Water Innovation and Water Governance:
Adaptive Responses to Regulatory Change and Extreme Weather Events

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Abstract

During the past several decades, many countries have achieved significant progress on environmental issues such as water pollution through the increased stringency of their water policies. While a few studies have examined the stringency of overall environmental policy and its impacts on innovation (Johnstone et al., 2012; Ghisetti and Pontoni, 2015), the direct link between water policies and water-related technological innovation has not yet been investigated. This paper focuses on three aspects of water policy (drinking water quality, water pollution, and water quantity) in the United States and examines the effects of federal and state level regulatory changes on the level of relevant technological innovation. We construct a unique panel dataset covering major amendments and regulated contaminants lists as stipulated in the legislative acts most relevant to each water policy area, along with a set of technological patents pertaining to drinking water quality, wastewater treatment, and water quantity, over a period of more than 30 years. We find that, in general, the impact of water regulation on innovation is both statistically and economically significant. In the case of drinking water, new regulations on national drinking water standards are found to have a stimulating effect on related patents. On water pollution, amendments to the Clean Water Act spur more water pollution-reduction technologies. Last, water quantity related technological patents respond positively to both state-level water policy and past economic damages due to water scarcity, and the latter has a more substantial impact on water quantity related technologies.

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1. Introduction

Increased policy stringency is largely credited with vastly improved environmental outcomes in many industrialized economies starting with the second half of the twentieth century. In general, requiring ever higher standards on air, water and land pollutants works provided that existing production processes can - in a cost-effective way - be modified to have a reduced ecological footprint and/or new 'greener' technologies can be adopted. For environmental policy to be successful in a broad sense, it needs to lead to a cleaner environment based not on a reduced scale of economic activity, but rather following what is called in the literature a strong 'technique effect', i.e. the adoption of cleaner methods of production. Improved technical efficiency of production across the economy augments the policy-driven, allocative efficiency-enhancing effect of internalizing detrimental environmental externalities. Therefore, technological innovation aimed at reducing pollutants per unit of production needs to be developed in lockstep with the adoption of higher environmental standards.

This is particularly true when it comes to policies governing the industrial and residential use of water. From the lead contamination of municipal drinking water supply in Flint, Michigan (2016) to the Deepwater Horizon oil spill in the Gulf of Mexico (2010), recent as well as more distant examples of accidents involving drinking water quality and water bodies pollution in the US abound, unfortunately. Due to their obvious importance for human health, these examples usually do deserve and attract a lot of attention. While many negative environmental outcomes can be attributed to 'natural' forces, others can be traced to 'man-made' failures of policy or insufficient regulation. This paper takes a closer look at the link between water policy and water-related technological innovation in the US. It focuses on the adoption and amendments of several critically important pieces of legislation driving water policy at the federal and state levels and it asks whether these acts spur a significant amount of related technological innovation.

To summarize our findings, the effects of water regulation on relevant innovation activity in the US is in general both statistically and economically significant. On *drinking water quality*, both amendments to the Safe Drinking Water Act and changes to the list of regulated contaminants are found to have a stimulating effect on patenting of related technologies. One newly added substance to the list of regulated chemicals leads on average to a 2% increase in relevant patents every year. On *water pollution*, federal legislation in the form of amendments to the Clean Water

Act are found to induce a 10% increase in general water pollution reduction technologies and a 32% increase in the precise regulated pollutant-specific patents. Last, *water quantity* related technological patents respond positively to past economic damages due to water scarcity. For instance, a $1 bn. draught-induced damage is predicted on average to stimulate a 25% to a 46% increase in relevant patents in our sample. The stimulating effect of state water plans is also positive, but not a robust determinant of specific water-saving technological innovation, while appearing statistically significant for the more general group of water-related technologies.

While adopting rules such as maximum allowable levels for various contaminants in the drinking water supply, as well as maximum pollutant concentration of effluents from industrial and agricultural processes should in itself result in substantial environmental and public health gains, induced technological innovation can produce additional social benefits, by allowing the public and private sectors to achieve those targets with a lower net resource cost. Innovation can also yield broader social benefits via its positive external effects due to its public good nature (Arrow, 1962) and learning (Aghion and Jaravel, 2015), among others, as documented in a vast specialized literature. Hence, by reducing negative environmental externalities and increasing positive innovation-related externalities, there is great potential for environmental regulations to be welfare-enhancing, and consequently substantial payoffs from understanding the underlying mechanisms. In addition, quantifying the impact of water regulation on water-related technological innovation is important for its immediate policy relevance.

This paper draws on two bodies of literature in Economics: work on induced innovation and on the optimal water resource management. The induced innovation literature sheds light on the economic mechanism of endogenous technological change. Hicks (1932) observed that changes in relative prices of factors of production spur innovations that economize on the use of the relatively more expensive factor. In the 1960s, this idea of directed innovation due to variation in factor prices was formalized and further developed as 'induced innovation' by Ahmad (1966), Kamien and Schwartz (1968), and Binswanger (1974), among others. The theory of induced innovation would later be applied to environmental policy and technological improvement. If government regulations such as pollution permits affect the shadow price associated with a resource, firms are motivated to seek 'cleaner' methods of production (Downing and White, 1986; Milliman and

Prince, 1989; Jaffe et al., 2003; Fischer et al., 2008).[1,2]

Accompanying this theoretical literature, a growing body of empirical research investigates the impact of public policy and induced technological change on a multitude of environmental issues.[3] A number of studies focus on energy-efficient technology, and suggest that government regulations affect firms' R&D expenditure and the direction of innovation (Jaffe and Palmer, 1997; Greening et al., 1997; Newell et al., 1999). Popp (2006) uses standards on nitrogen dioxide and sulphur dioxide across countries and finds that tightened standards stimulate more domestic innovations. In analyses of policy, Johnstone et al. (2010), Nesta et al. (2014) find renewable energy policy to have an influential impact on innovation of relevant technology within a country.

However, empirical evidence on the effect of public policy on water-related technological innovation remains scarce. A related stream of studies focus on a general category of 'environmental innovation,' which combines several different environmental domains, such as water, air, and soil. Brunnermeier and Cohen (2003) examine environmental innovations from US manufacturing industries and suggest that higher pollution abatement expenditures lead to more environmental innovation. Using cross-country patent data, Johnstone et al. (2012) and Ghisetti and Pontoni (2015) find environmental policy stringency to positively affect environmental innovation. Although these studies confirm that general 'environmental innovation' is affected by environmental regulations, very little has been uncovered on the specific topic of water regulations and water technology. A recent study by Conway et al. (2015) identifies water supply and demand technologies from a global patent dataset and analyzes recent trends in water technology. Their descriptive analysis suggests that water scarcity, water regulations, together with the available research capacity play a substantial role in the emergence and development of water supply and demand technology. In this paper, we investigate the impact of changes in water policy in the U.S. on several different categories of water technology, using U.S. patent data and water legislations. To the best of our knowledge, this is the first paper that provides empirical evidence on how water technology innovation respond to adoption and changes in relevant public policy.

As mentioned above, this paper also draws on a vast body of literature on optimal water

[1] For a review of the theory, see Jaffe et al. (2002) and Popp et al. (2010).

[2] Induced innovation is also one of the channels suggested to explain the underlying mechanism behind the Porter Hypothesis.

[3] For recent reviews of such empirical studies, see Jaffe et al. (2002) and Vollebergh (2007).

management. Much of this research discusses the efficiency and effectiveness of water governance structures and policy instruments in dealing with specific water issues (Convery, 2013). Although the vital role of water technology is widely discussed in water management and planning (Kundell, 2000; Wehn and Montalvo, 2014; Speight, 2015), there remains a paucity of evidence on how water regulations may contribute to shaping innovation on water technology. This issue is crucial in terms of designing water governance and improving social welfare, especially given the 'double externality' of environmental technology (Ghisetti and Pontoni, 2015), whereby new water technology both reduces negative externalities on water resources and generate positive externality to other sectors due to the spillover effect. In this paper, we investigate water policy as a determinant of water innovation in the U.S. and we provide empirical evidence that water innovation responds to water legislation and regulations. Our research sheds light on the potential impact of water policy on innovation, which should be taken into account in water management and planning.

2. Background

A brief review of the evolution over time of water management in the US can help build some understanding of the main kinds of water regulations and their potential impact on water technologies. This is particularly important since our empirical approach exploits the timing of water-related regulations as it related to changes in relevant technologies pertaining to either drinking water, wastewater pollution or water scarcity. Over the past century, water management in the US has seen substantial changes. In the nineteenth and early twentieth centuries, water resource development focused on finding ways to unlock the services provided by water as a primary resource. Both the private and the public sectors were mainly involved in projects such as canal and river improvements, flood control, water power, and irrigation. In 1802, as an outgrowth of the Gallatin Report of 1808, the US Army Corps of Engineers (USACE) was created as the first major water construction agency in the US and has since provided technical and engineering assistance to large-scale water projects across the US (Russell and Baumann, 2009).

Water resource management began to incorporate conservation and environmental protection objectives starting from the 1940s. The Senate Select Committee on Water Resources was established in 1959. Although the committee made no legislative actions, the studies and recommendations of this committee are viewed as 'a new era in water resources planning and development in the USA' (Warren Jr., 2009). The Water Resources Planning Act (WRPA) of 1965 was passed to encourage conservation and comprehensive planning of the nation's water and related resources. During the 1970s and 80s the federal government's major concern had shifted from water resources development to water quality and environmental protection. Several new pieces of legislation were established to address water quality concerns, such as the Water Pollution Control Act Amendments of 1972, the Safe Drinking Water Act (SDWA) of 1974, and the Clean Water Act (CWA) of 1977. A new regulatory agency, the US Environmental Protection Agency (EPA) was founded in 1970. While the EPA is largely considered to have been successful in governing federal environmental control programs, such as on water and air pollution, it also effectively separated the management of water quality from water quantity-related issues, such as managing water supply and demand.

Several different levels of government are presently involved in water resource governance in the US. While federal agencies such as USACE and the EPA play crucial roles in planning and developing water resources in the US, the majority of their focus has shifted to water quality and protection of water resources and restoration. Their role in other areas, such as water demand, supply and distribution, is currently limited. In contrast, state legislatures have dominant authority governing water issues related to construction, quantity, and distribution since the federal government has gradually abdicated that responsibility in the past half century. Most states have explicit water resource plans organized by water basins or resource types (e.g., surface water and groundwater), and many states have developed or are in the process of developing comprehensive state water plans, which address both water quality and water quantity issues within the state. Finally, local governments are mostly involved in drinking water supply, sewers and wastewater treatment.

2.1. Drinking Water Quality

Until the early 20th century, drinking water in the U.S. was managed by state and local governments. Federal regulation of drinking water did not begin until 1914, when the United States Public Health Service (PHS) standards were applied to drinking water provided by interstate carriers like ships, trains and buses. These standards were expanded and revised by the PHS three times from 1925-1962, and covered 28 substances in the 1962 version. At that time, the PHS standards were the most comprehensive drinking water standards and were followed by all 50 states as either regulations or guidelines for public drinking water quality (EPA, 1999). However, these standards were never mandated at the federal level (except for the said interstate carriers), and local laws of drinking water quality were often ignored or weakly enforced. Moreover, as a consequence of industrial and agricultural advances in the 20th century, many new man-made chemicals were released into the environment and entered drinking water supplies through various sources. The rising health concerns of drinking water in the US urged the federal government to conduct several studies on drinking water quality across the country. According to the survey findings of PHS (1970), more than half of the drinking water treatment facilities in the U.S. had major deficiencies in treatment processes. Another investigation by EPA (1972) found 36 chemicals in treated water from facilities along the lower Mississippi River. The increased prevalence of drinking water contamination and related health and environmental concerns eventually prompted Congress to take up and pass several legislative proposals, one of which was the Safe Drinking Water Act (SDWA) of 1974.

The objective of the SDWA is to ensure all public water supplies comply with the national standards. In 1974, the newly formed EPA was authorized by the SDWA to regulate public drinking water supplies by creating and revising national standards to control the levels of contaminants. However, new regulations on drinking water proceeded slowly: only 23 contaminants were regulated by the EPA during the decade after 1974. Congress was growing concerned with the slow progress under the EPA and unregulated water resources, and in 1986 the SDWA was significantly amended and reauthorized. In particular, the EPA was required to establish standards for 83 contaminants by 1989, and to add more contaminants periodically. The amendments also included monitoring of unregulated contaminants and suggesting 'best available technology' by the EPA.

The SDWA was subsequently amended several more times, and concurrently the role and responsibilities of the EPA on drinking water have been bolstered. In 1988, the Lead Contamination Control Act was passed as an amendment to the SDWA. In the early 1990s, issues such as lack of funding of local water treatment plants and missing public water quality information were brought to the public, and this raised the necessity of amending the SDWA again (Pontius, 2003).

The 1996 amendments protected drinking water quality 'from the source to the tap' (EPA, 2004) and enhanced the existing drinking water regulatory framework in two notable ways (EPA, 1999). First, scientific evidence on adverse health effects and data analysis on contaminant occurrence and risk reduction were emphasized as inputs in the creation of contaminant standards. Second, both financial and technical assistance on water system infrastructure was required to be made available to states to ensure compliance with the national drinking water standards. Later, other laws and acts have changed parts of the SDWA. In 2005, the Energy Policy Act amended the SDWA with the purpose of excluding underground injection in hydraulic fracturing operation. The 2011 amendment of the SDWA set a more stringent definition of 'lead-free' for pipes, fittings and other plumbing products. The latest amendments in 2015, the Drinking Water Protection Act, addressed algal toxins in drinking water and required the EPA to assess and manage the risk.

Today drinking water quality in the U.S. is mainly regulated by the SDWA, under which the responsibility of ensuring safe drinking water is undertaken by the EPA, together with the states, tribes and other stakeholders. The EPA sets the National Primary Drinking Water Regulations (NPDWRs) based on scientific evidence of health risks and available technology. The NPDWRs regulate mandatory maximum contaminant levels (MCLs) for specific contaminants and mandates treatment techniques to remove contaminants. For example, the MCL of Arsenic is 0.01mg/L, while lead and copper are regulated by a treatment technique. Currently 94 contaminants are regulated by NPDWRs, which apply to all public water systems in the U.S. Furthermore, the EPA provides guidance and assistance to states, local water suppliers and the public, and oversees the implementation of national standards. The direct oversight of implementation may be assigned to states, if the states adopt standards at least as strict as the EPA standards. This status is called 'primacy,' which gives states 'the authority to implement SDWA within their jurisdictions' (EPA, 2004). Except for Wyoming and Washington D.C., all other states have received primacy status and have state agencies responsible for implementation of drinking water standards such as the NPDWRs.

2.2. Water Pollution

During the 1940s and 1950s, protection and improvement of environmental quality, especially water resource issues, began to capture the public interest. However, the federal government lacked both statute and executive branch capability to evaluate water resources and develop water usage or pollution control plans. In 1948, as the first major law to address water pollution, the Water Pollution Control Act was passed with the purpose of developing comprehensive pollution control plans for interstate rivers. Nonetheless, the legislation did not enforce pollution abatement procedures unless the involved state approved the action. A national comprehensive pollution control plan and enforceable water pollution regulations were still missing up until the early 1970s. After two years of debates and hearings, the Water Pollution Control Act Amendments of 1972 were enacted. The objective was to 'restore and maintain the chemical, physical, and biological integrity of the Nation's waters' (33 U.S.C. 1251). The 1972 Amendments departed from the original act in many remarkable ways, such as creating technology-based effluent standards and increasing funding for waste treatment works. Moreover, it introduced a permit system, the National Pollutant Discharge Elimination System (NPDES), for point sources of pollution.[4]

In 1977, the Water Pollution Control Act was amended again and became commonly known as the Clean Water Act (CWA). In the amendments, the act was revised to correct several shortcomings, such as a lack of financial and technical assistance to municipalities and weak enforcement. Nevertheless, non-point sources (e.g. agricultural fields and urban stormwater) remained exempt from the CWA. With concerns about water pollution sources growing, in 1987, the Congress amended the CWA through the Water Quality Act. The amendments focused on controlling non-point sources: states were required to prepare non-point source management plans and the exemption of NPDES permits was removed for both industrial and municipal stormwater. In addition, the Clean Water State Revolving Fund was created to improve wastewater treatment facilities and assist with cleanup programs.

2.3. Water Quantity

States have jurisdiction over the legal quantitative allocation of water resources, and have a long history of conducting water planning. During the 1960s and 1970s, the federal government was the main driving force behind water resource planning. The WRPA of 1965 supported federal and state comprehensive water planning. However, the National Water Commission (NWC), which was responsible for national water planning, was terminated by the Reagan administration

[4] Point sources includes industrial facilities, municipal governments and a few agricultural facilities.

in 1981. Since then, there has been no successful attempt at national water planning legislation, and state water planning is not mandated or financially supported by the federal government. Due to the importance of planning water resources, to date, all states have water resource plans with respect to one or more aspects of water management, such as flooding, water quality, and water project funding. For example, North Carolina has statewide resource plans, but maintains separate management plans for water supply and water quality. Yet, many states have developed statewide comprehensive water plans.[5]

State comprehensive water planning is a holistic approach that addresses many aspects of water management, such as water quality, water quantity, and water resource protection. Although the structure and content may vary cross states, a comprehensive plan usually identifies pressures on water resources, articulates a statewide water vision, develops the framework of water management, and set forth state water policy and the role of related agencies. Therefore, comprehensive state water plans identify current and potential threats to water resources and are public signals of future policy directions.

3. Empirical Analysis

Previous studies of general environmental innovation include policy variables such as relative stringency and monitoring activities that measure the impact of environmental policy (Brunnermeier and Cohen, 2003; Johnstone et al., 2012). However, environmental laws and regulations usually are highly specific with respect to their object (e.g., drinking water, air, and wildlife), and general policy measurements do not precisely reflect the regulation status in a certain environmental area, such as drinking water. Therefore, in this paper we choose to focus separately on specific water issues like drinking water quality, water pollution, and water quantity, and we analyze the impact of direct regulatory changes in each of these domains on water-related technological innovation. The overarching mechanism we test for and measure in what follows is how the rate of water-related technological innovation in the US responds to specific changes in the regulatory framework governing each policy domain.

[5] To date, 28 states have published their state water plans. For an overview of water plan structures and water planning legislation cross states, please see Dyckman (2016).

3.1. Drinking Water Quality

For our purposes, we measure drinking water innovation in a state using the number of patents specifically pertaining to drinking water technology, such as arsenic removal and disinfection treatment. In the U.S., drinking water quality is mainly regulated at the federal level by the SDWA. Therefore, any changes to the SDWA and related drinking water regulations (i.e. NPDWRs) potentially increase the demand for newer drinking water technology, thus stimulating innovation. Three dummy variables capture changes to the SDWA and the NPDWRs. First, a dummy variable indicates whether there are amendments to the SDWA in a given year. Two other dummies measure national drinking water standards: one indicates whether there is any new contaminant added to the list NPDWRs, and the other one indicates whether there is revision or deletion to the NPDWRs. Additionally, the total number of regulated pollutants under the NPDWRs is also adopted as a substitute for the above two variables as a robustness check.

Besides drinking water statutes and regulations, we need to control for other factors that potentially influence innovation on drinking water technology in a state. Innovation in a specific domain is likely to correlate with the general innovative capacity of the local economy, which is captured by total patent counts, per capita GDP, the level of higher education research and development (R&D) expenditure, and R&D tax credit rates. First, total patent counts in a state represents the output of overall innovation activities and is used in the literature as a measure of generally innovation propensity (Johnstone et al., 2012; Conway et al., 2015). Additionally, the number of total patents in a state controls for any potential changes in the patent system in a given year. Second, the income level and R&D expenditure are shown to also have a positive influence on a region's overall innovation capacity (Ulku, 2007; Johnstone et al., 2012). Income level is proxied in our analysis by state-level per capita GDP. There is a recognized data paucity on aggregated state-level R&D expenditure. Thus, we use higher education R&D expenditure and R&D tax credit rates, which provide financial incentives to invest in R&D (Bloom et al., 2002; Wilson, 2009), in order to measure the input side of innovation. Since innovation may require many months of work to bring an idea to fruition, one-year lagged higher education R&D expenditure and R&D tax credit rates are used in the empirical analysis, however the regression results are robust to adopting different time lags.

Innovation aimed at improving drinking water quality in state i in year t, Y_{it}, is represented as a function of the past variation in policy stringency (i.e. changes to the SDWA and the NPDWRs in previous years) $S_{t-1}, ..., S_{t-n}$ and controlling for other determinants, as follows:

$$E\left[Y_{it}|S, X\right] = exp\left(\sum_{k=1}^{m} \boldsymbol{\beta_k S_{t-k}} + \boldsymbol{\mu X_{it,t-1}} + \eta_i\right), \tag{1}$$

where $X_{it,t-1}$ includes the following US state-level variables: total number of patents, per capita GDP, the higher education research and development (R&D) expenditures, and R&D tax credit rates. η_i is a state fixed effect that accounts for state specific factors such as water resource characteristics.

3.2. Water Pollution

Innovations aimed at reducing water pollution are measured as the number of patents pertaining to treatment of waste water, sewage, and sludge. Under the CWA - the primary law that regulates water pollution in the U.S. -, 126 toxic pollutants are analyzed and regulated by the EPA. In contrast to the NPDWRs of the SDWA, the pollutant list was revised only once since the 1977 amendments: three pollutants were removed from the list in 1981. In essence, the regulatory focus of water pollution can be characterized as more extensive than intensive, i.e. to expand regulations to exempted waste water sources rather than to enlarge the pollutants list. Indeed, previous amendments to the CWA have bolstered the authority of the EPA on those issues. As a result, the impact of any changes to the CWA is likely to have a long-term effect on technology. Therefore, we construct a cumulative variable of the amendments of the CWA: in a given year, it counts how many amendments have been enacted since the initial passing of the act in 1948.

Other factors may also determine innovation on water pollution in a state, such as the general propensity of innovation. Similarly with the analysis of drinking water innovations, the general propensity of innovation is controlled for by total patent counts, per capita GDP, the higher education research and development (R&D) expenditure, and R&D tax credit rate. Thus, innovation aimed at reducing water pollution, W_{it}, is represented as an exponential function of cumulative changes to the CWA, C_t, and controlling for other determinants $X_{it,t-1}$,

$$E\left[W_{it}|C, X\right] = exp\left(C_t + \boldsymbol{\mu X_{it,t-1}} + \eta_i\right), \tag{2}$$

where η_i stands for the state-level fixed effects that account for the water resource profiles in state i.

3.3. Water Quantity

In contrast to the mostly federally-regulated water quality issues discussed above, the management of water quantity is mainly carried out at the state level in the US. Therefore, state water regulations are likely to affect innovations aimed at reducing water shortages, especially given that states have power over water rights (i.e., the quantitative legal allocation of water use). However, policies managing water demand and supply vary substantially across states, and hence are not directly comparable. As an alternative, we use comprehensive state water plans as a proxy measure for the state water quantity policy. A comprehensive state water plan usually includes a description of available water resources, potential pressure on these resources and water management goals, and it establishes a policy framework for water management. Thus, state comprehensive water plans are public signals of how actively the state government is engaged in water management and policy making. Currently, 28 states have developed comprehensive state water plans. We create a dummy variable to indicate whether a state publishes or updates its comprehensive water plan in a given year.[6]

Innovations aimed at mitigating water scarcity are also likely to be affected by past water shortage conditions such as droughts. One explanation is that water scarcity episodes raises the demand for adaptive technologies, which in turn motivates the private sector to invent newer and more effective technologies for mitigating this shortage. This hypothesis is based on the *theory of protection motivation*, according to which past experiences affect individuals' future risk perception, which has positive effects on self-protective behavior (Rogers, 1983; Maddux and Rogers, 1983). Several studies have applied this theory to document a positive association between climate change impacts such as increasing water scarcity and natural disasters damage and self-protective decisions (Cameron and Shah, 2015; Mishra and Suar, 2007; Greening and Dollinger, 1992). The empirical analysis by Li (2016) show that drought damages stimu-

[6] North Carolina maintains separate comprehensive planning for water quantity and quality. Although the state does not have a comprehensive water plan, its water supply plan takes an integrated approach to address water quantity issues. Therefore, besides the 28 states, North Carolina is treated as a state with comprehensive plan (on water quantity). The empirical results are robust to different treatments.

late innovations aimed at reducing the impact of droughts. In summary, the demand for new technology increases due to protection motivation from water shortage, and the rising demand motivates more innovations targeted at reducing water shortage. Here we use economic losses from droughts to represent the past water shortage episodes since it represents the actual loss from water scarcity, as well as the potential market value of innovations aimed at mitigating water shortage.

Last, innovation activity aimed at mitigating water shortage in a state is again likely to be correlated with the overall innovation propensity in the state. Following the above Section 3.1 and 3.2: total patent counts, per capita GDP, higher education research and development (R&D) expenditures, and R&D tax credit rates are employed to control for general innovation capacity. Innovation aimed at reducing water shortage in state i in year t, V_{it}, are represented by a function of past state water plan dummies $P_{it-1}, ..., P_{it-n}$, past drought-related damages $D_{it-1}, ..., D_{it-n}$, other controls $X_{it,t-1}$ and state fixed effects η_i:

$$E\left[V_{it}|S, X\right] = exp\left(\sum_{k=1}^{m} \beta_k P_{it-k} + \sum_{k=1}^{m} \beta_k D_{t-k} + \boldsymbol{\mu X_{it,t-1}} + \eta_i\right). \tag{3}$$

4. Data

The dependent variables in our analysis are the total patents count of a certain type of water technology (e.g. conservation, purification, and wastewater treatment). These data were constructed through an extensive identification and matching process using the United States Patent and Trademark Office (USPTO) Patent Grant Bibliographic Text, which contains detailed patent information, including titles, abstracts, patent classes, and inventors' addresses of all granted patents since 1976. Note that another way to measure innovation is to count patent applications, both granted and declined. However, the patent application data are not quality-controlled and have crucial drawbacks, like the fact that publishing the application itself is at the applicant's latitude, hence published applications are only a subset of all actual patent applications.[7] Therefore, application data is not a precise measure of innovation activities at the state level. However, in order for us to capture the true timing effects of regulations, we use the

[7] For more details on this type of patent application data, see Li (2016).

date of application for all granted patents, rather than the date the patents were granted.

4.1. Drinking Water

Patents related to drinking water quality are identified through searching titles and abstracts using criteria based on classes and keywords. For example, the International Patent Classification (IPC) includes a designated class for water treatment: C02F 'Treatment Of Water, Waste Water, Sewage, Or Sludge,' which most patents on water technology belong to. Since the patent information in our database follows the United States Patent Classification (USPC), we refer to the USPC to IPC reverse concordance to search patents within the USPC classes corresponding to the IPC class C02F. [8] Note, however that restriction to certain patent classes may not be required if the search keywords are sufficiently specific. For example, one criterion includes searching for the phrase 'safe drinking water' in all patent classes. In our application, class C02F is combined with different such keyword searches in order to identify most related patents.

The keywords related to drinking water technology are compiled from EPA's publications on the SDWA (EPA, 1999, 2003, 2004), the NPDWRs, and drinking water technology indicated in state water plans. Depending on the types of keywords, the search criteria are divided into two categories: generic keywords and names of regulated contaminants. Search criteria with generic keywords (e.g., purification, filter, and disinfection) identify patents of drinking water treatment that is not specific to one contaminant.

On the other hand, patents on water technology aimed at eliminating specific contaminants are filtered through keywords derived from the names of the 97 contaminants listed in the NPDWRs. For instance, patents aimed at removing Cadmium from the drinking water are identified by searching for the keywords, 'Cadmium' and 'drinking' and 'water' in all classes. This search criterion applies to most of the contaminants regulated by the NPDWR. However, some substances listed as contaminants in the NPDWRs may also found in patents related to non-water technologies. In order to eliminate irrelevant patents and have accurate search results, special criteria are designed for groups of contaminants such as radionuclides and microorganisms. Take radionuclides as an example: four contaminants (Alpha/photon emitters, Beta photon emitters, Radium 226 and 228, and Uranium) are listed in the NPDWRs as radionuclides. The search

[8] The concordance is provided by the USPTO at `https://www.uspto.gov/web/patents/classification/international/ipc/ipc8/ipc_concordance/ipcsel.htm#a`.

for patents aimed at reducing radionuclides in water is restricted to class C02F, and the keywords include the common names of these radionuclides and process words such as 'treatment' and 'filter.' Additionally, all keywords (except names of contaminants) are stemmed to the root component of each word (e.g., search filt* for 'filter' or 'filtration') in order to capture all words that have the same meaning.

Table 2 lists search criteria for patents aimed at improving drinking water quality, based on generic words and contaminant names. The empirical results in Section 5 are provided for two search criteria: Criterion 1 focuses on specific contaminants, and Criterion 2 includes both generic and contaminant keywords.[9]

After obtaining patents pertaining to improving drinking water quality, the next step is to assign patents to states according to inventors' addresses. In the case of co-inventorship, each inventor's information is collected and used to calculate patent counts at the state level. First, one count is assigned to the state in the inventor's address. Nonetheless, if a patent has several co-inventors from the same state, repeated counts of inventors to a state can potentially cause a biased measurement of innovative activities. Hence, only one patent count is assigned to the state if a patent has more than one inventor from the same state.[10] For example, if a patent has five inventors, two have addresses in New York and three have addresses in California, one count is assigned to New York and one to California.

The total count of patents pertaining to drinking water technology is computed according to the above rules for each state, and then sorted by application year. Compared to patent grant years, application years are not affected by patent processing time, which is about 28-35 months on average (USPTO 2014). Another problem caused by patent processing time is that the number of granted patents drop dramatically in the final years of the sample period (many patents are still being processed and hence they are not published in the granted patent database). We take a conservative approach, which is also a prevalent method in the literature, and restrict

[9] Nine search criteria with different keywords and combinations were designed and tested in the empirical analysis. In general, the regression results are robust to different search criteria.

[10] Another method of counting patents at the state level is to assign $1/n$ to each inventor's residence state, as done in Hovhannisyan and Keller (2015). The empirical results from different counting methods are very close.

Table 1: Patent search criteria for drinking water technology

Category	Keywords	Classes
Generic keywords		
Safe drinking water	Safe drinking water, drinking water standards, drinking water regulations	all
Treatment	+“drinking water” + treat*	C02F
Purification	+“drinking water” + purif*	C02F
filter	+“drinking water” + (filt* or microfilt*)	C02F
Disinfect/Sterilize	+“drinking water” +(disinfect* or steriliz*)	C02F
contaminants	+“drinking water” +(contamin* decontamin*) -animal	C02F
toxic	+“drinking water” +toxic*	C02F
desalination	+“drinking water” +desalin*	C02F
portable	+“drinking water” +portable	C02F
Contaminants		
General Criteria (apply to all contaminants except for the ones below)	name of a contaminant + “drinking” + “water” e.g. “Cadmium” + “drinking” + “water”	all
Special Criteria		
Radionuclides	+water +(photon “alpha particle” “beta particle” “alpha emitter” “beta emitter” radium uranium radionuclid*) +(treat* purif* filter* disinfect* steriliz* contamin* toxic* desalin*)	C02F
Water additive as disinfectant	+drinking +water +(Chlorine “chlorine dioxide” chlorite chloramines dichloramines) +(remov* reduc* eliminat* deliminat* treat* purif* filter* decontamin* contamin* toxic*)	C02F
Microorganism	+water +(Microorganism Cryptosporidium crypto “fecal coliform” “E. coli” “escherichia coli” Giardia Legionella “Total Coliforms” Viruses enteric) +(remov* reduc* eliminat* deliminat* treat* purif* filter* disinfect* steriliz* decontamin* contamin* toxic*)	C02F
Microorganism: measurement	+drinking +water +(Turbidity “Heterotrophic plate count”) +(remov* reduc* eliminat* deliminat* treat* purif* filter* disinfect* steriliz* decontamin* contamin* toxic*)	C02F
Copper and lead	+drinking +water +copper +lead	C02F
Fluoride	+Fluoride +drinking +water +remov* -lead’	all
Nitrate and Nitrite	+(Nitrate nitrite) +drinking +water -sludge	all

the analysis to five years before the final year 2010.[11] Therefore, granted patent information is collected from USPTO for the years from 1977-2010, but the empirical analysis is limited to the period 1977-2005.

4.1.1. The SDWA and amendments

The SDWA was passed in 1974, and has been amended in 1986, 1988, 1996, 2005, 2011, and 2015. These amendments have significantly enhanced the authority of the SDWA in many aspects. For example, the 1988 amendment addressed lead and copper levels in drinking water, and the 1996 amendment required the EPA to strengthen the control of microbial contaminants and disinfectant byproducts. Thereby, as signals of more comprehensive and stringent regulations on drinking water, these amendments are likely to have stimulated the production of new drinking water technologies. A dummy variable is created to indicate whether there are amendments passed in a given year.

In addition to the amendments, the NPDWRs are national standards that are mandatory for all public drinking water systems. Any changes to the NPDWRs are likely to directly motivate innovations on drinking water technology. The NPDWRs are revised and expanded by the EPA from time to time, and the EPA maintains a timeline of any changes to the NPDWRs.[12] For each change, the record shows the year of Federal Register publication, name of the contaminants added, revised or deleted, and the total number of contaminants under regulation. Five variables are created from the information provided in the regulation timeline: whether there is a new regulation in a given year, number of contaminants newly regulated in a given year, whether there is revision or deletion in a given year, number of contaminants affected, and total number of contaminants under regulation. Table B.12 lists all changes to the SDWA and NPDWRs by year.

4.2. Water Pollution

Search criteria based on patent classes and keywords are designed to identify patents aiming to reduce pollutants in water effluents. We first use pollutant names and type of waste water

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[11] About 99% of granted patents were processed within five years in all patents pertaining to water quantity issues.

[12] The regulation timeline is published by the EPA at `https://www.epa.gov/dwregdev/regulation-timeline-contaminants-regulated-under-safe-drinking-water-act`

regulated by the CWA as keywords to identify patents targetting specific pollutants from water or other waste discharge. This criterion is supposed to be the most stringent and relevant to the regulations under CWA. In addition, in order to eliminate irrelevant patents or include as many directly relevant patents as possible, special criteria are designed for some groups of contaminants such as the insecticide dichlorodiphenyltrichloroethane (DDT). Next, we also design a more general criterion including many generic keywords, e.g., waste water and sewage, to search for innovations on general waste water treatment technology. In addition, a third criterion is devised as a combination of criteria 1 and 2.

After obtaining patents aimed at reducing water pollution, the next step is to assign patents to states according to inventors' addresses. The rule of assigning patents is similar to the one applied to patents pertaining to drinking water quality in Section 4.1: one count is assigned to the state that is in the inventor's address, and no repeated counts to the same states if there are multiple inventors in a patent. Different counting rules are employed (e.g., assign $1/n$ to each inventor's residence state), and the results are quite close. The total count of patents pertaining to water pollution technology is computed according to the above rules for each state, and then sorted by application years. The empirical analysis is limited to the years from 1977-2005 (five years before the ending year 2010 in our dataset) due to the processing time of the USPTO.

4.2.1. The CWA and amendments

The first major law to address water pollution, the Water Pollution Control Act was passed in 1948. However, the act did not enforce pollution abatement procedures across states. In 1972, the act was bolstered through major changes, namely the Water Pollution Control Act Amendments of 1972. In 1977, the Water Pollution Control Act was amended again and now is commonly known as the CWA. Since 1948, the CWA has been amended 23 times. A cumulative variable counts the total number of the changes (including the act and its amendments) that have been enacted since the initial pass of the act in 1948.

4.3. Water Quantity

Here we focus on water technologies related to reducing water demand or expanding water supply. Most of the state comprehensive water plans address the importance of water technology: "DWR provides technical and financial assistance to [that] ... encourages water conservation,

Table 2: Patent search criteria for waste water technology

Category	Keywords	Classes
Criterion 1	name of a pollutant +(“waste water” “waste waters” “waste streams” wastewater* sewage stormwater* effluent)	C02F
Special Criteria		
Methylene chloride	“Methylene chloride” +(“waste water” “waste waters” “waste streams” wastewater* sewage stormwater*)	C02F
Methyl chloride	“Methyl chloride” +(“waste water” “waste waters” “waste streams” wastewater* sewage stormwater*)	C02F
4,4-DDT, 4,4-DDE, 4,4-DDD	+(“4,4-DDT” “4,4-DDE” “4,4-DDD” Dichlorodiphenyltrichloroethane dichlorodiphenyldichloroethylene dichlorodiphenyldichloroethane) +(contamin* “waste water” “waste waters” “waste streams” wastewater* sewage stormwater* effluent)	C02F
2,3,7,8-TCDD	+(“2,3,7,8-TCDD”) +(“sludge” “waste water” “waste waters” “waste streams” wastewater* sewage stormwater* effluent)	C02F
Criterion 2	Criterion 1+ search criteria including generic keywords +(“sludge” “waste water” “waste waters” “waste streams” wastewater* sewage stormwater*) +(remov* reduc* eliminat* deliminat* treat* purif* filter* disinfect* steriliz* decontamin* contamin* toxic* desalin*)	C02F

explores conjunctive use of groundwater and surface water, provides planning and advice on water recycling and desalination programs” (Summary of State Water Planning, California).

From state water plans, keywords of technology related to water quantity (e.g. reducing water demand or expanding sources of water supply) are collected to search for patents addressing water quantity issues. For example, the following terms (and their variations) are used as keywords to search for those patents:‘water conservation,’ ‘saving water,’ ‘water desalination,’ and ‘water recycling.’ A complete list of the search criteria is given in Table 3. The identified patents are then assigned to states according to the inventors’ information, following the co-authorship attribution method described above.

The total count of patents pertaining to water quantity issues is thus computed and sorted by states and application years. Due to application processing delays at the USPTO, the analysis is again limited to five years before the ending year 2010 (the same procedure as described in Section 4.1). Thus, granted patent information is collected from USPTO for the years from 1977-2010, but the empirical analysis is confined to the period 1977-2005.

Table 3: Patent search criteria for technology on water supply and demand

Category	Keywords	Classes
Criterion 1		
Conservation	"water conservation", "water conserving", "conserve water", "conserves water", "conserving water", "conservation of water"	all
Saving water	"saving water" "save water" "saves water" "water saving"	all
Criterion 2		
Conservation	+water +conserv* -"energy conservation" -"conserving energy" -"conservation of energy"	all
Saving water	"saving water" "save water" "saves water" "water saving"	all
Desalination	+water +desalin*	all
Recycling	"water recycling" "water recycle" "recycled water"	all

4.3.1. State Water Plan

To date, 28 states have published state comprehensive water plans.Some states, such as California, Kansas and Missouri, have a more than 50-year comprehensive water planning history, while the comprehensive water planning efforts in other states, such as Colorado and Virginia, are more recent. A state water plan dummy indicates whether a state has a new version or a fully updated water plan in a given year. Nevertheless, when an old plan is updated, most states develop and publish a new version of the comprehensive water plan, whereas a few states, e.g., Montana, New Jersey and South Dakota, only update part of the old plan (e.g. for one section or for one region). Therefore, another dummy variable is created to capture a partly updated state water plan.

4.3.2. Drought Damage Data

Drought damage data is retrieved from the Spatial Hazard Event and Losses Database for the US (SHELDUS^{TM}) collected by the Hazards & Vulnerability Research Institute at the University of South Carolina. SHELDUS^{TM} contains economic losses (property damages and crop damages), fatalities and injuries for 18 types of natural hazard events.[13] Drought damage data is employed as a proxy for water scarcity, which is hypothesized to have a positive impact on innovations aimed at alleviating water shortage. In particular, we use economic losses from drought events, since

[13] The 18 types are drought, earthquake, flooding, fog, hail, heat, hurricane/tropical storm, landslide, lightning, severe storm/thunder storm, tornado, tsunami/seiche, volcano, wildfire, wind, winter weather, avalanche, and coastal.

economic losses are more representative than the much rarer fatalities or injuries in measuring drought-inflicted damages.

4.4. Other Controls

Innovation of water technology is likely to correlate with the state's overall innovation activities. Three variables are used to measure the overall innovation activities in a state: total patent counts, R&D expenditures for Science and Engineering in higher education, and R&D tax credits as financial incentives to research investment. Total patents in a state are extracted from the same source (USPTO Patent Grant Bibliographic Text) and are assigned to each state using the same algorithm described above for water-related technologies. Higher education R&D expenditures for Science and Engineering from all sources (e.g. federal, state government, and private sources) are publicly available from the Higher Education Research and Development Survey (HERD) conducted by the National Science Foundation (NSF). Wilson (2009) calculates the effective state R&D tax credit rate for each state since 1982, when state R&D tax credits were implemented for the first time in history. Another control variable is state-level per capita GDP, which comes from the Bureau of Economic Analysis (BEA) for 1977-2013. The state-level GDP accounting method was changed in 1997, and there is a notable upward shift of GDP after 1997. To account for this, a dummy variable indicating years post 1997 is added together with per capita GDP in regression analysis.

Table 4 reports the summary statistics of main variables in the empirical analysis. After merging the various data sets, our sample has 1,479 observations for 50 states and Washington D.C.

5. Empirical Results and Discussion

Since the dependent variable is the count of granted patents on water technology (i.e., drinking water quality, water pollution treatment, and water supply and demand), count data models are applied to estimate Eq. (1), (2) and (3).

The Poisson quasi-maximum likelihood estimator (Poisson QMLE) has been widely used in count data literature (Blume-Kohout, 2012; Cameron and Trivedi, 2013; Hovhannisyan and Keller, 2015), given its robustness to misspecification. First, the Poisson QMLE is robust to distributional misspecification, i.e. the dependent variable conditional on the explanatory variables

Table 4: Descriptive statistics

Variables	Mean	Max	Min	Variance
Drinking Water				
Patents (Criterion 1)	0.1244	0	4	0.1672
Patents (Criterion 2)	0.4226	0	8	0.8342
New_reg_SDWA	0.2414	0	1	0.1832
Rev_SDWA	0.2759	0	1	0.1999
Amend_SDWA	0.1379	0	1	0.1190
Water Pollution				
Patents (Criterion 1)	0.1690	0	5	0.2691
Patents (Criterion 2)	1.1427	0	17	3.5216
CumAmend_CWA	19.5862	12	22	9.2833
Water Quantity				
Patents (Criterion 1)	0.1941	0	12	0.4745
Patents (Criterion 2)	0.5321	0	17	1.5117
Update_SWP	0.0291	0	1	0.0282
Drought_dmg	1.1321	0	8.9593	3.0434
Other Controls				
PercapitaGDP	27.2351	9.7039	163.9650	263.0889
Total_patent	1.5205	0.0150	30.9330	7.4911
R&D_taxrate	-0.0117	-37.9457	0.2000	0.9755
Edu_R&Dexp	0.5148	0.0155	6.8104	0.5054

Number of observations for all variables is 1,479 for 50 states and Washington D.C. in the U.S. Total patents are in thousand counts. Drought damage and higher edu R&D expenditure is in billion dollars, and per capita real GDP is in thousand dollars. All dollar terms are adjusted to 2013.

does not have a Poisson distribution, given the conditional mean is correctly specified. Moreover, the pooled Poisson QMLE does not require strict exogeneity of regressors ($E[u_t|D_s] = 0$, for $\forall s$) for consistency (Cameron and Trivedi, 2013; Wooldridge, 2010).

However, the weakness of pooled Poisson QMLE is that the estimates are biased in the presence of group heterogeneity. In the case of water innovations, environmental and governance profiles, which are likely to impact water innovation, vary significantly across states. First, water resource profiles (e.g., abundance and composition) are heterogenous across states in the U.S. For example, Alaska has ample water resources, which are largely in the form of ice, while California has chronic drought conditions. Hence, it is necessary to control for states' intrinsic water profiles. In addition, water governance at the state level, such as water management frameworks, legislation, and agencies, is highly diverse. Therefore, it is crucial to control for state-level variation of environmental and governance factors. We use the Poisson fixed effect (Poisson FE) with multiplicative fixed effects and robust standard errors to address the heterogeneity across states. The Poisson FE controls for time-invariant characteristics, and it provides consistent estimates even equidispersion is not satisfied. Nevertheless, in the case of overdispersion, standard errors tend to be conservative and cause inflation of the t-stat in Poisson estimates. Therefore, conditional likelihood method for negative binomial fixed effect (NB FE) proposed by Hausman et al. (1984) is applied for comparison.[14] Note that both methods provide similar results.

In addition, given the large number of zero counts in the dependent variables (e.g., 65% of zero counts in patents of drinking water technology), zero-inflated poisson (ZIP) and zero-inflated negative binomial (ZINB) models are employed to test the robustness,[15] and in general, the results are closed to the ones by Poisson FE and NB FE. Nonetheless, zero-inflated models are less preferred for three reasons. First, although the dependent variables have excessive zero counts, overdispersion is not likely to be a concern. From Table 4, the unconditional variances are about one to three times of the means. The conditional variances usually are substantially reduced since explanatory variables and group variation are controlled (Cameron and Trivedi, 2013). Moreover, the Vuong tests do not indicate that zero-inflated models fit better than the underlying Poisson or NB models. Last, the NB FE model performs much better than zero-inflated models based on Akaike information criterion (AIC) and Bayesian information criterion (BIC) statistics, which is consistent with the findings by Allison (2012). Therefore, results from Poisson FE and NB FE models are reported in the following sections.

5.1. Drinking Water Quality

Table 5 and 6 report the results on patents pertaining to drinking water technology for two different patent search criteria. The individual coefficient of the lags of regulatory variables gives the short term (yearly) effect of any changes of the act and its regulations, while the cumulative effect estimates the long-term effect. The number of lags (5-year lags) is selected based on the Akaike information criterion (AIC) and the Bayesian information criterion (BIC).

The long-term effects (cumulative effects) of new regulations and amendments to the act are

[14] Note that Allison and Waterman (2002) explains that the NB FE method proposed by Hausman et al. (1984) is not qualified as a true FE model due to the incidental parameters problem. However, the impact of this problem in practice is still unclear.

[15] Please see Appendix A for density of the dependent variables and regression results.

Table 5: Patent counts (Criterion 1) in response to drinking water regulations

	SDWA dummies		Total number of contaminants	
	(1) Poisson FE	(2) NB FE	(3) Poisson FE	(4) NB FE
sdwa_reg_n			0.0216***	0.0207***
			(0.00437)	(0.00458)
L.sdwa_newreg	0.535	0.463		
	(0.382)	(0.317)		
L2.sdwa_newreg	0.291	0.277		
	(0.296)	(0.303)		
L3.sdwa_newreg	0.535	0.470		
	(0.333)	(0.359)		
L4.sdwa_newreg	0.582	0.627		
	(0.336)	(0.329)		
L5.sdwa_newreg	0.373	0.376		
	(0.445)	(0.442)		
Cumulative effect	2.315*	2.212*		
	(1.109)	(1.067)		
L.sdwa_revised	-0.441	-0.398		
	(0.333)	(0.317)		
L2.sdwa_revised	0.117	0.0730		
	(0.300)	(0.276)		
L3.sdwa_revised	0.198	0.154		
	(0.282)	(0.310)		
L4.sdwa_revised	0.344	0.289		
	(0.344)	(0.291)		
L5.sdwa_revised	0.243	0.185		
	(0.366)	(0.419)		
Cumulative effect	0.461	0.302		
	(0.839)	(0.798)		
L.sdwa_amend	0.280	0.400	0.154	0.254
	(0.328)	(0.344)	(0.317)	(0.302)
L2.sdwa_amend	0.627	0.603	0.492	0.499
	(0.428)	(0.378)	(0.284)	(0.256)
L3.sdwa_amend	0.399	0.322	0.180	0.138
	(0.339)	(0.367)	(0.204)	(0.243)
L4.sdwa_amend	0.339	0.437	0.151	0.218
	(0.270)	(0.283)	(0.261)	(0.219)
L5.sdwa_amend	0.211	0.294	0.181	0.237
	(0.291)	(0.316)	(0.237)	(0.222)
Cumulative effect	1.857*	2.055*	1.158	1.345*
	(0.753)	(0.929)	(0.635)	(0.644)
pcrealGDP	0.0588	0.0770*	0.0643	0.0772*
	(0.0355)	(0.0336)	(0.0364)	(0.0307)
patcount3	0.129*	0.124*	0.0970*	0.0979*
	(0.0627)	(0.0499)	(0.0487)	(0.0439)
L.rd_cr_st	0.271	0.115	0.129	0.0945
	(3.439)	(0.684)	(0.397)	(0.566)
L.t_edurdexpdf	-0.880	-0.816*	-0.691	-0.649*
	(0.452)	(0.360)	(0.393)	(0.329)
N	1479	1479	1479	1479

Pseudo R^2 is 0.2416 with Poisson QMLE controlling for state fixed effects in (1). Standard errors are clustered at the state level. Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6: Patent counts (Criterion 2) in response to drinking water regulations

	SDWA dummies		Total number of contaminants	
	(1) Poisson FE	(2) NB FE	(3) Poisson FE	(4) NB FE
sdwa_reg_n			0.0171***	0.0161***
			(0.00301)	(0.00250)
L.sdwa_newreg	0.647***	0.629***		
	(0.172)	(0.170)		
L2.sdwa_newreg	0.366*	0.360*		
	(0.143)	(0.167)		
L3.sdwa_newreg	0.294	0.342		
	(0.209)	(0.195)		
L4.sdwa_newreg	0.307	0.376*		
	(0.158)	(0.179)		
L5.sdwa_newreg	0.0112	0.000834		
	(0.252)	(0.244)		
Cumulative effect	1.625**	1.709**		
	(0.604)	(0.577)		
L.sdwa_revised	-0.557**	-0.607***		
	(0.180)	(0.176)		
L2.sdwa_revised	0.136	0.0953		
	(0.143)	(0.149)		
L3.sdwa_revised	0.318	0.292		
	(0.178)	(0.172)		
L4.sdwa_revised	0.379**	0.315*		
	(0.135)	(0.160)		
L5.sdwa_revised	0.316	0.307		
	(0.226)	(0.232)		
Cumulative effect	0.592	0.401		
	(0.497)	(0.452)		
L.sdwa_amend	0.379	0.407*	0.215	0.221
	(0.221)	(0.187)	(0.203)	(0.160)
L2.sdwa_amend	0.395	0.405*	0.383*	0.377**
	(0.247)	(0.201)	(0.174)	(0.141)
L3.sdwa_amend	0.0493	0.0357	0.0909	0.0856
	(0.216)	(0.200)	(0.0965)	(0.135)
L4.sdwa_amend	0.329**	0.358*	0.214	0.215
	(0.120)	(0.160)	(0.112)	(0.125)
L5.sdwa_amend	0.172	0.183	0.203	0.214
	(0.180)	(0.177)	(0.123)	(0.126)
Cumulative effect	1.325*	1.389**	1.105**	1.113**
	(0.565)	(0.507)	(0.406)	(0.352)
pcrealGDP	0.00716	0.0127	0.0136	0.0168
	(0.0301)	(0.0188)	(0.0316)	(0.0174)
patcount3	0.0689*	0.0665*	0.0381	0.0397
	(0.0312)	(0.0277)	(0.0230)	(0.0241)
L.rd_cr_st	0.121	0.117	0.0984	0.105
	(0.128)	(0.372)	(0.0953)	(0.379)
L.t_edurdexpdf	-0.433	-0.347	-0.244	-0.177
	(0.259)	(0.189)	(0.228)	(0.167)
N	1479	1479	1479	1479

Pseudo R^2 is 0.3132 with Poisson QMLE controlling for state fixed effects in (1). Standard errors are clustered at the state level. Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

positive and significant across different model specification and patent search criteria. Nonetheless, the short-term effect (e.g., individual coefficient of lags of sdwa_newreg) is less consistent across time and different model specifications. A possible reason is that the innovation process is unpredictable, and patents as an outcome of this process may not be regularly generated every year. Moreover, including multiple lags of a variable results in substantial collinearity. Therefore, the individual coefficient of the regulatory variables (i.e. *sdwa_newreg, sdwa_revised*, and *sdwa_amend*) may not be properly estimated. However, according to Wooldridge (2009), the linear combination of the entire bundle of collinear variables is well-estimated. Hence, the individual short-term effect is not all positive and significant over time, whereas the long-term effect provides accurate estimation of the overall impact.

In general, if there are new contaminants added to the NPDWRs, patents on drinking water technology are substantially stimulated in the next five years (columns (1) and (2) in Table 5 and 6). Since *sdwa_newreg* is a dichotomous variable that measures whether there are any new contaminants added to the NPDWR in a given year, the marginal effect from its coefficient does not provide information for the impact of *one* newly regulated contaminant. Nonetheless, this impact can be calculated from regressions on total number of regulated contaminants (columns (3) and (4) in Table 5 and 6). The coefficients of total regulated contaminants are all positive and significant with different estimation methods and search criteria, which indicates that patents of drinking water technology are positively affected by the NPDWRs. On average, a newly regulated contaminant in the NPDWRs is predicted to stimulate the creation of related patents on drinking water technology by 1-2% in the given year.[16]

The SDWA amendments also lead to more patents pertaining to drinking water technology. For patents of technology aimed at removing specific contaminants (Criterion 1), amendments in a given year are predicted to result in 540% increase in the following five years (based on the coefficient 1.857 in Table 5). For patents pertaining to more general drinking water technology (Criteria 2), amendments in a given year would lead to 276% more of such patents in the following five years (based on the coefficient 1.325 in Table 6). It is expected that the impact of amendments is more substantial than the impact of a regulated contaminant. A likely reason is that drinking

[16] The effect is based on the coefficents 0.0216 in Table 5 and 0.0161 in 6. All marginal effects are calculated using the transformation $e^{\beta} - 1$.

water quality is protected nationally by the federal law, and any change to the legislation is a clear signal of substantial improvements on drinking water governance across the country. Last, there is no evidence that revisions of the NPDWRs affect drinking water patents.

Note that, in general, the results are similar for patent search criteria 1 and 2. Nonetheless, the impact of the SDWA amendments on patents is not significant in all cases for patents searched by Criterion 1. Patents searched by the names of contaminants are innovations aimed at specific contaminants regulated by the NPDWRs. Thus, it is expected that this type of innovation responds significantly to any new regulations in the NPDWRs, but not strongly to the SDWA and its amendments.

5.2. Waste Water and Water Quality

Table 7: Patent counts in response to the CWA amendments

	Criterion 1		Criterion 2	
	(1) Poisson FE	(2) NB FE	(3) Poisson FE	(4) NB FE
cwa_amendcum	0.277**	0.278***	0.101**	0.100**
	(0.0882)	(0.0837)	(0.0356)	(0.0319)
pcrealGDP	0.0116	0.0109	0.00132	0.00233
	(0.0342)	(0.0337)	(0.0128)	(0.0120)
patcount3	0.00740	-0.000634	0.0461*	0.0461*
	(0.0298)	(0.0417)	(0.0199)	(0.0185)
L.rd_cr_st	0.111	0.107	0.0766	0.0801
	(0.0902)	(0.608)	(0.0403)	(0.153)
L.t_edurdexpdf	-0.161	-0.0493	-0.395**	-0.357**
	(0.229)	(0.304)	(0.142)	(0.133)
post_97	0.0129	0.0418	-0.133	-0.147
	(0.637)	(0.692)	(0.299)	(0.257)
year	-0.0799	-0.0847	0.00250	0.000219
	(0.0465)	(0.0488)	(0.0190)	(0.0180)
N	1479	1479	1479	1479

With Poisson QMLE controlling for state fixed effects, Pseudo R^2 is 0.3193 and 0.3911 for patents searched by Criterion 1 and 2, respectively. Standard errors are clustered at the state level. Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 7 reports the results of Eq. (2) for two patent search criteria on waste water treatment technology. Patents pertaining to wastewater treatment respond positively to changes of the CWA. On average, any amendments to the CWA in a given year are predicted to stimulate a 10% yearly increase in patents aimed at reducing water pollution (columns (3) and (4) in Table 7). Moreover, pollutant-specific patents respond more significantly: on average, amendments to the CWA would result in 32% more of such patents, as given in columns (1) and (2) in Table 7 (coefficient 0.277). In summary, legislations on water pollution lead to more innovations pertaining to pollution treatment technology.

5.3. Water Quantity

Table 8 reports the results of Eq. (3) for patents pertaining to water supply and demand. In general, the long-term effect of state water plans is positive and significant.[17]. Criterion 1 is based on water conservation technology, while Criterion 2 covers broader categories of water technology including water conservation, desalination and recycling. Compared to the results of Criterion 1, the impact of state water planning is more significant for Criterion 2, which covers broader water supply and demand technology. A likely explanation is that state comprehensive water plans address broader water pressures and tend to lead the overall development of water supply and demand technology. Take the coefficient in column (4) as an example (1.328), a new state water plan would spur 277% more patents on water supply and demand technology in the given state in the following five years.

In addition to water planning, national drought damages also positively affect patents pertaining to water supply and demand. According to the cumulative effects in Table 8, $1 billion drought damages are predicted to stimulate 25% to 46% more patents on water supply and demand technology in the next five years. Water scarcity episodes, measured by drought damage, are likely to motivate private sectors to invest and innovate technologies that reduce water demand and expand water supply. The results also confirm and extend the findings by Li (2016): drought damages spur related adaptation technologies.

6. Conclusion

Growing population and economic activities are placing increasing pressure on the water resources in the U.S. Water planning, water legislation and specific regulations are adopted to address water quality and quantity issues. These water governance practices have resulted in substantial improvements of environmental quality and public health. Additionally, more stringent water policy also induces the creation of new technology aimed at reducing water

[17] The exception is the cumulative effect of water plans given in column (2). Nonetheless, it is marginally significant at 10%)

Table 8: Patent counts in response to water planning and water scarcity

	Criterion 1		Criterion 2	
	(1) Poisson FE	(2) NB FE	(3) Poisson FE	(4) NB FE
L.waterplannew	0.139	0.0759	0.101	0.0952
	(0.343)	(0.319)	(0.139)	(0.174)
L2.waterplannew	0.123	0.0811	0.174	0.130
	(0.240)	(0.346)	(0.174)	(0.200)
L3.waterplannew	0.706*	0.578	0.441*	0.358
	(0.308)	(0.311)	(0.210)	(0.207)
L4.waterplannew	0.333*	0.271	0.346	0.246
	(0.166)	(0.317)	(0.222)	(0.193)
L5.waterplannew	0.393	0.394	0.451*	0.498*
	(0.227)	(0.305)	(0.190)	(0.212)
Cumulative effect	1.694*	1.493	1.512**	1.328**
	(0.768)	(0.987)	(0.554)	(0.585)
L.tdmg_c	0.0734	0.0608	0.0452	0.0395
	(0.0426)	(0.0353)	(0.0277)	(0.0219)
L2.tdmg_c	0.0993*	0.0800*	0.0721**	0.0668***
	(0.0394)	(0.0361)	(0.0221)	(0.0192)
L3.tdmg_c	0.105***	0.0981**	0.0671***	0.0623**
	(0.0286)	(0.0308)	(0.0188)	(0.0199)
L4.tdmg_c	0.0520	0.0497	0.0197	0.0155
	(0.0270)	(0.0350)	(0.0193)	(0.0208)
L5.tdmg_c	0.0486	0.0536	0.0353	0.0365
	(0.0344)	(0.0335)	(0.0220)	(0.0223)
Cumulative effect	0.379***	0.342***	0.239***	0.220***
	(0.113)	(0.094)	(0.0706)	(0.0552)
pcrealGDP	-0.00754	-0.00784	0.0240	0.0250***
	(0.0346)	(0.0306)	(0.0130)	(0.00701)
patcount3	-0.0146	0.00380	-0.00417	0.00647
	(0.0443)	(0.0407)	(0.0288)	(0.0254)
L.rd_cr_st	3.480	3.148	3.346	3.038
	(2.235)	(2.400)	(2.135)	(1.748)
L.t_edurdexpdf	-0.0918	-0.158	-0.261	-0.321*
	(0.312)	(0.288)	(0.200)	(0.157)
post_97	-0.369	-0.319	-0.615	-0.600**
	(0.801)	(0.735)	(0.328)	(0.214)
N	1479	1479	1479	1479

With Poisson QMLE controlling for state fixed effects, Pseudo R^2 is 0.3750 and 0.3540 for patents searched by Criterion 1 and 2, respectively. Standard errors are clustered at the state level. Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

pollution or water shortage in a more efficient way. In this paper, we focus on water governance of three water issues: drinking water quality, water pollution, and water quantity. Starting from a comprehensive review of water governance history in the U.S., we first identify the major legislation and governance bodies pertaining to different water issues. Using data on water legislation and comprehensive water plans, the state-level empirical analysis reveals that water regulations and water plans have a stimulating effect on water-related innovation. For technology aimed at improving drinking water quality, innovations respond positively to new regulations under NPDWR and also to SDWA amendments. One newly regulated contaminant would lead to a 2% increase in relevant patents every year. Regarding water pollution issues, the CWA amendments lead to more innovations on waste water treatment technology. Our result shows that the amendments to the CWA would spur a 32% increase in patents targeting regulated pollutants. Last, innovation on water supply or demand technology is stimulated by state water planning and water scarcity measured by drought damage. General water supply or demand technology would increase by 277% in five years as a result of current state water planning and by 25% as a result of $1 billion drought damages.

Our research contributes to the large body of literature on induced innovation by providing first empirical evidence on innovation induced by water regulations. Moreover, our results have immediate policy implications on water management and policy design. Water regulations not only reduce negative environmental externalities but also induce water-related innovation that generates positive innovation-related externalities. Therefore, there is great potential for water regulations to be welfare-enhancing. Our empirical evidence contributes to quantifying the impact of water regulation on water-related technological innovation and hence to cost-benefit analysis of policy adoption.

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APPENDIX:

Appendix A. Overdispersion and Zero Counts

The discrete densities of dependent variables in three water issues are plotted in Figure A.1, A.2, and A.3. In general, the proportions of zero counts are 40-65% in the dependent variables of the three water issues. Given the large number of zeros, zero-inflated poisson (ZIP) and zero-inflated negative binomial (ZINB) models are employed to address excessive zero counts and potential overdispersion. The regression results for three water issues (i.e. drinking water quality, water pollution, and water quantity) are reported in column (3) and (4) of Table A.9, A.10, and A.11.

In addition, the Poisson quasi-maximum likelihood estimator (Poisson QMLE) has been widely used in count data literature (Blume-Kohout, 2012; Cameron and Trivedi, 2013; Hovhannisyan and Keller, 2015) due to its robustness to distributional misspecification (e.g., the dependent variable conditional on the explanatory variables does not have a Poisson distribution). As a comparison, the NB model is employed to address the potential overdispersion caused by excessive zeros. The results are presented in column (1) and (2) of Table A.9, A.10, and A.11 for three water issues.

In general, the results confirm the findings using Poisson FE and NB FE models. The Poisson FE and NB FE models fit better than other Poisson MLE, NB, ZIP, and ZINB in all three cases, according to the AIC and BIC. For example, the AIC and BIC scores are 819.56 and 920.69 for Poisson FE model applied to Eq. (1), which are smaller than all values of AIC and BIC reported in Table A.9. A likely reason is that the excessive zeros and potential overdispersion largely attribute to the cross-state variation. In terms of water technology, there is substantial state-level variation of innovations. For instance, Arkansas has zero patent count (search by Criterion 1 of drinking water technology) over time, while California has few zero count cross years. Therefore, fixed effect models that capture the cross-state variation provide better fit. Moreover, overdispersion is not likely to be a concern after controlling the state fixed effect. Although from Table 4, the unconditional variances is larger than the means, the conditional variance is very likely to be substantially reduced since cross-state variation are controlled.[18]

Appendix A.1. Drinking Water Quality

[18] According to Cameron and Trivedi (2013), the conditional mean remains similar to the unconditional mean. However, the conditional variance is usually smaller than the unconditional mean, especially when cross-group or cross-time variation are controlled.

Table A.9: Patent counts (Criterion 1) in response to drinking water regulations

	(1) Poisson QMLE	(2) NB	(3) ZIP	(4) ZINB
pat4_3				
L1sdwa_newreg	0.535	0.545	0.479	0.487
	(0.386)	(0.375)	(0.309)	(0.311)
L2sdwa_newreg	0.291	0.276	0.298	0.295
	(0.299)	(0.306)	(0.318)	(0.315)
L3sdwa_newreg	0.535	0.494	0.539	0.526
	(0.336)	(0.343)	(0.345)	(0.348)
L4sdwa_newreg	0.582	0.556	0.549	0.541
	(0.339)	(0.353)	(0.344)	(0.347)
L5sdwa_newreg	0.373	0.351	0.359	0.353
	(0.450)	(0.457)	(0.411)	(0.413)
Cumulative effect	2.315*	2.222	2.223*	2.203*
	(1.203)	(1.226)	(1.078)	(1.084)
L1sdwa_revised	-0.441	-0.430	-0.415	-0.416
	(0.336)	(0.330)	(0.333)	(0.330)
L2sdwa_revised	0.117	0.145	0.0896	0.0987
	(0.303)	(0.322)	(0.289)	(0.297)
L3sdwa_revised	0.198	0.218	0.0783	0.0863
	(0.285)	(0.292)	(0.293)	(0.294)
L4sdwa_revised	0.344	0.385	0.208	0.228
	(0.338)	(0.356)	(0.341)	(0.358)
L5sdwa_revised	0.243	0.267	0.210	0.218
	(0.370)	(0.388)	(0.361)	(0.366)
Cumulative effect	0.461	0.584	0.171	0.215
	(0.847)	(0.910)	(0.831)	(0.843)
L1sdwa_amend	0.280	0.322	0.273	0.287
	(0.331)	(0.317)	(0.346)	(0.337)
L2sdwa_amend	0.627	0.596	0.622	0.611
	(0.432)	(0.429)	(0.370)	(0.373)
L3sdwa_amend	0.399	0.379	0.347	0.345
	(0.342)	(0.336)	(0.377)	(0.370)
L4sdwa_amend	0.339	0.372	0.285	0.298
	(0.272)	(0.275)	(0.255)	(0.259)
L5sdwa_amend	0.211	0.231	0.203	0.209
	(0.294)	(0.303)	(0.274)	(0.273)
Cumulative effect	1.857*	1.900**	1.731*	1.749*
	(0.753)	(0.929)	(0.903)	(0.920)
N	1479	1479	1479	1479
AIC	971.3	973.1	926.0	975.7
BIC	1156.8	1169.2	1016.0	1198.3
Log lik.	-450.7	-449.6	-446.0	-445.9

All regressions control for total number of patents, per capita GDP, higher education R&D expenditures, R&D tax credit rates, and state fixed effects. State-level total number of patents is employed as the predictor of excessive zeros in ZIP and ZINB models. The cumulative effect of *sdwa_newreg* in (2) is significant at 10% level. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

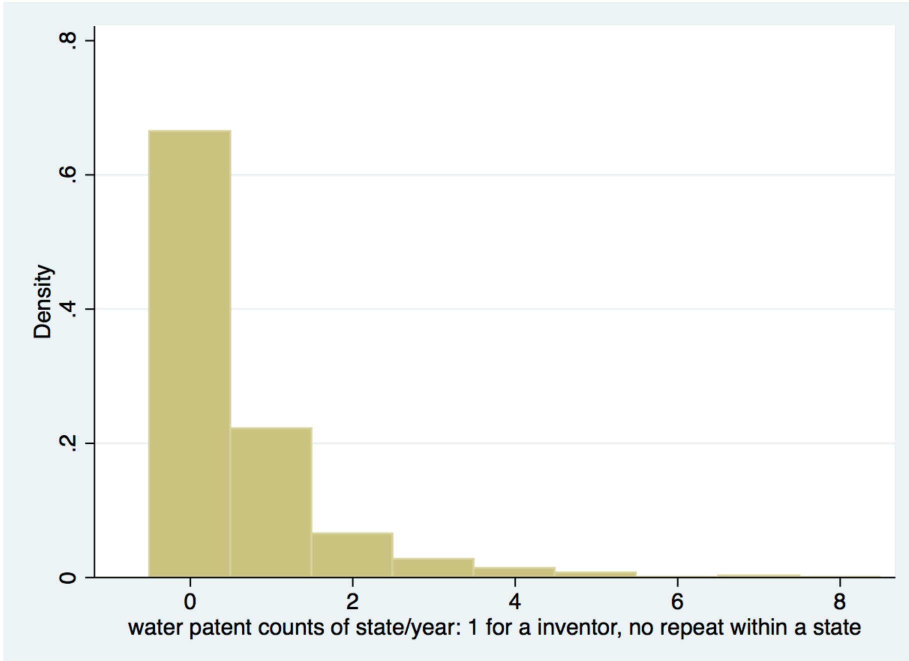

Figure A.1: Histogram of patents pertaining to drinking water technology

Appendix A.2. Water Pollution

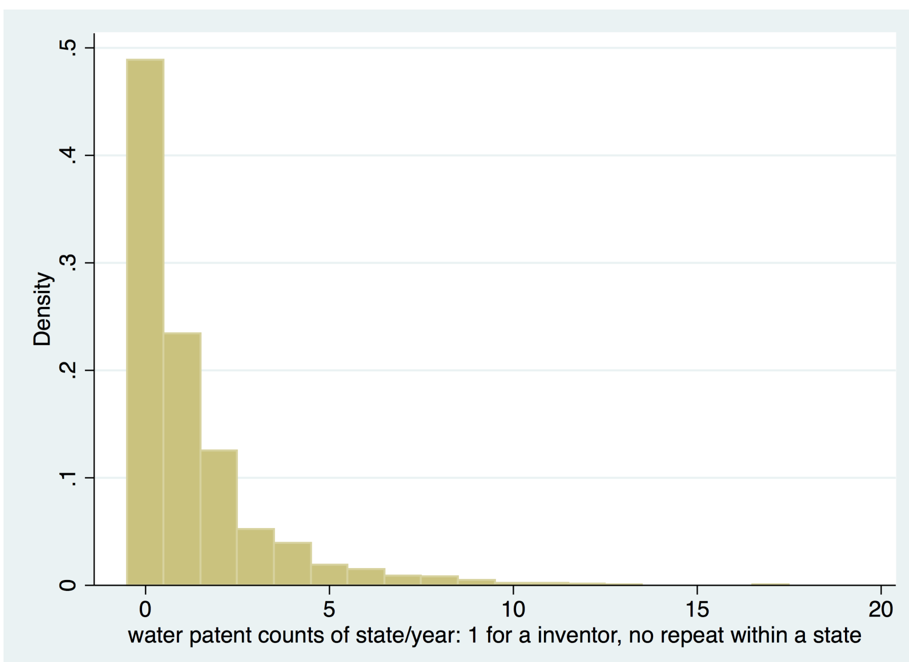

Figure A.2: Histogram of patents pertaining to water pollution treatment technology

Table A.10: Patent counts (Criterion 1) in response to the CWA amendments

	(1) Poisson QMLE	(2) NB	(3) ZIP	(4) ZINB
cwa_amendcum	0.277**	0.270**	0.271**	0.271**
	(0.0891)	(0.0926)	(0.0880)	(0.0880)
pcrealGDP	0.0116	0.0120	0.00859	0.00860
	(0.0345)	(0.0349)	(0.0338)	(0.0338)
patcount	0.00740	0.00754	0.00414	0.00414
	(0.0301)	(0.0307)	(0.0296)	(0.0296)
rd_cr_st$_{t-1}$	0.111	0.114	0.118	0.118
	(0.0915)	(0.0979)	(0.111)	(0.111)
t_edurdexpdf$_{t-1}$	-0.161	-0.163	-0.132	-0.132
	(0.232)	(0.233)	(0.229)	(0.229)
post_97	0.0129	-0.00234	0.0783	0.0781
	(0.643)	(0.650)	(0.642)	(0.642)
N	1479	1479	1479	1479
AIC	1079.0	1072.5	1076.7	1068.7
BIC	1227.4	1205.0	1225.0	1195.8
Log lik.	-511.5	-511.3	-510.3	-510.3

All regressions control state fixed effects. State-level total number of patents is employed as the predictor of excessive zeros in ZIP and ZINB models. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix A.3. Water Quantity

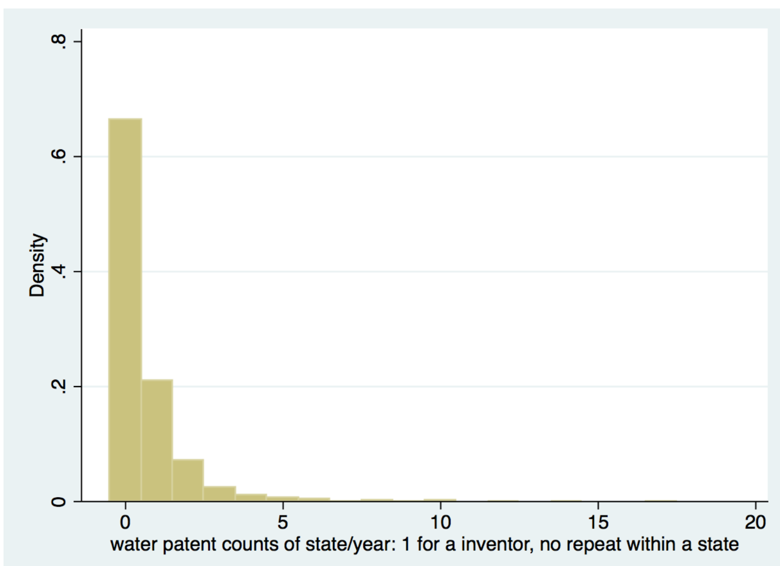

Figure A.3: Histogram of patents pertaining to water supply and demand technology

Table A.11: Patent counts (Criterion 1) in response to water planning and water scarcity

	(1) Poisson QMLE	(2) NB	(3) ZIP	(4) ZINB
L1waterplannew	0.139	0.0638	0.107	0.0880
	(0.346)	(0.433)	(0.347)	(0.434)
L2waterplannew	0.123	0.0756	0.136	0.110
	(0.243)	(0.295)	(0.241)	(0.291)
L3waterplannew	0.706*	0.611	0.885*	0.662
	(0.311)	(0.371)	(0.380)	(0.385)
L4waterplannew	0.333*	0.269	0.348	0.316
	(0.167)	(0.250)	(0.183)	(0.268)
L5waterplannew	0.393	0.424	0.370	0.439
	(0.229)	(0.281)	(0.225)	(0.267)
Cumulative effect	1.694*	1.444	1.846*	1.615
	(0.775)	(1.032)	(0.886)	(1.080)
L1tdmg_c	0.0734	0.0656	0.0644	0.0652
	(0.0430)	(0.0470)	(0.0391)	(0.0554)
L2tdmg_c	0.0993*	0.0820	0.0872*	0.0806
	(0.0398)	(0.0522)	(0.0360)	(0.0686)
L3tdmg_c	0.105***	0.0978**	0.0946***	0.0931**
	(0.0288)	(0.0329)	(0.0267)	(0.0342)
L4tdmg_c	0.0520	0.0481	0.0424	0.0395
	(0.0273)	(0.0310)	(0.0280)	(0.0306)
L5tdmg_c	0.0486	0.0541	0.0365	0.0429
	(0.0348)	(0.0385)	(0.0367)	(0.0437)
Cumulative effect	0.379***	0.348**	0.325**	0.321*
	(0.114)	(0.132)	(0.105)	(0.147)
pcrealGDP	-0.00754	-0.00248	-0.00978	-0.0143
	(0.0349)	(0.0358)	(0.0359)	(0.0496)
patcount3	-0.0146	0.00350	-0.0275	-0.00144
	(0.0447)	(0.0624)	(0.0476)	(0.0617)
rd_cr_st$_{t-1}$	3.480	2.987	3.173	2.771
	(2.257)	(2.433)	(2.129)	(2.429)
t_edurdexpdf$_{t-1}$	-0.0917	-0.209	-0.0238	-0.0707
	(0.315)	(0.443)	(0.338)	(0.475)
post_97	-0.369	-0.409	-0.317	-0.340
	(0.809)	(0.798)	(0.831)	(0.965)
N	1479	1479	1479	1479
AIC	1148.3	1144.3	1153.4	1137.6
BIC	1333.8	1324.5	1365.4	1317.8
Log lik.	-539.2	-538.2	-536.7	-534.8

All regressions control for state fixed effects. State-level total number of patents is employed as the predictor of excessive zeros in ZIP and ZINB models. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix B. Changes to the NPDWR and the SDWA

Table B.12: Changes to the SDWA and the NPDWRs

Year	Total of newly regulated	Total of revised	All contaminants	New regulation dummy	Revision dummy	SDWA Amendaments	Notes
1974	0	0	0	0	0	1	SDWA passed
1976	22	0	22	1	0	0	NPDWRs
1979	1	0	23	1	0	0	Total Trihalomethanes Rule
1986	1	1	23	0	1	1	1986 Amendments
1987	8	0	31	1	0	0	Phase I
1988	0	0	31	0	0	1	1986 Amendments: Lead Contamination Control Act
1989	4	2	35	1	1	0	Surface Water Treatment Rule and revision of total Coliform Rule
1991	28	12	62	1	1	0	Phase II and Lead and Copper, silver deletion
1992	22	1	84	1	1	0	Phase V
1995	0	0	83	0	0	0	Remand of nickel
1996	0	0	83	0	0	1	1996 Amendments
1998	7	3	90	1	1	0	Stage I Disinfectant and Disinfection Byproduct Rule Interim Enhanced Surface Water Treatment Rule
2000	1	6	91	1	1	0	Radionuclides, Lead and Copper Rule
2001	0	2	91	0	1	0	Revision: Arsenic
2002	0	2	91	0	1	0	
2005	0	0	91	0	0	1	2005 Amendments: the Energy Policy Act of 2005
2006	3	3	94	1	1	0	
2007	0	2	94	0	1	0	Revision: lead and copper
2009	0	1	94	0	1	0	Airline Drinking Water Rule
2011	0	0	94	0	0	1	2011 Amendments: the Reduction of Lead in Drinking Water Act
2013	0	2	94	0	1	0	Revised the total Coliform Rule
2015	0	0	94	0	0	1	2015 Amendments: the Drinking Water Protection Act