.035)		
Year 1996	0.233*** (0.027)		192.428*** (192.919)

Table 4. Linear and Count Data Model Estimates, Health Violations Only			
Variable	**Linear Year Effects (1)**	**Linear Time Trend (2)**	**Poisson IRRs (3)**
Year 1997	0.190*** (0.025)		
Year 1998	0.179*** (0.022)		164.118*** (165.431)
Year 1999	0.163*** (0.021)		
Year 2000	0.199*** (0.022)		163.318*** (164.624)
Year 2001	0.141*** (0.022)		
Year 2002	0.189*** (0.025)		108.108*** (109.181)
Year 2003	0.063*** (0.012)		
Number of Obs.	6830	6830	3694
Number of Groups	517	517	272

Notes: Dependent variable is annual health violations. Coefficient estimates are reported for linear models, and incident-rate ratios for Poisson model. Standard errors are in parentheses and are robust to heteroskedasticity and serial correlation in columns 1 and 2. Asterisks denote statistical significance: *** at α=.01; ** at α=.05; and * at α=.10. All models include supplier fixed effects, and linear models (columns 1 and 2) include a constant. CCR=1 in 1998-2003, and CCR Mailed=1 1998-2003 for water systems serving more than 10,000 people. Due to the prevalence of all-zero outcomes with individual year effects, year effects are in groups of two in column 3. Year effects are relative to 1990 in columns 1 and 2, and relative to 1990-91 in column 3.

Table 5. Regressions of Fixed Effects on Explanatory Variables
Health Violations Only

Model and Variables	Coefficient Estimate	Standard Error
Dependent variable: time effects from linear model		
CCR	-0.040	(0.033)
Number_MCLs	0.004***	(0.001)
N=14 R^2=0.66		
Dependent variable: supplier FEs from linear model		
Purchaser	0.016	(0.072)
Publicly owned	0.066***	(0.020)
000 service connections	0.022***	(0.006)
Surface water primary source	0.046	(0.039)
Purchaser*Public	-0.059	(0.071)
Purchaser*000 service connections	-0.002	(0.002)
Purchaser*Surface	0.031	(0.061)
Public*000 service connections	-0.001	(0.005)
Public*Surface	0.018	(0.044)
Surface*000 service connections	-0.020***	(0.005)
N=464 R^2=0.33		

Notes: Dependent variable in first row is year parameters from column 1 of Table 4. Dependent variable in second row is supplier fixed effects (unreported) from column 1 of Table 4. Robust standard errors reported in column 2. Asterisks denote statistical significance: *** at α=.01; ** at α=.05; and * at α=.10. Row 2 model also includes fixed effects for 50 source basins, jointly significant (F (38, 404) = 474.48) but not reported here. Both models include a constant.

Table 6. Fixed-Effects Logit Models

Variable	Total Violations: Odds ratios Time Trend (1)	Total Violations: Odds ratios Year Effects (2)	Health Violations: Odds ratios Time Trend (3)	Health Violations: Odds ratios Year Effects (4)
CCR	1.220 (0.171)		0.852 (0.185)	
CCR Mailed	0.533*** (0.101)	0.506*** (0.096)	0.491** (0.170)	0.491** (0.169)
CCR Size	0.993* (0.004)	0.995 (0.004)	1.008 (0.019)	1.009 (0.019)
CCR Size^2	0.000* (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)
Number MCLs	1.052*** (0.007)		1.026** (0.011)	
Time	1.677*** (0.158)		2.299*** (0.330)	
Time^2	0.964*** (0.005)		0.954*** (0.007)	
Number of Obs.	6306	6306	3694	3694
Number of Groups	470	470	272	272

Notes: Each column reports odds ratios from a panel logit model with supplier fixed effects. Dependent variable is equal to one if a supplier incurs any violations, and zero otherwise, in columns 1 and 2; we use the same dependent variable, for health violations only, in columns 3 and 4. Standard errors are in parentheses. Asterisks denote statistical significance: *** at α=.01; ** at α=.05; and * at α=.10. Column 2 includes annual dummy variables, 1991-2003, each (except 1991) significant at 0.01. Column 4 includes dummy variables for each group of two years, 1992-2003, each significant at 0.01 (except 2002-2003, significant at 0.05).

Table 7. Fuzzy Regression Discontinuity Models

	Regression Discontinuity Parameter Estimates, by Year						
Variable	**1998 (1)**	**1999 (2)**	**2000 (3)**	**2001 (4)**	**2002 (5)**	**2003 (6)**	**Panel (98-03) (7)**
Suppliers Serving 8-12,000 People	N=25	N=28	N=25	N=26	N=26	N=26	N=156 (26 grps)
CCR Mailed Actual	-27.723 (12.279)	-0.612 (1.015)	-2.661 (9.305)	2.276 (8.171)	-0.025 (3.599)	1.880 (1.696)	0.597 (2.030)
Distance to mailing threshold	0.016 (0.007)	0.000 (0.000)	0.001 (0.006)	-0.002 (0.007)	-0.001 (0.002)	-0.001 (0.001)	-0.001 (0.001)
Distance to mailing threshold ^{2}	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Suppliers Serving 6-14,000 People	N=56	N=64	N=60	N=64	N=61	N=59	N=364 (67 grps)
CCR Mailed Actual	4.574 (23.365)	1.677 (3.183)	-0.715 (1.406)	-1.259 (1.512)	-0.857 (3.661)	1.633 (1.308)	-0.008 (0.721)
Distance to mailing threshold	0.000 (0.001)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Distance to mailing threshold ^{2}	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)

Notes: Dependent variable is annual violations. Columns 1 through 6 report two-stage least squares (2SLS) regression results, in which we instrument for CCR Mailed Actual using CCR Mailed, equal to 1 for systems serving 10,000 or more. Column 7 reports a panel (random effects) instrumental variables model. Robust standard errors in parentheses. Asterisks denote statistical significance: ** at α=.05; * at α=.10. All models include basin fixed effects (unreported).

Figure 1

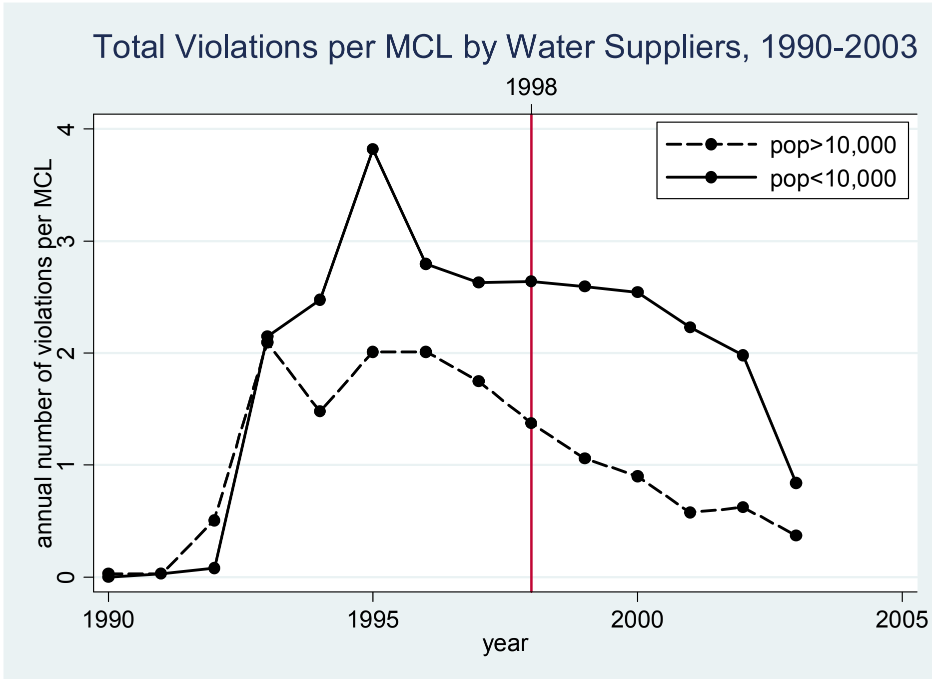
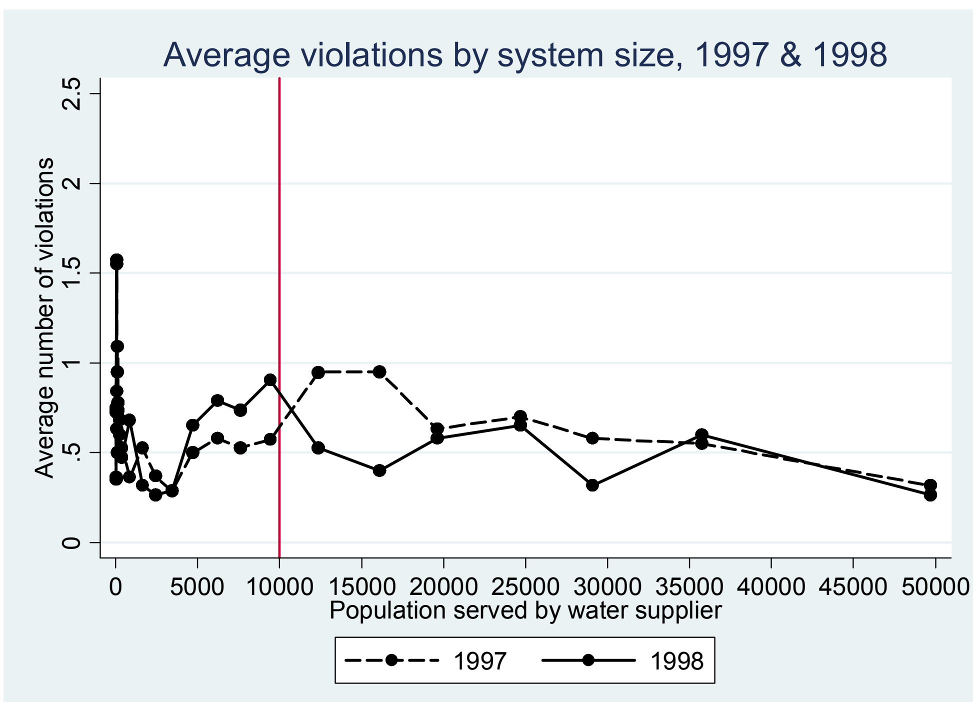


Figure 2



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